

New Approaches for Meta-Heuristic Frameworks: A Position Paper

David Alfred Ostrowski

System Analytics and Environmental Sciences
Research and Advanced Engineering
Ford Motor Company
dostrows@ford.com

George M. Schleis

Knowledge Based Systems
Global Analytics
Ford Motor Credit Company
gschleis@ford.com

Abstract

This paper summarizes our position on the use of AI-based techniques applied to the development and support of metaknowledge. Our intent is to derive higher level abstractions using current heuristic methods to the goal of plan development and selection. A generalized framework is discussed, allowing for development of strategic plans coupled with an interchangeable learning mechanism. Along with this framework we present potential issues and conditions to address during the development phases that are of importance to the institutionalization of these concepts. We feel that the highest potential exists at the determination of meta-level (control and strategic) knowledge – specifically using a hybrid approach incorporating current expert system paradigms in conjunction with Machine Learning (EC, NN) techniques.

1. Introduction.

Metaknowledge can be simply defined as knowledge about knowledge. Specifically, metaknowledge is knowledge about the use and control of domain knowledge in an expert system. (Waterman 1986). Metaknowledge implemented in rule form as Metareasoning can be defined within a generalized framework consisting of three categories: Doing, Reasoning and Metareasoning (figure 1.).

One of the earliest applications of meta-level understanding is the MYCIN application (Adams 1976). Established as a tool for expert analysis in medical infections, the MYCIN application applied a higher level of control through the establishment of Metaknowledge supporting the relevance of a specific rule to a given state. Davis developed these techniques further, by supporting a higher level of distinction between rules (Davis 1976). He described a three step process towards the development of a meta-level control strategy including retrieval, refinement and execution. Within the retrieval phase, patterns are used to select a knowledge source (rules). During refinement, the set of knowledge rules is reordered to support a finer degree of control. In the final phase one can reserve one of the knowledge sources in the revised rule set to be

applied to the problem. These concepts were applied in the TEIMIS application. Mussi developed a method for the representation of common sense in diagnostic expert systems. His work extended the rule-based approach to the preferences and maintenance of human expert beliefs applying, often unconsciously, heuristic considerations. The application of this belief mechanism was referred to as 'strategic common sense' (Mussi 1990)(Mussi 1993).

The PARULEL system supported parallel execution of rule languages that could be used to effectively determine the allocation of mortgage pools. This technique was found to be highly advantageous dealing with this combinatorial optimization problem as applied by financial institutions that trade in mortgage-backed securities (Stolfo 1991). Metaheuristics have also found utility in simulation based environments. An example of this is (Hoogendoorn 2005) who has developed design of decision knowledge acquired from the domain experts. His approach clearly expanded earlier interpretation towards a framework defined as objects, meta and meta-meta rules.

We view the distinctive metaknowledge rules as a clearly defined AI problem. In support of rules that define rules we examine this activity as a separate search problem. Drawing inspiration from hybrid systems we see the development of control parameters as a unique opportunity to the future expansion of expert systems analysis (Negnevitsky 2001). In Section Two we present additional concepts influencing metareasoning development that motivates the application of guided learning techniques to be applied to this problem. In Section Three, we present our description of a generalized framework. In section Four we present considerations towards the development of this framework and Section Five presents our conclusions.

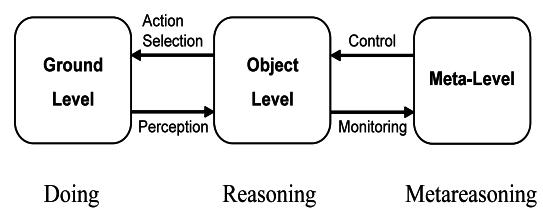


Figure 1. (Cox 2008)

