

Knowledge Science and Technology: Operationalizing the Enlightenment

Brian R. Gaines
Knowledge Science Institute
University of Calgary
Alberta, Canada T2N 1N4
gaines@ucalgary.ca

Abstract: The aspirations and achievements of research and applications in knowledge-based systems are reviewed and placed in the context of the evolution of information technology, and our understanding of human expertise and knowledge processes. Future developments are seen as a continuation of a long-term process of operationalizing the rational stance to human knowledge processes adopted in the enlightenment, involving further diffusion of artificial intelligence technologies into mainstream computer applications, and incorporation of deeper models of human psychological and social processes.

1 Introduction

This is the fifteenth year of the KAW meetings. On the cusp of a new millennium it is fitting to look back at what has been achieved and to look forward to the challenges and opportunities that await. There have been 30 KAW, EKAW and PKAW/JKAW/AKAW meetings prior to PKAW'2000 at which over 1,000 papers have been presented and published. Why did we start, what has been achieved, and have we satisfied the original aspirations?

2 AI and ES as Information Technologies

One of the major areas of activity of the Knowledge Science Institute has been tracking the knowledge economy, in particular, modeling and forecasting the evolution of information technology (Gaines and Shaw, 1986; Gaines, 1991b). This has involved projects such as setting the Japanese fifth and sixth generation projects within a historic context (Gaines, 1984; Gaines, 1986), and modeling the convergence of computer and communications technologies in the information highway (Gaines, 1998). This article takes a similar approach to AI, ES and KA, analyzing the expectations and achievements, setting them within the general evolution of information technology, and concluding with an analysis of recent developments in the understanding of human expertise and knowledge processes.

2.1 Expectations of AI/ES in the 1980's

John Boose and I founded the KAW series in 1986 at the peak of the artificial intelligence boom in the context of the industrial acceptance of an expert systems 'breakthrough.' IJCAI'85 in Los Angeles had attracted over 7,500 participants and had the atmosphere of a rock concert with thousands of participants avid to attend presentations in theatres that could seat 500 or less. The exhibition was like a major technology trade show with lavish stands demonstrating AI tools from innovative companies and tables sagging under the weight of a burgeoning AI literature. KAW'86 was intended to be a workshop on knowledge acquisition for some 40 specialists, but some 120 papers were submitted and we had over 400 requests to attend.

Those were heady days after the publicity for the Japanese 'fifth generation' project commencing in 1982 (Moto-oka, 1982; Gaines, 1984), with massive projections for the growth of revenues from the 'AI Industry' as shown in Figure 1.

Market Area	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990
Expert Systems	4	9	17	38	74	145	245	385	570	810
Natural Language	5	8	18	40	59	125	210	320	465	650
Visual Recognition	10	22	51	116	168	260	370	500	660	840
Voice Recognition	5	7	11	20	33	55	85	140	200	270
AI Languages	3	5	8	12	21	35	45	65	80	105
AI Computers	28	56	103	217	364	510	710	970	1250	1570
Government Contracts	20	30	40	50	95	150	150	155	175	200
Total	55	107	208	443	719	1130	1665	2380	3225	4245

Figure 1 Projection of AI Market in 1985

The received wisdom of the early 1980's was captured by Hayes-Roth (1984) in a workshop on AI Applications for Business in May 1983:-

"For the past 15 years, applied work in artificial intelligence has focused increasingly on the use of knowledge to build 'expert systems.' These systems achieve levels of performance in complex tasks that equal or even exceed that of human experts. Because they incorporate much human knowledge, these systems are called knowledge-based expert systems or, simply, knowledge systems...The industrialization of knowledge engineering began in 1981 with the formation of two commercial spin-offs from the Stanford university Heuristic Programming Project...Teknowledge focuses on industrial and commercial uses of knowledge engineering. Sales this year will be \$3 million to \$6 million."

Hayes-Roth also characterized situations that instigate knowledge engineering initiatives:-

- 1 The organization requires more skilled people than it can recruit or retain.
- 2 Problems arise that require almost innumerable possibilities to be considered.
- 3 Job excellence requires a scope of knowledge exceeding reasonable demands on human training and continuing education.
- 4 Problem solving requires several people because no single person has the needed expertise.
- 5 The company's inability to apply its existing knowledge effectively now causes management to work around basic problems.

This positive stance to AI/ES applications in the 1980's was a major change from the 1970's when the initial optimism about major advances in, and applications for, artificial intelligence had been undermined by a series of negative reports by influential contributors to the field such as: Bar Hillel's (1964) on the possibility of machine translation; Pierce's (1969) on the possibility of speech recognition; and Weizenbaum's (1976) on the possibility of artificial intelligence. In addition there were highly critical appraisals from influential outsiders such Dreyfus (1972) and Lighthill (1973), with the report of the latter having had a highly negative impact on the funding of AI research world-wide (Fleck, 1982). As shown by the data above, in the mid-1980's there was a strong feeling based on industrial acceptance of expert systems that the critics had been proved wrong and that artificial intelligence research had been successful in creating a major new industry.

2.2 State of AI/ES in the 1990's

From the current perspective, some 15 years later, how have the expectations of AI/ES been fulfilled? The attendance at AAAI/IJCAI conferences has dwindled and the exhibit floors have virtually disappeared. The market projections for an AI industry in Figure 1 do not seem to have materialized. Teknowledge still exists with some 50 employees and revenue growth to \$12M a year, which barely keeps pace with inflation. Neuron Data has become Blaze Software largely concerned with supplying technology for personalizing web sites. The expert systems shell FAQ at CMU (ftp://ftp.cs.cmu.edu/user/ai/pubs/faqs/expert/expert_1.faq) lists over 60 products but has not been updated since 1997 and, when one traces the companies listed today, most do not exist and those that do have generally migrated to the ecommerce industry.

Figure 2 characterizes the growth of the literature in AI and ES through to 1999 by plotting the number of books in the library catalog of a world-class university with a strong AI research area. The number of books with 'expert systems' in the title shows a standard sigmoidal learning curve (Crane, 1972), with the peak growth during the 1986 to 1992 period and publication waning thereafter. The number of books with 'artificial intelligence' in the title is still growing and it is difficult to accurately characterize the peak growth period but the data so far is consistent with that being from 1986 through to 1998.

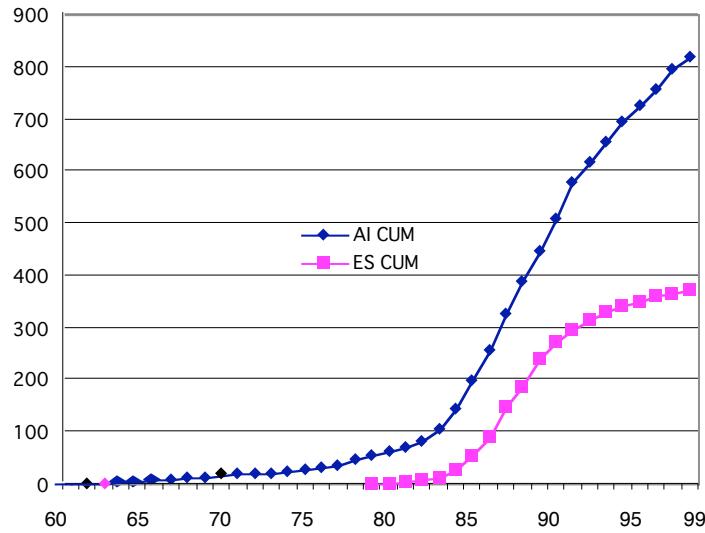


Figure 2 Growth in number of AI and ES books held in a library

It might be reasonable to conclude from this that there was false euphoria in the 1980's and that critical appraisals from the previous decades had been correct. However, the story is by no means that simple and the following sections provide perspectives and examples that elucidate what has happened and provide a basis for predicting and planning future developments.

2.3 Ongoing ES Applications and AI Achievements

One answer to the conundrum is that, while the AI/ES industry may not have grown as much as expected, expert systems are still being developed and applied that do satisfy the original aspirations. Gensym was founded in 1986 and had revenues of \$36M from a range of AI-related products and services including its G2 expert system shell. Its web site highlights some 25 corporate success stories in ES deployment (<http://www.gensym.com/>). The continuing health of the applications track at the British Computer Society annual conference on Expert Systems and of the Innovative Applications of AI track at the AAAI annual conference support this position.

More significantly, papers are being published in the professional literatures of the application areas that tell of the success of ES applications exactly as predicted by Hayes-Roth. For example, the April and July 2000 issues of InTech Magazine published by the ISA, the Instrumentation, Systems and Automation Society, has a two-part paper from Eli Lilly on the deployment of an expert system in its fermentation plant. The evaluation in 2000 is in wording that corresponds well to Hayes-Roth's predictions in 1984:-

Within a few weeks, Phil was satisfied that the expert system reliably came to the same conclusions he would have by looking at the same data (i.e., the system did what it was purported to do, which was an application and validation objective). The expert system then took over this part of Phil's job, freeing up 40 hours per month of his time for other work. Of course, whenever G2 detected a problem fermentor, or one it was unsure of, Phil, or an assistant, would be immediately paged. This application became affectionately known as "Phil in a box." Phil retired from Lilly in 1993 when the company offered an early retirement program. In fact, many of the experienced fermentation personnel at this plant, as well as several at other Lilly plants, also retired. (Alford, Cairney, Higgs, Honsowetz, Huynh, Jines, Keates and Skelton, 2000)

There have also been major advances in the theoretical foundations of artificial intelligence, notably major improvements in the bounds on rational processes of deductive and inductive reasoning such as those originally formulated by Gödel (Davis, 1965), Chomsky (1956) and Gold (1967). The theory of computational complexity (Garey and Johnson, 1979) when applied to formal knowledge representation languages shows that inference in even moderately rich representations is inherently worst-case intractable (Nebel, 1990), and there is now a comprehensive taxonomy of representation capabilities and their complexity implications (Donini, Lenzerini, Nardi and Nutt, 1997). In machine learning, complexity measures have been at the heart of inductive algorithms from the early days (Blum and Blum, 1975) and the intractability of an exhaustive search approach to fitting a model to data is an intrinsic constraint for any reasonable class of models (Gaines, 1977). Algorithmic learning theory has become a well-founded discipline encompassing such results (Natarajan, 1991), and the major theoretical advances have been in formally defining and developing approximately correct modeling approaches that are tractable (Valiant, 1974), and in demonstrating how meaningful learning can take place through socio-cultural processes (Kirby, 1999).

2.4 Assimilation of AI/ES Technologies in Mainstream Data Processing

However, a small but reasonably successful industry only captures part of the story. From the earliest days of AI pioneers such as Donald Michie have noted that an intrinsic feature of the field is that problems are posed such that all those involved accept that any solution must involve ‘artificial intelligence’ but, when the solution is developed and the basis for it is clear, the resultant technology is assimilated into standard information processing and no longer regarded as ‘intelligent’ in any deep sense. When the magician shows you how the trick was done the ‘magic’ vanishes. Much of what has been developed through AI/ES research has diffused in this way into routine information technology, the *Michie effect*.

One example of the Michie effect is the assimilation of expert systems technology into mainstream database technologies. Blaze Software supports the ‘business rules’ layer in the IBM/Microsoft three-layer client server enterprise model through use of the powerful knowledge modeling tools that were developed for the expert system shell NEXPERT. Teknowledge’s patents relating to such applications are being contested in a lawsuit by SAP, the world’s third-largest independent software supplier with revenues of over \$5B/year employing over 21,700 people in more than 50 countries in which SAP denies violating Teknowledge patents.

There are many books, manuals and white papers now available on business rules and their development. Date, the author of the standard text on relational databases, has one entitled *What Not How: The Business Rules Approach to Application Development* (Date, 2000). Seiler, the founder of Rule Machines Corporation, has a nice paper on managing business rules which shows their role within an enterprise architecture (Figure 3) and emphasizes that they are not expert systems or database triggers but rather a way in which end-user management can specify activities in terms of “business speak” (Seiler, 1999). In KA terms, the business rules are intended to support knowledge modeling by end-users, a major objective of one line of research at the KAW workshops.

The middle layer in Figure 3 can range from the operationalization of procedures manuals, internal to the company or external such as the tax or building codes, to the incorporation of sales, marketing and financial expertise that is not normally captured in procedures or training manuals. The back-end databases are usually pre-existing relational systems and the client user interface increasingly uses web browsers with HTML as the GUI programming language. The middle layer allows rich ontological models to be incorporated in terms comprehensible to managerial end users such that they can incorporate procedures based on their knowledge and requirements with the minimal of mediation by programmers. An early experiment in encoding an oil company’s procedure manual in this way was reported by Kremer (1991) at KAW’91, and noted that the use of rules with exceptions was the most natural way of encoding the constraints in the manual.

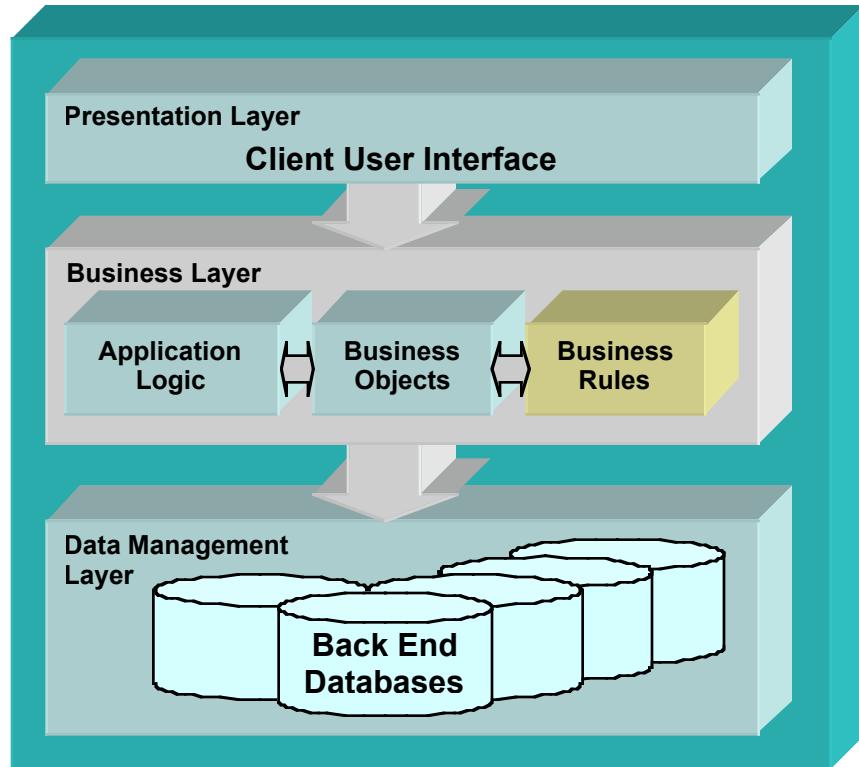


Figure 3 Business rules within n-tier application architecture (Seiler, 1999)

A related example of the Michie effect is the ongoing assimilation of AI concepts and frameworks into the mainstream data processing industry in the work of the IEEE Standard Upper Ontology (SUO) study group developing a standard for high-level database integration (<http://ltsc.ieee.org/suo/>) which draws heavily on the people and research of the KIF and CG communities. The business rules and standard ontology technologies can all be seen as the development of support for *knowledge management* within organizations, the “management of organizational knowledge for creating business value and competitive advantage” (Tiwana, 2000). The primary Japanese literature on knowledge management emphasizes the knowledge acquisition processes involved in converting ‘tacit knowledge’ into overt operational knowledge (Nonaka and Takeuchi, 1995; Von Krogh, Ichijo and Nonaka, 2000). The issues of supporting such conversion are strongly reminiscent of those of developing expert systems, and knowledge management web sites link into the KA literature (e.g., <http://www.km-forum.org/papers.htm>).

Another instance of the Michie effect has been the adoption of rule induction techniques in the scientific community to analyze databases with the results significant for, and reported in, the relevant scientific literature, for example, in research on the carcinogenetic properties of chemical compounds (Lee, Buchanan and Rosenkrantz, 1996). Langley (2000) provides a wide range of examples such AI computational support of scientific discovery. KA tools have also proved useful in helping a research community develop a consensual and comprehensible framework for its research program (Gaines and Shaw, 1994).

A different area of assimilation of AI techniques into mainstream data processing is the routine use of neural networks in conjunction with statistical techniques to model complex datasets. For example, neural networks are being used routinely in geography to develop nonlinear models of ecological (Lek and Guégan, 2000) and climatic data (Smolka and Volkheimer, 2000).

Knowledge discovery from databases (KDD, Fayyad, 1996) has clear roots in machine learning, but combines statistical tools, ontology and rule induction with graphic human interaction to provide a new hybrid technology subsuming and merging the other techniques within its own

conceptual framework. As KDD techniques becomes clearly defined and classified they will in turn merge with on-line analytical processing (OLAP, Hackney, 1997) techniques for extracting management information from data warehouses, and their AI roots will be primarily of historic interest. The Michie effect is pervasive and inevitable, but is a sign of achievement not failure.

2.5 Advances in Information Technology Solving AI Problems by Other Means

In projecting the future for artificial intelligence research it is also important to recognize that parallel advances in information technology have provided alternative solutions to some aspects of what had been regarded as 'AI problems.' For example, Hayes-Roth's list in Section 2.1 emphasizes the role of expert systems "when organization requires more skilled people than it can recruit or retain," and a classical approach to such labor shortages is through training. E-learning has also developed extensively during the same period as expert systems and there is now a major industry supporting 'corporate universities' (Meister, 1998), and providing on-the-job training and just-in-time learning (Wills, 1998). For example, the Learn4life division of SAIC, a \$10B/year company, provides modules targeted on the full range of emergency services, law enforcement, fire service and search and rescue (<http://www.Train4life.com/>), and Motorola University offers courses in a wide range of core skills areas where recruitment is problematic such as software engineering (<http://mu.motorola.com/>).

Pace Bar-Hillel, automatic translation is a freely available service on the web. Typing Wiggenstein's famous aphorism, "Wovon man nicht sprechen kann, darüber muß man schweigen" into Altavista (<http://babelfish.altavista.digital.com/translate.dyn>), one gets back "about which one cannot speak, over it one must be silent", which captures the essence quite nicely. *Pace* Pierce, speech recognition has also become a routine office product from major corporations such as IBM and Fujitsu, again without significant relations to AI developments.

Some of the most dramatic examples of 'machine intelligence' in recent years, arousing massive public interest, have been the Kasparov versus Deep Blue chess games. In 1996, Kasparov won the series but it was clear that the computer program was playing chess effectively at grandmaster level (Newborn, 1997). In the 1997 re-match Deep Blue won the series and, as Schaeffer and Platt (1997) note in regard to game 2:

"If a game such as this were ever used for a Turing Test, few would peg the computer as playing White. In fact, most grandmasters would have been thrilled to have played such a nice a game as White, regardless of who was playing the Black pieces."

Chess playing has been regarded as a benchmark 'AI problem' but the number-crunching search strategy of Deep Blue based on special chess-oriented hardware was not an AI or ES approach, and provides little insight into human chess-playing strategies.

A major advance in information technology that was not even on the horizon at KAW'86 was the development of the World Wide Web. Berners-Lee's (1989) proposal to CERN for managing its documents effectively was still three years away. His first paper about the web was relegated to a poster at Hypertext'93, and it was not until the mid-90's when Andreessen had developed what became the *Mosaic* browser and eventually *Netscape* and *Internet Explorer* that the web exploded into a ubiquitous and revolutionary technology. The web is important not only because it diverted effort from AI activities to communication technologies, but also because it provided alternative solutions to the problem of accessing expertise. The significance of discourse in the human communities collaborating through the net has been underestimated in the stress on 'artificial' intelligence in computer research. Net email and web services provide access to a far more powerful 'expert system' of human agents and their products than any currently conceivable through AI techniques.

Structured search strategies of digitally represented scientific literature have also been used in the automated development of new scientific discoveries in a way that addresses an AI problem without using AI techniques. For example, Swanson (1990) has reported on the success of a methodology that searches for implications of the form A implies B, and B implies C, in two

papers from different literatures neither of which generally cites the other. The connection that A implies C has been used to derive significant new results in some medical areas.

2.6 Convergence Between Web and AI Technologies

Developing search engines for the web has involved the use of text analysis techniques that draw primarily on information retrieval technologies rather than AI but result, in their latest versions such as Google (<http://www.google.com/>), in such precise access to a massive corpus of knowledge that they should certainly count as an advance in knowledge acquisition techniques.

Web browsers have, as in many other application areas, also provided a convenient interface to AI, ES and KA applications using HTML to program their user interfaces in a standard, and platform-independent, manner. Ontology editors for a range of KR and KA systems have been made available through the web, for example, Ontolingua (Farquhar, Fikes and Rice, 1996), Protégé-II (Rothenfluh, Gennari, Eriksson, Puerta, Tu and Musen, 1996), VITAL (Motta, Stutt, Zdrahal, O'Hara and Shadbolt, 1996), and others, as have personal construct psychology approaches such as WebGrid-II (Gaines and Shaw, 1997).

There is also an interesting convergence between web and AI techniques in the W3 'Semantic Web' framework and its implementation using the Resource Description Framework (RDF). As Tim Berners-Lee notes:

The Web was designed as an information space, with the goal that it should be useful not only for human-human communication, but also that machines would be able to participate and help. One of the major obstacles to this has been the fact that most information on the Web is designed for human consumption, and even if it was derived from a database with well defined meanings (in at least some terms) for its columns, that the structure of the data is not evident to a robot browsing the web. Leaving aside the artificial intelligence problem of training machines to behave like people, the Semantic Web approach instead develops languages for expressing information in a machine processable form. (<http://www.w3.org/DesignIssues/Semantic.html>)

The KA community has established an international working group to develop technologies for the semantic web (<http://www.semanticweb.org/>), and launched a Semantic Web journal in the Electronic Transactions on Artificial Intelligence (ETAI, <http://www.etaij.org/seweb/>) series.