2. AI and Strategic Knowledge.

Metareasoning environments can be viewed as the construction of small worlds that attempt to approximate larger world models. In this construction, it is assumed that the underlying state space is known and well defined. When reasoning within such a model (Laskey and Lehner 1994) addressed four issues. 1.) formulating the problem 2) deciding whether to trust the results 3) knowing what to do when you have decided not to trust your model 4) building a better small world. In addressing these concepts, it is ruled that decision theory does not currently treat any of these metareasoning issues. This is consistent with studies involving computational decision models which find that people do not manage uncertainty in ways which closely resemble probabilistic reasoning (Fox 1980). It is within these constructs that we find the higher opportunity for further application of learning methods at the metareasoning level. The reasoning within such a model can be identified as the study of perturbation tolerance – or the ability of a system to quickly recover after an unexpected event. This can also be described as 'brittleness' (Anderson 2004).

Prior knowledge has also been related towards the application of guiding learning mechanisms in order to more effectively deal with real world situations. Multitask learning has incorporated dependencies between tasks into an inductive learning system (Barthai 2004). A multitask learning system uses the input-output examples of related tasks in order to improve the general performance. This approach has demonstrated value in terms of being able to overcome characterizations of non-stationarity and extreme noisiness.

The maintenance of prior knowledge supports the concept of beliefs which have long been applied in the context of evolutionary computation solutions. Reynolds introduced a framework in the context of evolutionary computation in which beliefs were maintained and influenced by each generation (Reynolds 1994). Termed as Cultural Algorithms, they modeled the characteristic of a belief system or knowledge that is maintained over a biologically inspired evolutionary process. Representations of this environment included hierarchical representations for the purpose of maintaining abstractions of data (Isles 2000).

We feel that the most successful approach towards development of a framework that can suit our needs is to be able to develop a mechanism that supports a self-guided approach to the development of a perturbation-tolerant learning mechanism. This is accomplished through integrating a learning process to support the development of control parameters.

3. A Generalized Framework

In figure 2, the proposed generic architecture is presented for our meta-knowledge framework. The components de-

note processes, solid lines denote information and dotted lines denote a separation between the hierarchy of information. The bottom level (application level) describes the real world information which includes the end user application, related data from the real world as well as feedback from the interaction with the domain experts. The middle level is the execution of our heuristical information in which the rule based decisions are implemented. This represents the knowledge base implemented when expert analysis is applied. The upper middle level identifies the 'control' rules. This can be considered as rules that define (KB) rules. A self guided learning mechanism adjust parameters to be used by the control rules influenced by a feedback loop. Here 'base' rules are initialized with proxy controls and evaluate through either historical or simulated data to converge to an acceptable characterization through application of a learning algorithm. At the highest level are of strategic heuristics can be identified a set of rules from which to make a selection. A secondary planning component involves the selection of learning components to be applied to gain convergence.

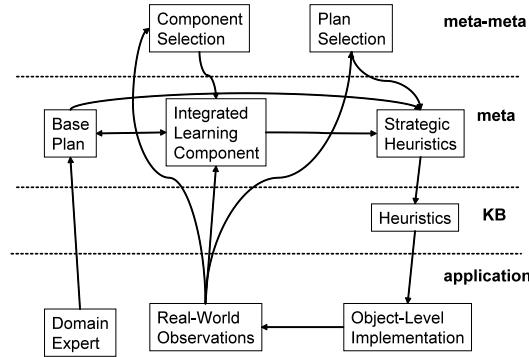


Figure 2. Metarules framework

4. Considerations

We identify the issues regarding the application of these concepts. We address these items to support the institutionalization of a metaknowledge framework.

- Learning About Control** Rather than maintaining assumptions about control tasks, we are interested in their representation to support application of a guided search. With this goal in mind, we represent all control parameters as dynamic in nature to allow convergence to a more successful set of parameters. In the context of viewing this problem as a guided search, we feel that this level can exist as a test bed for different searching algorithms.
- System Autonomy** We feel that metareasoning environments should be subject to external adjustment in response to environmental changes or variance in expert domain knowledge. The framework should exist as a semi-automatic application and not be required to be completely autonomous. Calibration of the model should not be consid-

ered a failure of the learning mechanism, but rather a means of being able to support a more profitable outcome.