3 Evolution of Information Technology

Information technology based on the stored-program digital computer has seen a rate of growth in the past fifty years that is unsurpassed by any other technology. The vacuum-tube based flip-flop memory cell enabled the development of the first generation of computers in the 1947-49 period. Reliability and performance were increased with the advent of solid-state transistors in 1959, and the number of devices on a chip increasingly exponentially since then to some billion currently has induced a similar improvement in computer performance. However, electronic devices and computers could not have been developed over nine orders of magnitude performance improvement without the use of computers themselves to support the design and fabrication of circuits and computers. This is one example of a positive feedback loop within the evolution of computers through which the computer industry has achieved a learning curve that is unique in its sustained exponential growth. Each advance in computer technology has supported further advances in computer technology.

3.1 Positive Feedback and the Tiered Learning Curves of Information Technology

Such positive feedback is known to give rise to emergent developments in biology (Ulanowicz, 1991) whereby systems exhibit major new phenomena in their behavior. The history of computing shows the emergence of major new industries concerned with activities that depend upon, and support, the basic circuit development but which are qualitatively different in their conceptual frameworks and applications impacts from that development. For example, programming has led to a software industry, human-computer interaction has led to an

interactive applications industry, document representation has led to a desktop publishing industry, and so on.

Each of these emergent areas of computing has had its own learning curve (Linstone and Sahal, 1976), and the growth of information systems technology overall may be seen as the cumulative impact of a tiered succession of learning curves, each triggered by advances at lower levels and each supporting further advances at lower levels and the eventual triggering of new advances at higher levels (Gaines, 1991b). It has also been noted in many disciplines that the qualitative phenomena during the growth of the learning curve vary from stage to stage (Crane, 1972; De Mey, 1982; Gaines and Shaw, 1986).

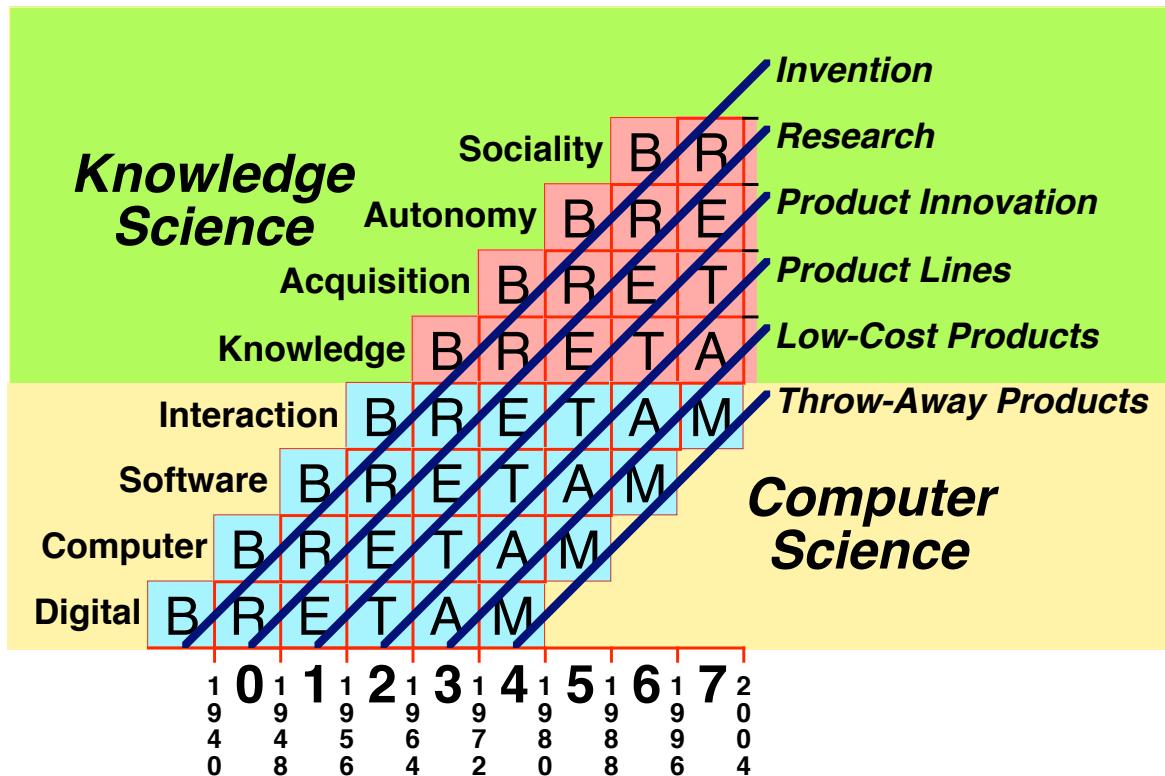
The era before the learning curve takes off, when too little is known for planned progress, is that of the inventor having very little chance of success but continuing a search based on intuition and faith. Sooner or later some inventor makes a *breakthrough* and very rapidly his or her work is *replicated* at research institutions world wide. The experience gained in this way leads to *empirical* design rules with little foundation except previous successes and failures. However, as enough empirical experience is gained it becomes possible to model the basis of success and failure and develop *theories*. This transition from empiricism to theory corresponds to the maximum slope of the logistic learning curve. The theoretical models make it possible to *automate* data gathering, analysis and associated manufacturing processes. Once automaton has been put in place, effort can focus on cost reduction and quality improvements in what has become a *mature* technology.

The dependent technologies themselves develop along their own learning curves and come to support their own dependents. Figure 4 shows a tiered succession of learning curves for information technologies in which a breakthrough in one technology is triggered by a supporting technology as it moves from its research to its empirical stage. Also shown are trajectories indicating the eras of *invention*, *research*, *product innovation*, *long-life product lines*, *low-cost products*, and *throw-away products* for different forms of information technology.

The breakthrough in *digital electronics* leading to the zeroth generation is placed at 1940 about the time of the Atanasoff and Berry experiments with tube-based digital calculations. The first breakthrough generating a computing infrastructure was Mauchly's introduction of the *general-purpose stored program computer architecture* which led to the transition from the ENIAC to the EDVAC designs. The next level of breakthrough was in *software* to bridge the gap between machine and task through the development of problem-orientated languages. The next level of breakthrough was in continuous *interaction* becoming a significant possibility as the mean time between failures of computers began to be hours rather than minutes in the early 1960s. These lower levels of electronics, computer architecture, software and human-computer and computer-computer interaction define the domain of classical *computer science*.

3.2 Emergence of Knowledge Science

The four learning curves of the tier at the top of Figure 4, of *knowledge representation*, *acquisition*, *autonomous agents* and *socially structured systems* constitute the domain of *knowledge science* where the convergence between artificial intelligence, expert systems, knowledge acquisition, databases, the web, and so on, is situated. From an AI perspective, the knowledge level breakthrough corresponds to the development of DENDRAL (Buchanan, Duffield and Robertson, 1971) for inferring chemical structures from mass-spectrometry data and MYCIN (Shortliffe, 1976) for the diagnosis of microbial infections in the early 1970s. However, it is important to note that the knowledge level also encompasses the digitization of the classical knowledge representation media through which typographic text, diagrams, pictures, sounds and videos became storable, indexable and retrievable through digital computers. Thus the breakthroughs in the 1970's represented by the introduction of raster graphics, word-processing software, MEDLINE, SGML and PostScript, are also critical events for the knowledge level learning curve.



- **Breakthrough:** creative advance made
- **Replication period:** experience gained by mimicing breakthrough
- **Empirical period:** design rules formulated from experience
- **Theoretical period:** underlying theories formulated and tested
- **Automation period:** theories predict experience & generate rules
- **Maturity:** theories become assimilated and used routinely

Figure 4 The infrastructure of information technology

Similarly, at the acquisition level, the AI breakthroughs may be seen as AM learning mathematics by discovery (Davis and Lenat, 1982) and the successful inductive inference of expert rules for plant disease diagnosis (Michalski and Chilausky, 1980). However, developments in scanning, optical character recognition, interactive graphics and page makeup systems were also significant advances in the digitization of knowledge in machine processable form. At all levels, research in robotics and machine vision has been a major source of innovation and a driving force for technologies at the upper levels involving some degree of autonomous behavior and social organization.

Figure 4 provides a context within which to model the assimilation of AI and ES technologies into standard information processing as discussed in the preceding sections. The deductive and inductive inferences processes that are seen as core to human rational intelligence, when modeled in the computer, become data processing capabilities that can be understood as such and used as computational resources where appropriate in any application. Similarly, the peripheral perceptual processes when modeled effectively become statistical pattern-recognition techniques which can again be assimilated as computational resources. The representation of knowledge at a semantic level through rich ontological structures is a natural extension of data base technology and has become assimilated as such. In particular, to the extent that the knowledge representation is natural and comprehensible to people, it becomes assimilated as part of the upper level human-

computer interface where the objective is to make the programming and use of computers natural and comprehensible to people.

From this perspective, what could not be assimilated so readily would be systems that achieved intelligent behavior in incomprehensible ways. For example, if the various experiments in electro-chemical perceptron-like elements in the 1960's had produced effective intelligent systems they might not have been so readily assimilated except as black-box peripherals. However, the history of AI research to date has been one of achieving successful performance at some task by some means, and then afterwards deconstructing that achievement to rationalize it in algorithmic form. Magic has always been transformed into science. One can see this process at work in research on quantum computing where the underlying mechanism is radically different from that of current digital computers but where science-based engineering design is being used to develop fresh approaches to the massive search tasks whose computational complexity undermines current AI algorithms (Grover, 1996). It is the advances in the understanding of inference algorithms in relation to knowledge representation schema noted in Section 2.3 that make it possible to contemplate using such alternative approaches. Both deductive and inductive inference have become precise computational sciences.

3.3 Knowledge Support Systems

What are the implications of this for the next generation of AI/ES/KA developments? One can see from Figure 4 that the line of throw-away products now encompasses the entire arena of classical computing. High-quality computer hardware, compilers, development environments, and interactive interfaces, are all now ubiquitous consumer products in the developed nations. Access to raw knowledge through the web comes at low-cost ranging from the willingness to tolerate advertising to a few hundred dollars a year for professional journals. Knowledge acquisition tools through professional services such as DIALOG are more expensive, but potentially low-cost as techniques such as those used in Google are applied to electronic versions of journals. Autonomous agents are proving their practical worth in robotics (Shen and Norrie, 1998), and research on social structures of agents is changing our theories of knowledge processes (Kirby, 1999).

In all these areas the integration of mature AI technologies such as ontology and ripple-down rules editors and inference engines can be applied to provide improved performance embodying human knowledge and expertise. For example, the selective dissemination of information (SDI) has become critical as the volume of available digitized information has increased beyond the bounds of individual utility. Current methods based on keyword searches are crude in their selectivity and difficult to customize effectively. The selection of an appropriate ontology from a library and its development through an individualized sub-ontology incorporating rules with exceptions to manage the retrieval process could be the basis of a next generation of much more effective SDI systems that are also active *awareness* agents drawing attention to emerging information and trends.

Such developments would be consistent with the notion of *knowledge support systems* introduced at KAW'87 as a framework for integrating ES, KA and multimedia knowledge sources (Shaw and Gaines, 1987). This was extended at KAW'89 to encompass a wide range of knowledge support systems shown in Figure 5, a diagram which establishes reasonable targets still valid today for the assimilation of a variety of information technologies, including AI, ES and KA, into highly interactive computational systems that amplify human expertise. It provides the content and human dimension to current developments of distributed grid architectures (Foster and Kesselman, 1999).



Figure 5 Computer-based knowledge support processes (Gaines, 1990)

It is interesting to go back even further in time to Shortliffe and Clancey's (1984) list of desiderata in the early 1980's for the second decade of ES research. Users surveyed said the systems should:

- Be able to explain their decisions to users
- Be portable and flexible so that users can access them at any time and place
- Display an understanding of its own knowledge
- Improve cost-efficiency
- Automatically learn new information when interacting with experts
- Display common sense

and system developers said that research should focus on:

- Psychological studies providing new insights into simulating expert decision-making
- Techniques for representing and using causal and mechanistic relationships allowing reasoning from first principles
- Methods for acquiring expert knowledge, encoding it and checking it for consistency and completeness

- Explanation facilities guided by understanding of how people explain things to one another and adapt to the knowledge and experience of the person requesting advice
- New machine architectures supporting high-performance decision-making programs
- Melding of symbolic techniques drawn from artificial intelligence and analytic techniques of statistics, pattern recognition and decision theory
- Novel ways in which personal computing and graphics might improve the acceptability and cost-effectiveness of systems aiding decision-making tasks.

We are now entering the fourth decade of ES development, but this list is as valid today as it was nearly 20 years ago.

3.4 Trends and Limitations

Returning to Figure 4, the line of invention leaves the existing framework, giving no indication of the areas in which breakthroughs in the current era might be expected. I have considered a third major level, of *memetics*, reflecting the autonomy of ideas within Popper's World 3 (Gaines, 1978), but do not yet have confidence in projections at that level.

The most effective technological forecasting techniques are those that identify a social need and analyze the state-of-the-art in the technical pre-conditions for it to be satisfied (Gilfillan, 1937). Most of our social needs today stem from the continued environmental impact of exponentially increasing population and the ensuing problems of famine, disease and social unrest (Meadows, Meadows and Randers, 1992). Alain Rappaport (personal communication) has drawn my attention to the migration of AI scientists into genetic engineering projects, and that is obviously one area focused on addressing current needs related to health and food. Genetic technology has a tiered structure of learning curves of its own commencing with the breakthrough in molecular biology through Watson and Crick's discovery of the double helix model of DNA in 1953 (Gaines and Shaw, 1986). We would expect convergence of computing and genetic technology on the basis of their common foundations in information encoding whether in silicon or DNA.

Perhaps the most significant conclusion to draw from Figure 4, however, is that knowledge representation and acquisition, conceived as digital computer technologies, are in the late stages of their learning curves. This may be surprising because, if one looks back to the aspirations of expert systems research in the 1980's, there is still a major gap in information technologies despite the assimilation of AI and ES techniques, and that is in the emulation of human expertise and its transfer from human experts to the computer. It is not that there has been no progress. The examples in Section 2.3 and the ongoing application of, for example, ripple-down rule techniques to building effective expert systems demonstrate that the emulation and transfer of human expertise is feasible in some domains (Compton, Edwards, Kang, Lazarus, Malor, Preston and Srinivasan, 1992). However, the large-scale emulation and transfer that fired the industrial enthusiasm of the 1980's has failed to materialize. The next section provides a framework for understanding the constraints to achieving such emulation and transfer of human expertise within existing computing frameworks.

4 The Nature of Expertise and Knowledge

When we moved to Canada in 1982 one of my first tasks was to return to the UK to act as the neutral chair of a Science Councils workshop considering funding of UK expert systems research in the light of the Japanese fifth generation initiative. My recollection of that meeting is of eminent cognitive psychologists explaining to enthusiastic computer scientists why modeling human expertise was unlikely to be effective or useful. Dreyfus and Dreyfus (1986) have presented the arguments very clearly, and the KAW meetings have from the beginning had cognitive psychology tracks addressing the fundamental issues. In particular, Bill Clancey (1997) has through the KAW meetings and a wide range of publications deconstructed simplistic notions of the nature and transferability of human expertise with the credibility of a major

pioneering contributor to expert systems development. What have we come to know of expertise, its computer emulation and transfer?

4.1 What is an Expert?

Webster's dictionary definition of *expert* as a noun is:

“a person who has special skill or knowledge in some particular field; specialist; authority,”

and as an adjective is:

“possessing special skill or knowledge; trained by practice; skillful or skilled.”

These definitions capture some significant connotations of expertise and it is useful to deconstruct them carefully.

First the use of the terms “has” and “possessing” gives skill and knowledge connotations of a substance that may be possessed. This association of expertise with substance can lead to a perspective that sees that substance as something to be transferred to a computer. It may also give the impression that to possess that substance is to be an expert.

The first association is misleading in the sense that in many cases the only evidence one has for possession of something is that an expert is capable of skilled performance in a task. One may reason that there must be some basis for this performance, and it is a possible metaphor to view this as possession of a substance. However, the ‘substance’ is an imputed hidden variable and hypothesizing its existence gives little insight into the nature of expertise. The metaphor may also be misleading in locating expertise within the expert rather than as a process of interaction between expert and situation.

The association of skill and knowledge in both definitions is part of this metaphor in implying that knowledge is the substance underlying skill. Skill is defined as both:

the ability, coming from one's knowledge, practice, aptitude, etc., to do something well,

and as

competent excellence in performance; expertness; dexterity.

The problem of relating these two definitions of skill, the first causal and the second phenomenological, involves major ontological, epistemological and psychological issues.

Knowledge is defined as:

acquaintance with facts, truths, or principles, as from study or investigation.

What are facts, truths and principles and how does acquaintance with them lead to competent excellence in performance? Does skilled behavior indicate the possession of knowledge?

The impression that the *possession* of skill is adequate to capture the normal usage of the term expert is also misleading. One would term someone skilled who can perform a task well, but to term someone expert has connotations going beyond mere skill, of being able to perform well in difficult situations, of maintaining the performance in changing, unexpected and novel circumstances. These are the connotations which Schön (1983) emphasizes in his discussion of “reflective practitioners” who do not attempt to merely preserve their existing capabilities but to extend them continually in order to match changing circumstances.

The auxiliary terms in the definitions are interesting in suggesting other aspects of expertise. It is *specialist*, not a general attribute like intelligence, and hence can be seen as a situated role that a person can play rather than a general property of that person. Its being associated with *authority* suggests that it plays a social role in that others must allow an expert:

the power to determine, adjudicate, or otherwise settle issues or disputes; jurisdiction; the right to control, command or determine.

Its association with being *trained by practice* indicates one, but only one, of the many processes whereby expertise is acquired.

The problems introduced by attempting to model human action as derived from knowledge have been extensively discussed in the literatures of philosophy and sociology. Gadamer, in his critique of Hegel's theory of knowledge, highlights the fundamental issues underlying the relation of expertise to knowledge:

For Hegel, it is necessary, of course, that the movement of consciousness, experience should lead to a self-knowledge that no longer has anything different or alien to itself. For him the perfection of experience is 'science', the certainty of itself in knowledge. (Gadamer, 1972)

However, Gadamer argues:

The nature of experience is conceived in terms of that which goes beyond it; for experience can never be science. It is in absolute antithesis to knowledge and to that kind of instruction that follows from general or theoretical knowledge. The truth of experience always contains an orientation towards new experience. That is why a person who is called 'expert' has become such not only through experiences, but is also open to new experiences. The perfection of his experience, the perfect form of what we call 'expert', does not consist in the fact that someone already knows everything and knows better than anyone else. Rather, the expert person proves to be, on the contrary, someone who is radically undogmatic; who, because of the many experiences he has had and the knowledge he draws from them is particularly equipped to have new experiences and learn from them. (Gadamer, 1972)

In the expert systems literature, Clancey has criticized approaches to expert system development based the assumption that expertise can be captured in overt knowledge, and comes to similar conclusions:

The new perspective, often called situated cognition, claims that all processes of behaving, including speech, problem-solving, and physical skills, are generated on the spot, not by mechanical application of scripts or rules previously stored in the brain. Knowledge can be represented, but it cannot be exhaustively inventoried by statements of belief or scripts for behaving. Knowledge is a capacity to behave adaptively within an environment; it cannot be reduced to representations of behavior or the environment. (Clancey, 1989)

He argues that overt representations of knowledge are only partial models of the knowledge processes underlying human behavior:

A representation is not equivalent to knowledge

A representation of what a person knows is just a model of his or her knowledge, a representation of a capacity. Knowledge cannot be reduced to (fully captured by) a body of representations. Knowledge cannot be inventoried.

The meaning of a representation cannot be made explicit

Meaning can be represented, but it cannot be defined once and for all, captured fully by representations. The meaning of a representation is open, though there are culturally stable representations of meaning (e.g., word senses).

The context in which a program is used cannot be made explicit

Context can be represented, but the world cannot be objectively and exhaustively described; cultural or social circumstances cannot be reduced to a set of facts and procedures. (Clancey, 1993)

4.2 What is the Basis of Expertise?

The nature of human capabilities and knowledge have been a major topic studied by philosophers from the earliest times, and it is not surprising that artificial intelligence research has not resolved their nature in its comparatively short history. Indeed, any fundamental resolution would be highly unlikely, and any pragmatic technological resolution would be expected to have limited application. However, the issues and aspirations will not, and should not, go away. Minimally, the computer is a powerful tool for operationalizing a theory, allowing us to simulate its application and consequences, and at the same time testing whether the theory is sufficiently clearly expressed to have well-defined applications and consequences.

Much of the current thought on the nature of expertise and knowledge can be seen as stimulated by the later works of Wittgenstein, in particular, his arguments that the notion of human behavior “following a rule” is paradoxical:

This was our paradox: no course of action could be determined by a rule, because every course of action could be made to accord with the rule... ‘obeying a rule’ is a practice... If I have exhausted the justifications I have reached bedrock, and my spade is turned. Then I am inclined to say: “This is simply what I do.” (Wittgenstein, 1953, 201, 202, 217)

Given that the majority of expert systems technology attempts to emulate human expertise through representation as rules, and that the majority of knowledge acquisition methodologies are concerned to derive those rules from human behavior, one would expect that attempts to model human behavior that address Wittgenstein’s arguments might be particularly relevant to AI/ES. Pierre Bourdieu, the French philosopher and sociologist, has generated a major literature on human psychology, culture and sociology, that stemmed from just this consideration:

I can say that all my thinking started from this point: how can behaviour be regulated without being the product of obedience to rules? (Bourdieu, 1990, 65)

The answer to this question from a wide variety of sources is that all human behavior is generated within a rich *background*, to use Searle’s (1992) terminology, that is implicit and not consciously represented, and is constituted through acculturation processes that internalize the historic development of a particular society or institution.

Bourdieu builds on the previous analyses of Aristotle, Hegel, Nietzsche, Husserl, Schutz, Wigggenstein, Heidegger and Merleau-Ponty, to provide a very detailed analysis of socially-embedded human behavior in terms of three major constructs: *habitus* which is a system of dispositions extending Aristotle’s analysis of *hexis*; *field* which is a network of influences and power relations extending Lewin’s analysis of behavior within a social field; and *symbolic capital* abstracting and generalizing Marx’s analysis of capital formation and Weber’s extension of it to cultural domains. Bourdieu’s output in books and papers is prolific, ranging from detailed ethnographic and statistical studies through sociological models of a wide range of institutions to deep theoretical analyses—a good starting point is the interviews and essay in Bourdieu (1990).