- **Inference Engine Distinction** The same inference engine should be used for the implementation of our rules. However, there should be a substantial means of distinction between the hierarchy levels in order to support the separate activities. Higher level software engineering principles such as utilization of Frame-based expert system architectures should provide assistance.
- **Fast Prototyping** Our environment should support the highest level of flexibility. This occurs on several levels. First our process of developing control rules (strategic heuristics) should be proxy driven considering estimates to be applied to the learning component. Second the handling of such rules and associated parameters must support rapid integration with learning mechanisms for means of performance evaluation and training of test data. Lastly both control rules and associated parameters must be interchangeable to be efficiently handled by the plan selection layer.
- **System Concurrency** The system must support a parallel execution of configurations (learning algorithms and rule sets) to enable rapid evaluation of control and planning strategies among each other.

5. Conclusions

A framework for the presentation of rules has been presented. We have also demonstrated concepts which apply to the application of implementing heuristics. A method for integrating metaheuristics for the purpose of first control (rules defining rules) and then planning (strategy) has been presented. Our view has held that there should be a strong separation in the layers of thinking. Our framework supports a fast-prototyping software development lifecycle and is attributed of the means of being able to determine an effective solution.

Our framework includes support for rapid prototyping and high integration with emphasis on the metaheuristic environment to be viewed as an independent search problem. By setting these goals we feel expert systems can reach more effective levels.

References

- Waterman, D.A. *A Guide to Expert Systems*, Addison-Wesley, Reading MA, 1986
- Cox, M.T., and Raja, A. 2007 *Metareasoning: A Manifesto*, Technical Report, BBN TM-2028 BBN Technologies <http://www.mcox.org/Metareasoning/Manifesto/> manifesto.pdf
- Adams, J.B., A Probability Model of Medical Reasoning and the MYCIN model, Math, Biosciences 32(1976) 177-186
- Davis, R., *Meta-Rules: Reasoning about Control*, Artificial Intelligence, pp 179-220 1980
- Mussi, Silvano, Morpurgo, Rosamaria, Acquiring and Representing knowledge in the diagnosis domain, Expert Systems, August 1990, Vol. 7, No. 3
- Mussi, Silvano, A Method for Putting Strategic Common Sense into Expert Systems, IEEE Transactions On Knowledge and Data Engineering, Vol 5. No. 3, June 1993
- Stolfo, Salvadore J. , Chan, Philip K., Woodbury, Leland Glazier, Ohsie, David, PARULEL: Parallel rule processing using metarules for redaction, Journal of Parallel and Distributed Computing, 1991
- Hoogendoorn, M., Jonker C., A Meta-Level Architecture for Strategic Reasoning in Naval Planning, IEA/AIE 2005, LNAI 3533, pp. 848-850, 2005
- Negnevitsky, Michael, *Artificial Intelligence A Guide to Intelligent Systems*, Addison Wesley
- Laskey, Kathryn Blackmond, Lehner, Paul E., Lehner, *Metareasoning and the Problem of Small Worlds*, IEEE Transactions on Systems, Man and Cybernetics, Vol 24, No. 11, November 1994
- Anderson, Michael L., Perlis, Donald R., Logic, self-awareness an self-improvement. *The metacognitive loop and the problem of brittleness*. Journal of Logic and Computation 14, 2004
- Fox J. ,*Making Decisions Under Influence of Knowledge*, Psychological Review, pp. 191-121 Barthai, Kai, Gutjahr, Steffen, Nakhaeizadeh, Gholamena, *Incorporating Prior Knowledge About Financial Markets Through Neural Multitask Learning*.
- Reynolds R.G., An Introduction to Cultural Algorithms, The Proceedings of the 3rd Annual Conference on Evolutionary Programming, A.V. Fogen, L.H. River Edge, NJ World Scientific Publishing, 1994, pp131-139
- Isles, R. "Reasoning About Genetic Program Function and Structure Using Cultural Algorithms, Masters Thesis, Wayne State University, 2000