Bourdieu’s model of *habitus* is particularly important to the modeling of human expertise:

I am talking about dispositions acquired through experience, thus variable from place to place and time to time. This ‘feel for the game’, as we call it, is what enables an infinite number of ‘moves’ to be made, adapted to the infinite number of possible situations which no rule, however complex, can foresee. (Bourdieu, 1990, 65)

Action guided by a ‘feel for the game’ has all the appearances of the rational action that an impartial observer, endowed with all the necessary information and capable of mastering it rationally, would deduce. And yet it is not based on reason. (Bourdieu, 1990, 65)

Bourdieu has had no interest in artificial intelligence and little as yet in technology, but Searle (1992) has used this model of human behavior as founded on an implicit background or *habitus* to critique cognitive science and computational analogies of the operation of the human mind, and it is at the heart of the Dreyfus (1986) critique of expert systems.

What are the implications of an understanding of human behavior in terms of *habitus* for research in AI and ES, apart from suggesting that the task of developing expert systems comparable in their competence to people is a difficult, if not impossible, one? It is, perhaps, salutary here to reverse the analysis and examine the quality of judgement of experts. In a survey of studies of the accuracy of human subjective probability judgements, Tversky and Koehler conclude:

The evidence reported here and elsewhere indicates that both qualitative and quantitative assessments of uncertainty are not carried out in a logically coherent fashion, and one might be tempted to conclude that they should not be carried out at all. However, this is not a viable option because, in general, there are no alternative procedures for assessing uncertainty. (Tversky and Koehler, 1994)

In the domain of expertise in scientific research, Feyerabend (1975) has argued that there is no evidence of a rational methodology, and Fortun and Bernstein (1998) have provided a compelling account of scientific progress as 'muddling through.' In *Voltaire's Bastards*, Saul argues:

Among the illusions which have invested our civilization is an absolute belief that the solution to our problems must be a more determined application of rationally structured expertise. The reality is that our problems are largely the product of that application. (Saul, 1993, 8)

4.3 The Dynamics of Expertise Formation

How is it that imperfect human capabilities are construed as expertise and that muddling through is effective? One answer is that human expertise arises in the context of human action as a pragmatic process of dealing with present contingencies knowing that there will be further opportunities to deal with the consequences of our actions at a later stage. The decision to treat a patient in a certain way is an *experiment* that entails monitoring the consequences with a view to planning future treatment. Human action takes place in a control loop with imperfect information at each decision point, and with the unfolding process continually changing the state of play.

In many situations it is more important to act in a way that is not wildly wrong rather than to compute the optimum action, particularly when available information is inadequate, inaccurate, expensive to obtain, and so on. It is generally important to know who has the authority to act and who is accountable for monitoring the consequences, taking follow-up action, and so on. The giving, or taking, of the authority to be in control in a particular domain demarcates the abstract role of an 'expert' in that domain relative to the social norms of the institution that accepts ownership of the domain.

A simple analysis of the phenomenon of such assignment of authority in a society of learning agents shows that actual expertise, in the sense of greater capabilities, arises naturally through the positive feedback processes involved in proto-experts having greater access to learning experiences (Gaines, 1988). An extended analysis shows that society can optimize the rate at which the proto-experts learn without having any understanding of either the underlying of the domain, the basis of expert performance in it, or the processes of learning involved (Gaines, 1997). The management of expertise formation in a society of learning agents can be highly successful while being remarkably knowledge-free in all its aspects.

Figure 6 is a diagram from KAW'88 of the processes of expertise formation through a variety of feedback processes (Gaines, 1989). The central loop showing the client-expert dialog derives from studies by Hawkins (1983) of industrial experts in mineral exploration, and emphasizes that the generation of advice is a feedback process of discourse and modeling. The upper and lower ovals showing the expert's interaction with his or her professional and client communities is what I would now want to describe in terms of the development of the expert's habitus, using Bourdieu's term deliberately to avoid any implication of the development within the expert of explicit knowledge (and disliking the adjective 'explicit' in this statement because the implicature of thus allowing the term 'implicit knowledge' may be highly misleading). That is, I would say today that the process shown in Figure 6 captures much of the dynamics of expertise formation but would want to make the matters of 'knowledge acquisition' and 'knowledge formation' the subject of a different level of discussion.

The client community in Figure 6 constitutes the domain of practice for the expert, and the role of knowledge-level explanation in that community might be expected to be very different from that in the professional community which, among other things, constitutes the domain of reflection. The conditions of satisfaction in the client community are ones of achievement in problem-solving, not necessarily success but at least the assessment of 'as well as might be expected.' Discourse is at the level of potential outcomes, contingency plans, risk management, about what might happen and how the contingencies may be managed under different action plans rather than why questions involving foundational considerations of underlying models.

The conditions of satisfaction in the professional community are ones of effective expertise development and transmission, of access through apprenticeship, case reports, evaluation of procedures, rationalization through links to existing models, related literatures and so on. Discourse is at the level of managing the formation of expertise and this may involve reflective processes raising why questions and addressing foundations, but note that the objective of these is to develop expertise, a coaching function, rather than to discover 'truth' or uncover 'reality.' Rationalizations are valid to the extent that they help the development of expertise, and that development does not necessarily leave any residue of the rationalization in the expert's mind. It is possible to have an effective knowledge-level approach to expertise development without basing it on a knowledge-level approach to expert performance (Vickers, 1990).

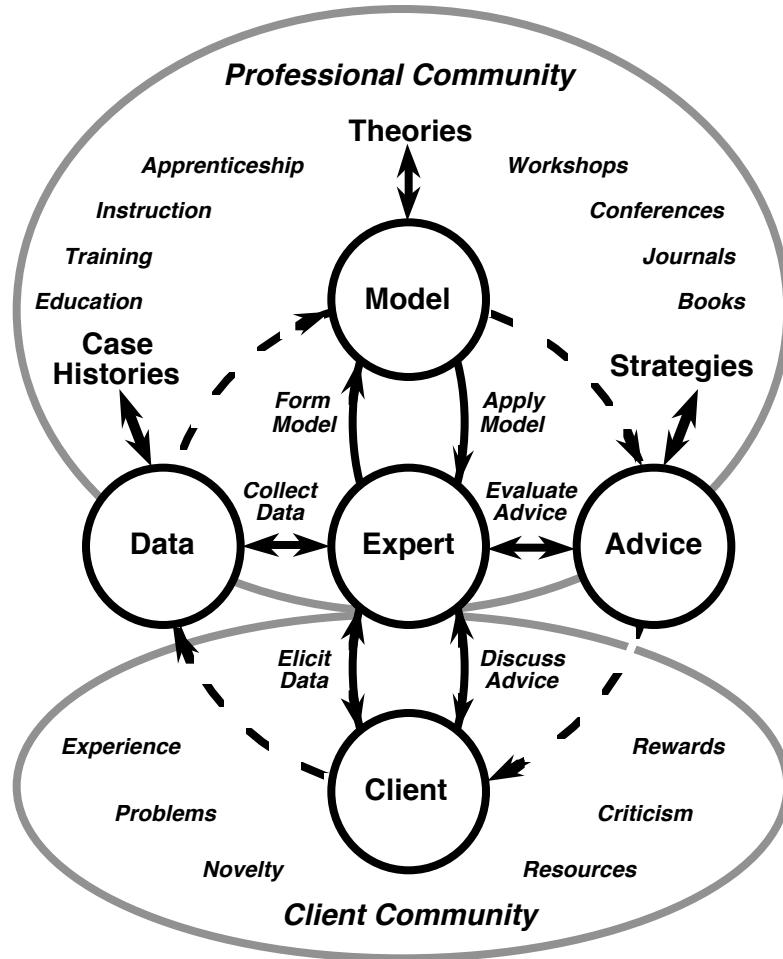


Figure 6 Expertise formation through expert-community interaction

Bourdieu's other dimensions of field and social capital may also be exemplified in terms of Figure 6. The expert acts in a specific situation within a social network of power relations with clients, colleagues, regulatory agencies, and so on, and competes within that field for symbolic capital that will affect his or her ongoing and future status within such fields. That is, the decisions and recommendations made are not just an outcome of the problem situation and the expert's dispositions through his or her habitus, but also reflect the interaction of habitus and field, in particular, the impact upon the expert's symbolic capital of the possible outcomes. The solution of any particular problem is situated within the processes of developing the overall competence of the community as a social network. Shapin (1994) has documented the importance of the power relations and symbolic capital in the development of science.

4.4 An Overall Framework for Human Activity

Figure 7 is the latest version of an evolving model that we have used at many KAW meetings and in many publications in an attempt to capture the entire conceptual framework for human psychology, sociology, action and knowledge in a simple diagram.

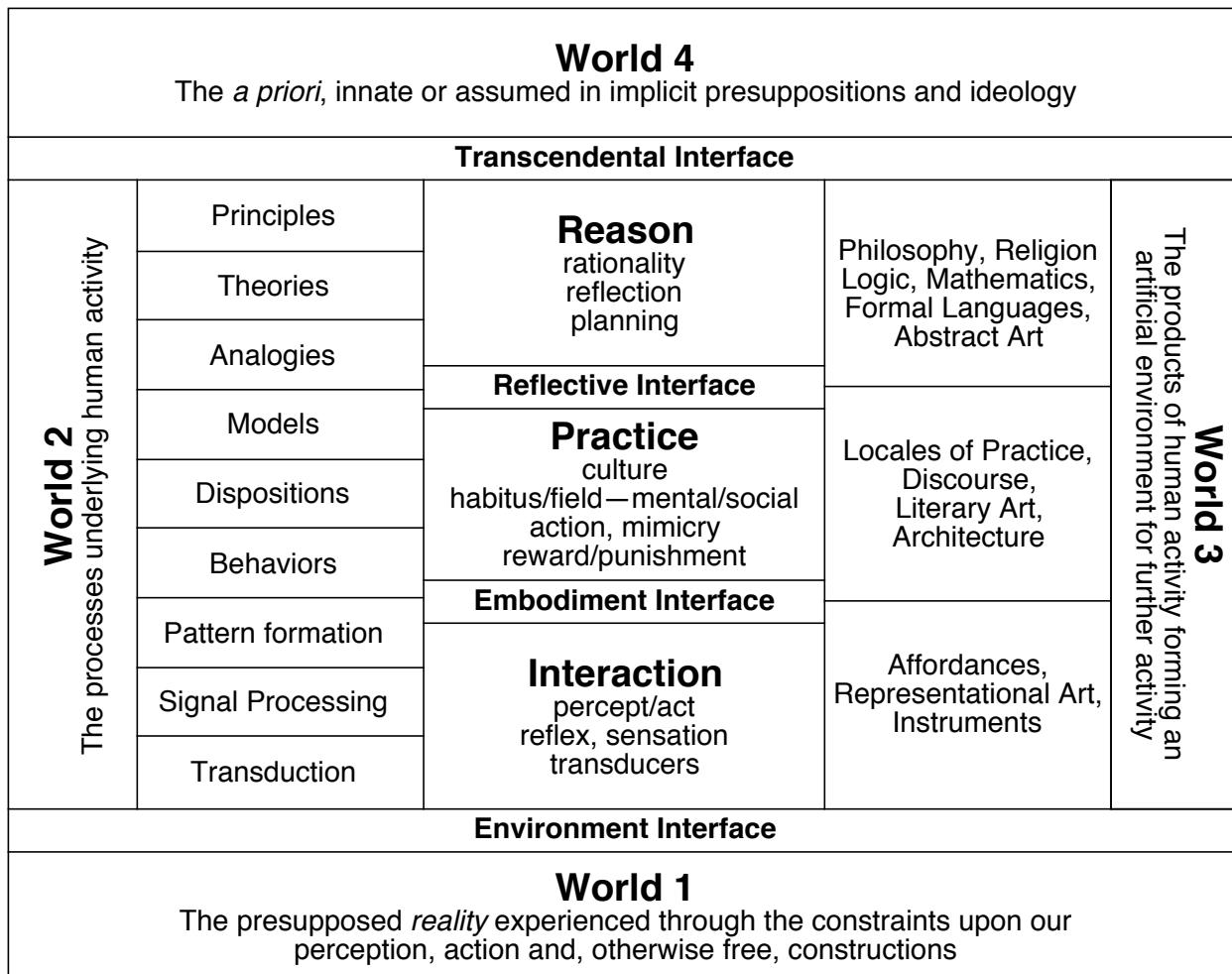


Figure 7 Levels and worlds of being

The central region presents a three-layer model of human entities, whether roles, people, groups, institutions or societies. At the bottom are the processes of interaction with the environment, of percepts, acts, reflexes, sensation, transducers, and so on. This is the level that is being emulated and extended with increasing effectiveness through neural networks (Elman, Bates, Johnson, Karmiloff-Smith, Parisi and Plunkett, 1999). At the top are the processes of reason, of rationality, reflection, planning and so on. This is the level that is being emulated with increasing effectiveness through digital computation. In the middle are the processes of practice, of culture, habitus and field characterizing the mental and the social, action, mimicry, reward and punishment. This is the level where neither neural networks nor digital computation have so far provided adequate emulation, and lack of such emulation is the greatest impediment to the development of expert systems.

The four surrounding boxes set human entities within the context of Popper's (1968) *three worlds*, as we have done in many previous papers, but adding a fourth world at the top to balance the presupposed World 1 of physical reality with an equally presupposed World 4 of transcendental *a priori* presuppositions and ideology. Popper would probably have placed our

World 4 in his World 3, as a human artifact, but we separate it here to emphasize its psychological and cultural status as something presupposed not constructed. Friedman (1999) has presented a reconstruction of the work of the logical positivists, particularly Carnap, suggesting that their contribution is best understood as offering a new conception of *a priori* knowledge and its role in empirical knowledge, the link between our Worlds 4 and 1. Searle (1998) has argued that realism is based on a presupposition of a real world underlying all our further discourse and hence is not itself subject to empirical study, and there are other such presuppositions.

The box on the left of the central core attempts to situate in relation to the three layers of the core a hierarchy of World 2 levels of construction similar to those we previously derived from Klir's (1976) *epistemological hierarchy* generated through a system of distinctions (Gaines and Shaw, 1984), and have used to model various forms of knowledge transfer in individuals and organizations (Gaines, 1994). The box on the right of the central core attempts to situate in relation to the three layers of the core some major World 3 products, with Giddens' (1986) *locales* of practice in the center, and Gibson's (1979) *affordances* at the bottom. One feature of this representation of World 3 in relation to World 2 is that it stresses how human activity is not just culturally situated in its habitus and socially situated in its field, but also artifactually situated in a humanly built world that exists in major part to trigger off the dispositions within a habitus. Our being is essentially embedded not only in the being of others with whom we interact but with that of others who have left artifacts from their activities within which ours take place.

4.5 Implications for Research

There are many implications for research in the diagram above, far too many since research in AI, ES and KA cannot be expected to take on the *problematiques* of each and every discipline represented in Figure 7. However, one can delineate some realistic research agendas.

There are two major research areas currently concerned with eroding the central territory of practice in Figure 7 by extending the areas of interaction below it and reason above it. Connectionist research has had major practical achievements in emulating human pattern learning capabilities at the interaction level, and is seen by many researchers as capable of emulating higher brain functions including the domain of practice. Spitzer's (1999) *The Mind Within the Net: Models of Learning, Thinking and Acting* is a good exposition of the state of the art. Lenat's Cyc project may be seen as an attempt to emulate human practice by extending the domain of reason downwards and developing a rich habitus based on a massive knowledge base coupled with a range of inference methods from logical deduction, through statistical induction, to speculative reasoning based on analogy (Lenat and Guha, 1990). DARPA continues to fund the development and application of Cyc through Cycorp (<http://www.cyc.com/>), and it is the core system in a range of well-funded DARPA projects such as High-Performance Knowledge Bases (HPKB, Cohen, Schrag, Jones, Pease, Lin, Starr, Gunning and Burke, 1998).

It is early days to forecast how far connectionism may move up or Cyc-like systems may move down. One would expect success in domains where the habitus is strongly circumscribed, such as highly specific roles that people play that, given the state-of-the art of emulation of human sensory-motor systems, also involve strongly circumscribed interaction with the world. An example domain of this nature that has been extensively studied is that of pronunciation of words from text. DECTalk is a text-to-speech expert system with human capabilities modeled through rules with exceptions, and one of the achievements of connectionism has been to show that a neural net, NETtalk, can learn to speak better than the expert system (Sejnowski and Rosenberg, 1987). Later, Dietterich, Hild and Bakiri (1995) found that better performance than both DECTalk and NETtalk could be achieved through standard machine learning algorithms. This is an example of a significant but highly circumscribed habitus being modeled through approaches from below and above, and a bridge being created between the modeling of human practice in the expert system, connectionism from below, and machine learning from above. This is also a domain where there are major literatures on child development, educational practice,

psychological studies, cognitive models, and so on, where it might be reasonable to expect an exhaustive synthesis to be feasible.

One form of habitus that should be more amenable to modeling by rules is where the behavioral regularities are induced by normative rules such as government codes, company operating procedures or equipment operation manuals. These examples characterize major areas of successful application of expert systems technology. Business rules are generally imposed, not induced from behavior, and it is notable also that Gensym's list of success stories largely relates to industrial process control. In such applications the expert system is put in place not so much to model the habitus but to manage it. However, knowledge acquisition from experts is still relevant because normative rule sets are rarely complete and require interpretive guidelines and extensions often derived from practice.

The role of field and symbolic capital is also significant for expert system development. One needs to situate the experts in their institutional setting and analyze their roles within their social networks. What is their organizational function, how are they recruited, how do they acquire expertise, to whom do they report, on whom do they rely for support, and how does all this play out in terms of tasks, action, monitoring and control? A cognitive stance attempting to look within the experts' minds needs to be complemented with an institutional stance examining their situations. In conventional systems development, task and situational analyses are routine techniques and often lead to organizational redesign that simplifies or by-passes the need to incorporate existing roles and expertise.

What technologies might be most effective in modeling habitus? It is interesting to note that the Wittgenstein-derived literature on the incoherence of rules (e.g. Kripke, 1982), and the Goodman-derived literature on the incoherence of inductive inference (e.g. Stalker, 1994) both use exceptions to rules in their counter-examples, that is breakdowns in rules are fixed by adding exceptions. Paul Compton and I (Compton and Jansen, 1990; Gaines, 1991a; Compton et al., 1992; Gaines and Compton, 1995; Gaines, 1996; Richards and Compton, 1998) have long promoted the representation of expertise through rules with multi-level exceptions as one that arises naturally, is easy to acquire, update and understand, provides a pragmatic fit to complex human action but supports reflection to extract the principled knowledge that corresponds to insight. One can embed such rule-based model in as rich a representational schema as one wishes, derived from pre-existent ontologies, just-in-time extensions to them or pattern-formation in neural networks.

The major extension I would see as necessary to use such systems to more richly model habitus is that multiple, prioritized rule sets need to be used and the conclusions need to be general constraints not specific values so that the output is more a structured constraint system than a single outcome (multiple-classification RDR go some way towards this, Kang, Compton and Preston, 1995). This would allow for the resolution of conflicting constraints which no possible action satisfies but where there is a set of *admissible* actions that satisfy the constraints, and where the selection of a particular action among them is indeterminate. This indeterminacy is realistic in terms of human practice and desirable since the role of randomness in breaking out of sub-optimal behavioral loops and learning outcomes has been known since the early days of AI (Gaines, 1969).

What theoretical developments are promising for modeling human expertise? I have already discussed Pierre Bourdieu's work on habitus, field and symbolic capital. John Searle (1998) seems to me to be providing the richest and most operational framework for modeling human intentional behavior that is consistent with the notion of habitus. Niklas Luhman (1995) has provided a complementary framework for institutions based on his appropriation of the notion of autopoiesis in the context of social systems. The appropriate mathematical foundations are to be found in the literature on chaos theory and its application in the social sciences (Vallacher and Nowak, 1994; Eve, Horsfall and Lee, 1997).

5 Conclusions—Operationalizing the Enlightenment

This paper has had the pragmatic objective of attempting to provide some perspectives on research in artificial intelligence, expert systems and knowledge acquisition that will be useful in formulating future research agendas. It has recalled the initial excitement, expectations, and aspirations, reviewed what has happened to date, shown the extent of the Michie effect whereby AI developments, once understood, are assimilated into mainstream information technology, and suggested research opportunities for knowledge support systems within the current ethos of convergence and integration.

It has addressed the continuing impediments to the computer emulation of human expertise that stem from inadequate theories of the nature of that expertise, and has surveyed developments in psychological, cultural and sociological research that promise greater understanding of human practice. It has suggested further research opportunities that bring those developments into the ambit of artificial intelligence and support new approaches to expert and knowledge support systems.

I subtitled this article, *operationalizing the enlightenment*, because it seems to me that computer technology is the latest of many powerful tools that have been developed to further the processes that we associate with Greek enlightenment's invention of new modes of thought and argument (Solmsen, 1975), and the seventeenth century enlightenment's application and extension of those intellectual tools, together with material tools resulting from advances in technology, to create modern science (Cohen, 1994). The notion of enlightenment has been a focus of discussion for some centuries with many responses, reactions and evaluations. Zöllner's question, what is enlightenment?, in the *Berlinische Monatsschrift* of December 1783 prompted a range of distinguished replies. Moses Mendelssohn saw it as "related to theoretical matters: to (objective) rational knowledge and to (subjective) facility in rational reflection about matters of human life." Karl Reinhold saw it as "the making of rational men out of men who are capable of rationality." Immanuel Kant saw it as "mankind's exit from its self-inflicted immaturity...the inability to make use of one's own understanding without the guidance of another" and added the aphorism "If it is asked 'Do we now live in an enlightened age?' the answer is 'No, but we do live in an age of enlightenment.'" (Schmidt, 1996)

The notions of rationality, and the freedom to be rational, are still with us as enlightenment objectives, and Kant's aphorism is as valid today as it was over two centuries ago. The enlightenment is a project of which we all, as scholars and researchers, are part. The computer is *par excellence* a tool for making rationality operational, for mechanically developing the consequences of our postulates in an environment that ruthlessly exposes sloppy definitions and invalid derivations. It is the ultimate tool of the enlightenment as we have conceived it so far.

However, from the discussion in Section 4 and the literature cited it should be clear that human beings and their institutions are not naturally rational in this sense—enlightenment rationality is a stretch goal, not a natural consequence of our being. And it may be a dangerous goal. Horkheimer and Adorno (1972) have argued "the fully enlightened earth radiates disaster triumphant." Wojciechowski (1983) has exemplified this in the way that the majority of the world's problems now stem from knowledge, yet can only be solved by developing more knowledge, the ultimate escalatory positive feedback loop. Bickerton (1990) has argued that our higher level capabilities may not be survival traits for the species. Bourdieu (1988) has turned the spotlight of his analysis of habitus on *homo academicus* and shown how scholarly practices conform to the same principles as other behavior which we would not regard as rational by our idealistic canons. Rationality is not a path to utopia but, in the developed world at least, it has become one of those presuppositions that is core to the habitus created by our educational systems. We could only attempt to reject it, in most spheres of our society, within a framework that accepts it.

I believe these deep discussions at the species level parallel significant discussions that need to take place at the institutional level. Why should knowledge management that attempts to derive explicit knowledge from implicit knowledge be expected to improve some evaluative measure of an institution? Our habitus leads to this intuition, but that is as much a source of blindness as insight. The entire conceptual framework needs deconstruction: what do we mean by ‘implicit knowledge’; does it exist; what is it to make it explicit; can we do this; how should we proceed; what outcomes should we expect; how can we measure the cost of doing all this and the benefits, if any, that result? In practice, as with expert systems, some organizations will experiment, claim benefit, and use this to advance their competitive position through their marketing stance, true or not. That is the nature of practice, and the engineering of rationality is embedded in the socio-economic practices of those responsible for it, like any other engineering project.

This is not to pour scorn on those who advocate some form of knowledge management. The social practices that are described by major authors in this area are often interesting, innovative and attractive, advocating more open and sharing institutions promoting the emergence of leadership and teaming appropriate to changing contingencies. One can well imagine that the processes advocated can be effective in improving performance, and that the rationale provided is comprehensible, meaningful, acceptable and motivating. However, none of that connects the rationale to the underlying processes that lead to these outcomes in any rational, scientific way. Research on knowledge management does, however, as did that on expert systems, provide an experimental playing field in which scientific research on those underlying processes might be conducted. There are important opportunities to be grasped.

In conclusion, I think the field of knowledge acquisition research is as exciting, challenging and rewarding as it was twenty years ago. It is far more daunting for the young researchers entering the field because of the accumulated literature of many thousands of papers with links to other rich literatures. It is less fashionable because industry’s focus of attention has moved elsewhere, and start-up fields with small literatures are easier to enter and promise more rapid chances for establishing one’s reputation. However, there are rich opportunities for major scientific and technological contributions, and I hope this article has helped to indicate some of them.

Acknowledgment

Financial assistance for this work has been made available by the Natural Sciences and Engineering Research Council of Canada. I am grateful to Paul Compton for the opportunity to make this presentation and for his stimulating collegial support and generous access to his research materials over many years.

References

Alford, J., Cairney, C., Higgs, R., Honsowetz, M., Huynh, V., Jines, A., Keates, D. and Skelton, C. (2000). Real rewards from artificial intelligence. **InTech** (April) 52-55.

Bar-Hillel, Y. (1964). **Language and Information: Selected Essays on Their Theory and Application**. Reading, Massachusetts, Addison- Wesley.

Berners-Lee, T. (1989). Information Management: A Proposal. CERN, Geneva. <http://www.w3.org/History/1989/proposal.html>.

Bickerton, D. (1990). **Language and Species**. Chicago, University of Chicago Press.

Blum, M. and Blum, L. (1975). Toward a mathematical theory of inductive inference. **Information and Control** 28(2) 125-155.

Bourdieu, P. (1988). **Homo Academicus**. Cambridge, Polity Press.

Bourdieu, P. (1990). **In Other Words: Essays Toward a Reflexive Sociology**. Oxford, Polity.

Buchanan, B.G., Duffield, A.M. and Robertson, A.V. (1971). An application of artificial intelligence to the interpretation of mass spectra. Milne, G.W.A., Ed. **Mass Spectrometry Techniques and Applications**. New York, John Wiley.

Chomsky, N. (1956). Three models for the description of a language. **I.R.E. Transactions on Information Theory** **2** 113-124.

Clancey, W.J. (1989). Viewing knowledge bases as qualitative models. **IEEE Expert** **4**(2) 9-23.

Clancey, W.J. (1993). The knowledge level reinterpreted: modeling socio-technical systems. **International Journal of Intelligent Systems** **8**(1) 33-49.

Clancey, W.J. (1997). **Situated Cognition: On Human Knowledge and computer Representation**. Cambridge, UK, Cambridge University Press.

Cohen, H.F. (1994). **The Scientific Revolution: A Historiographical Inquiry**. Chicago, University of Chicago Press.

Cohen, P., Schrag, R., Jones, E., Pease, A., Lin, A., Starr, B., Gunning, D. and Burke, M. (1998). The DARPA High-Performance Knowledge Bases Project. **AI Magazine** **19**(4) 25-49.

Compton, P., Edwards, G., Kang, B., Lazarus, L., Malor, R., Preston, P. and Srinivasan, A. (1992). Ripple down rules: turning knowledge acquisition into knowledge maintenance. **AI in Medicine** **4**(6) 463-475.

Compton, P. and Jansen, R. (1990). A philosophical basis for knowledge acquisition. **Knowledge Acquisition** **2**(3) 241-258.

Crane, D. (1972). **Invisible Colleges: Diffusion of Knowledge in Scientific Communities**. Chicago, University of Chicago Press.

Date, C.J. (2000). **What Not How: The Business Rules Approach to Application Development**. Reading, MA, Addison-Wesley.

Davis, M. (1965). **The Undecidable: Basic Papers on Undecidable Propositions, Unsolvable Problems and Computable Functions**. Hewlett, N.Y., Raven Press.

Davis, R. and Lenat, D.B. (1982). **Knowledge-Based Systems in Artificial Intelligence**. New York, McGraw-Hill.

De Mey, M. (1982). **The Cognitive Paradigm**. Dordrecht, Holland, Reidel.

Dietterich, T.G., Hild, H. and Bakiri, G. (1995). A comparative study of ID3 and backpropagation for English text-to-speech mapping. **Machine Learning** **18** 51-80.

Donini, F.M., Lenzerini, M., Nardi, D. and Nutt, W. (1997). The complexity of concept languages. **Information and Computation** **134**(1) 1-58.

Dreyfus, H.L. (1972). **What Computers Can't Do: A Critique of Artificial Reason**. New York, Harper & Row.

Dreyfus, H.L. and Dreyfus, S.E. (1986). **Mind over Machine: The Power of Human Intuition and Expertise in the Era of the Computer**. New York, Free Press.

Elman, J.L., Bates, E.A., Johnson, M.H., Karmiloff-Smith, A., Parisi, D. and Plunkett, K. (1999). **Rethinking Innateness: A Connectionist Perspective on Development**. Cambridge, MA, MIT Press.

Eve, R.A., Horsfall, S. and Lee, M.E. (1997). **Chaos, Complexity, and Sociology: Myths, Models, and Theories**. Thousand Oaks, CA, Sage.

Farquhar, A., Fikes, R. and Rice, J. (1996). The Ontolingua server: a tool for collaborative ontology construction. Gaines, B.R. and Musen, M.A., Ed. **Proceedings of Tenth Knowledge Acquisition Workshop**. pp.63-1-63-7 (<http://ksi.cpsc.ucalgary.ca/KAW/KAW96/farquhar-demo/farquhar-demo.html>).

Fayyad, U.M. (1996). **Advances in Knowledge Discovery and Data Mining**. Menlo Park, CA, AAAI & MIT Press.

Feyerabend, P., Ed. (1975). **Against Method**. London, NLB.

Fleck, J. (1982). Development and establishment in artificial intelligence. Elias, N., Martins, H. and Whitley, R., Ed. **Scientific Establishments and Hierarchies**. pp.169-217. Holland, D.Reidel.

Fortun, M. and Bernstein, H.J. (1998). **Muddling Through: Pursuing Science and Truths in the 21st Century**. Washington, Counterpoint.

Foster, I. and Kesselman, C. (1999). **The Grid: Blueprint for a New Computing Infrastructure**. San Francisco, Morgan Kaufmann.

Friedman, M. (1999). **Reconsidering Logical Positivism**. Cambridge, Cambridge University Press.

Gadamer, H.G. (1972). **Wahrheit und Methode**. Tübingen, Mohr.

Gaines, B.R. (1969). Stochastic computing systems. Tou, J., Ed. **Advances in Information Systems Science**, 2. pp.37-172. New York, Plenum Press.

Gaines, B.R. (1977). System identification, approximation and complexity. **International Journal of General Systems** 2(3) 241-258.

Gaines, B.R. (1978). Computers in world three. **Proceedings of the International Conference on Cybernetics and Society**. pp.1515-1521. NY, IEEE (78CH-1306-0-SMC III).

Gaines, B.R. (1984). Perspectives on fifth generation computing. **Oxford Surveys in Information Technology** 1 1-53.

Gaines, B.R. (1986). Sixth generation computing: a conspectus of the Japanese proposals. **ACM SIGART Newsletter** 95 39-44.

Gaines, B.R. (1988). Positive feedback processes underlying the formation of expertise. **IEEE Transactions on Systems, Man & Cybernetics SMC-18**(6) 1016-1020.

Gaines, B.R. (1989). Social and cognitive processes in knowledge acquisition. **Knowledge Acquisition** 1(1) 251-280.

Gaines, B.R. (1990). Knowledge support systems. **Knowledge-Based Systems** 3(3) 192-203.

Gaines, B.R. (1991a). Integrating rules in term subsumption knowledge representation servers. **AAAI'91: Proceedings of the Ninth National Conference on Artificial Intelligence**. pp.458-463. Menlo Park, California, AAAI Press/MIT Press.

Gaines, B.R. (1991b). Modeling and forecasting the information sciences. **Information Sciences** 57-58 3-22.

Gaines, B.R. (1994). The collective stance in modeling expertise in individuals and organizations. **International Journal of Expert Systems** 7(1) 21-51.

Gaines, B.R. (1996). Transforming rules and trees into comprehensible knowledge structures. Fayyad, U.M., Piatetsky-Shapiro, G., Smyth, P. and Uthurusamy, R., Ed. **Knowledge Discovery in Databases II**. pp.205-226. Cambridge, Massachusetts, AAAI/MIT Press.

Gaines, B.R. (1997). Knowledge management in societies of intelligent adaptive agents. **Journal for Intelligent Information Systems** 9(3) 277-298.

Gaines, B.R. (1998). The learning curves underlying convergence. **Technological Forecasting and Social Change** 57(1) 7-34.

Gaines, B.R. and Compton, P. (1995). Induction of ripple-down rules applied to modeling large databases. **Journal for Intelligent Information Systems** 5(3) 211-228.

Gaines, B.R. and Shaw, M.L.G. (1984). Hierarchies of distinctions as generators of system theories. Smith, A.W., Ed. **Proceedings of the Society for General Systems Research International Conference**. pp.559-566. Louisville, Kentucky, Society for General Systems Research.

Gaines, B.R. and Shaw, M.L.G. (1986). A learning model for forecasting the future of information technology. **Future Computing Systems** 1(1) 31-69.

Gaines, B.R. and Shaw, M.L.G. (1994). Using knowledge acquisition and representation tools to support scientific communities. **AAAI'94: Proceedings of the Twelfth National Conference on Artificial Intelligence**. pp.707-714. Menlo Park, California, AAAI Press/MIT Press.

Gaines, B.R. and Shaw, M.L.G. (1997). Knowledge acquisition, modeling and inference through the World Wide Web. **International Journal of Human-Computer Studies** **46**(6) 729-759.

Garey, M.R. and Johnson, D.S. (1979). **Computers and Intractability: A Guide to the Theory of NP-completeness**. San Francisco, W. H. Freeman.

Gibson, J.J. (1979). **The Ecological Approach to Perception**. Boston, Houghton Mifflin.

Giddens, A. (1986). **The Constitution of Society: Outline of the Theory of Structuration**. California, University of California Press.

Gilfillan, S.C. (1937). The prediction of inventions. Ogburn, W.F., Ed. **Technological Trends and National Policy, Including the Social Implications of New Inventions**. Washington, U.S. Government Printing Office.

Gold, E.M. (1967). Language identification in the limit. **Information and Control** **10**(5) 447-474.

Grover, L.K. (1996). A fast quantum mechanical algorithm for database search. **Proc. 28th Annual Symposium on the Theory of Computing**. pp.212-218. New York, ACM Press.

Hackney, D. (1997). **Understanding and Implementing Successful Data Marts**. Reading, MA, Addison-Wesley Pub. Co.

Hawkins, D. (1983). An analysis of expert thinking. **International Journal of Man-Machine Studies** **18**(1) 1-47.

Hayes-Roth, F. (1984). The industrialization of knowledge engineering. Reitman, W., Ed. **Artificial Intelligence Applications for Business**. pp.159-177. Norwood, New Jersey, Ablex.

Horkheimer, M. and Adorno, T.W. (1972). **Dialectic of Enlightenment**. New York, Herder and Herder.

Kang, B., Compton, P. and Preston, P. (1995). Multiple classification ripple down rules: evaluation and possibilities. **Proceedings of the 9th AAAI-Sponsored Banff Knowledge Acquisition for Knowledge-Based Systems Workshop**. Banff, Canada, University of Calgary.

Kirby, S. (1999). **Function, Selection, and Innateness: The Emergence of Language Universals**. Oxford, Oxford University Press.

Klir, G.J. (1976). Identification of generative structures in empirical data. **International Journal of General Systems**, **3** 89-104.

Kremer, R.C. (1991). Experience in applying KRS to an actual business problem. Boose, J.H.G., B.R., Ed. **Proceedings of the Sixth AAAI Knowledge Acquisition for Knowledge-Based Systems Workshop**. pp.11-1-11-12. Calgary, Canada, University of Calgary.

Kripke, S.A. (1982). **Wittgenstein on Rules and Private Language: An Elementary Exposition**. Oxford, Blackwell.

Langley, P. (2000). The computational support of scientific discovery. **International Journal of Human-Computer Studies** **53**(3) 393-410.

Lee, Y., Buchanan, B.G. and Rosenkrantz, H.S. (1996). Carcinogenicity predictions for a group of 30 chemicals undergoing rodent cancer bioassays based on rules derived from subchronic organ toxicities. **Environmental Health Perspectives** **104**(Suppl 5) 1059-1063.

Lek, S. and Guégan, J.-F. (2000). **Artificial Neuronal Networks : Application to Ecology and Evolution**. New York, Springer.

Lenat, D.B. and Guha, R.V. (1990). **Building Large Knowledge-Based Systems**. Reading, Massachusetts, Addison-Wesley.

Lighthill, J. (1973). Artificial intelligence: a general survey. **Artificial Intelligence: a paper symposium**. UK, Science Research Council.

Linstone, H.A. and Sahal, D., Ed. (1976). **Technological Substitution: Forecasting Techniques and Applications**. New York, Elsevier.

Luhmann, N. (1995). **Social Systems**. Stanford, CA, Stanford University Press.

Meadows, D.H., Meadows, D.L. and Randers, J. (1992). **Beyond the Limits: Confronting Global Collapse, Envisioning a Sustainable Future**. Mills, Chelsea Green.

Meister, J.C. (1998). **Corporate Universities : Lessons in Building a World-class Work Force**. New York, McGraw-Hill.

Michalski, R.S. and Chilausky, R.L. (1980). Knowledge acquisition by encoding expert rules versus computer induction from examples—A case study involving soyabean pathology. **International Journal of Man-Machine Studies** **12** 63-87.

Moto-oka, T., Ed. (1982). **Fifth Generation Computer Systems**. Amsterdam, North-Holland.

Motta, E., Stutt, A., Zdrahal, Z., O'Hara, K. and Shadbolt, N. (1996). Solving VT in VITAL: A study in model construction and knowledge reuse. **International Journal of Human-Computer Studies** **44**(3/4) 333-371.

Natarajan, B.K. (1991). **Machine Learning: A Theoretical Approach**. San Mateo, CA, Morgan Kaufmann.

Nebel, B. (1990). Terminological reasoning is inherently intractable. **Artificial Intelligence** **43** 235-249.

Newborn, M. (1997). **Kasparov Versus Deep Blue: Computer Chess Comes of Age**. New York, Springer.

Nonaka, I. and Takeuchi, H. (1995). **The Knowledge-Creating Company**. Oxford, Oxford University Press.

Pierce, J.R. (1969). Whither speech recognition? **Journal of the Acoustical Society of America** **46** 1049-1051.

Popper, K.R. (1968). Epistemology without a knowing subject. Rootselaar, B.V., Ed. **Logic, Methodology and Philosophy of Science III**. pp.333-373. Amsterdam, North-Holland.

Richards, D. and Compton, P. (1998). Taking up the situated cognition challenge with ripple down rules. **International Journal of Human Computer Studies** **49**(895-926)

Rothenfluh, T.E., Gennari, J.H., Eriksson, H., Puerta, A.R., Tu, S.W. and Musen, M.A. (1996). Reusable ontologies, knowledge-acquisition tools, and performance systems: PROTEGE-II solutions to Sisyphus-2. **International Journal of Human-Computer Studies** **44**(3/4) 303-332.

Saul, J.R. (1993). **Voltaire's Bastards: The Dictatorship of Reason in the West**. Toronto, Penguin.

Schaeffer, J. and Plaat, A. (1997). Kasparov versus Deep Blue: The Re-match. **Journal of the International Computer Chess Association** **20**(2) 95-101.

Schmidt, J., Ed. (1996). **What is Enlightenment?** Berkeley, University of California Press.

Schön, D.A. (1983). **The Reflective Practitioner**. New York, Basic Books.

Searle, J.R. (1992). **The Rediscovery of the Mind**. Cambridge, MA, MIT Press.

Searle, J.R. (1998). **Mind, Language and Society: Philosophy in the Real World**. New York, NY, Basic Books.

Seiler, H. (1999). Managing business rules: a repository-based approach. Rule Machines Corporation. www.RuleMachines.com.

Sejnowski, T.J. and Rosenberg, C.R. (1987). Parallel networks that learn to pronounce English text. **Complex Systems** 1 145-168.

Shapin, S. (1994). **A Social History of Truth: Civility and Science in Seventeenth-Century England**. Chicago, University of Chicago Press.

Shaw, M.L.G. and Gaines, B.R. (1987). KITTEN: Knowledge initiation and transfer tools for experts and novices. **International Journal of Man-Machine Studies** 27(3) 251-280.

Shen, W. and Norrie, D.H. (1998). An Agent-Based Approach for Distributed Manufacturing and Supply Chain Management. Jacucci, G., Ed. **Globalization of Manufacturing in the Digital Communications Era of the 21st Century: Innovation, Agility, and the Virtual Enterprise**. pp.579-590. Dordrecht, Kluwer.

Shortliffe, E.H. (1976). **Computer-Based Medical Consultations: MYCIN**. New York, Elsevier.

Shortliffe, E.H. and Clancey, W.J. (1984). Anticipating the second decade. Clancey, W.J. and Shortliffe, E.H., Ed. **Readings in medical artificial intelligence : the first decade**. pp.463-472. Reading, MA, Addison-Wesley.

Smolka, P. and Volkheimer, W. (2000). **Southern Hemisphere Paleo- and Neoclimates: Key Sites, Methods, Data and Models**. Berlin, Springer.

Solmsen, F. (1975). **Intellectual Experiments of the Greek Enlightenment**. Princeton, N.J., Princeton University Press.

Spitzer, M. (1999). **The Mind Within the Net: Models of Learning, Thinking, and Acting**. Cambridge, MA, MIT Press.

Stalker, D.F. (1994). **GRUE!: The New Riddle of Induction**. Chicago, Open Court.

Swanson, D.R. (1990). The absence of co-citation as a clue to undiscovered causal connections. Borgman, C.L., Ed. **Scholarly Communication and Bibliometrics**. pp.129-137. Newbury Park, Sage Publications.

Tiwana, A. (2000). **The Knowledge Management Toolkit**. NJ, Prentice-Hall.

Tversky, A. and Koehler, D.J. (1994). Support theory: a nonextensional representation of subjective probability. **Psychological Review** 101(4) 547-567.

Ulanowicz, R.E. (1991). Formal agency in ecosystem development. Higashi, M. and Burns, T.P., Ed. **Theoretical Studies of Ecosystems: The Network Perspective**. pp.58-70. Cambridge, Cambridge University Press.

Valiant, L.G. (1974). A theory of the learnable. **Communications of the ACM** 27 1134-1142.

Vallacher, R.R. and Nowak, A. (1994). **Dynamical Systems in Social Psychology**. San Diego, Academic Press.

Vickers, J.N. (1990). **Instructional Design for Teaching Physical Activities: A Knowledge Structures Approach**. Champaign, Illinois, Human Kinetics.

Von Krogh, G., Ichijo, K. and Nonaka, I. (2000). **Enabling Knowledge Creation: How to Unlock the Mystery of Tacit Knowledge and Release the Power of Innovation**. Oxford, Oxford University Press.

Weizenbaum, J. (1976). **Computer Power and Human Reason: From Judgement to Calculation**. San Francisco, W.H.Freeman.

Wills, G. (1998). **The Knowledge Game: The Revolution in Learning and Communication in the Workplace**. London, Cassell.

Wittgenstein, L. (1953). **Philosophical Investigations**. Oxford, Blackwell.

Wojciechowski, J.A. (1983). The impact of knowledge on man: the ecology of knowledge. **Hommage a Francois Meyer**. pp.161-175. Marseille, Laffitte.