A Revisionist View of Blackboard Systems

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Abstract

Despite the continued popularity of the *blackboard model* of problem solving, recent AI texts hardly mention it. This is probably largely due to the decision to adopt formal frameworks into which the blackboard model does not appear to fit. In this paper, we explore the relationship between blackboard-based and belief network approaches to interpretation problems. In this way we begin to reinterpret the blackboard model, to show how it can be explained in terms of modern AI concepts.

Introduction

The *blackboard* model of problem solving arose from the *Hearsay-II* (HSII) speech understanding system (Erman et al. 1980). It has proven to be popular, and in the years since HSII a variety of blackboard-based systems have been developed. For example, blackboard architectures have been used for interpretation problems such as speech understanding, signal understanding and image understanding; planning and scheduling; and arrangement-assembly (structure identification). A commercial blackboard framework, *GBB*, is currently available and is being used for a variety of real-world applications. These include a mission control system for a Canadian Space Agency satellite, a logistics analysis and planning system for the US Army, and in design engineering projects at Ford. GBB was also recently selected by *Object Magazine* as one of their ten favorite object-technology products.

Despite its popularity, the blackboard model gets only three sentences in a Historical Notes section in Russell and Norvig's recent 932 (!) page AI text (Russell and Norvig 1995) and even less in some other texts. Clearly, one reason for this is the authors' decision to adopt logical and probabilistic frameworks to unify their presentation. Older, less formal AI models like blackboards end up largely ignored, even though they are still being used—and are still useful. This is unfortunate since students using these texts end up without any exposure to these techniques, and when they do come across them they do not fit into the conceptual frameworks presented in their texts.

The purpose of this paper is to begin to provide a reinterpretation of the blackboard model. That is, to explain the reasons for its characteristics in terms of more modern and more formal AI techniques and concepts. There are good reasons why somebody might still want to use the blackboard model, and these reasons can be framed in terms of the properties of *interpretation problems*, *belief networks*, and search algorithms. Blackboard-based interpretation systems have great flexibility: they can apply approximate problem-solving techniques and perform sophisticated searches for solutions. Because of this, they can deal with resource limitations as data loads, ambiguity, and system goals change. More formal approaches currently lack this flexibility.

For this paper, familiarity with belief networks (Bayesian networks) will be assumed at the level of *AIMA* (Russell and Norvig 1995). We will not assume that readers are familiar with the blackboard model, though our introduction will be limited. The next section contrasts interpretation problems with diagnosis problems, since the differences are key to understanding the power of the blackboard model. This is followed by two sections that summarize the blackboard model and the *dynamic belief network* model. We then compare the characteristics of these two approaches for solving interpretation problems.

Interpretation vs. Diagnosis

The blackboard architecture was developed to deal with the difficult characteristics of *interpretation problems* like speech understanding. To appreciate the power of the blackboard model one must understand the characteristics of interpretation problems—particularly as they differ from superficially similar problems.

Interpretation problems involve the determination of abstract, conceptual *explanations* of sensor data and/or other informaton. An *interpretation* is a set of *hypotheses* about "events" that might have caused the data (and so explain it). For example, events could be vehicles moving through the environment or the speaking of words/sentences. Each hypothesis explains some subset of the data and together an interpretation's hypotheses explain all of the data. Typically, we are interested in interpretations whose hypotheses are from a subset of the abstraction types—what Pearl has termed the *explanation corpus* (Pearl 1988). The process of interpretation is based on a causal model that relates data characteristics to types of "events." An interpretation system uses this model to make *abductive inferences* that identify possible explanations (causes) for the data (Carver and Lesser 1991).

Interpretation is an inherently uncertain process. In general, there will be multiple possible interpretations of any data set—i.e., multiple alternative sets of "events" that could have caused the data. In addition, many interpretation domains involve significant "noise" in the data from things like sensor errors, environmental factors, and so forth. Because of this uncertainty, there must be some way to assess the strength of the evidence for the alternative interpretations. The *solution* to an interpretation problem is the interpretation that is judged "best" according to some criteria. In a probabilistic context, one possible definition of best is the *most probable explanation* (MPE) (Pearl 1988).[1]

For simplicity, we will refer to the kinds of problems that have typically been studied in research on abductive inference and probabilistic network inference as *diagnosis problems* (e.g., (Peng and Reggia 1990; Pearl 1988)). The key characteristics of diagnosis problems are that they have a *fixed* set of interpretation hypotheses (e.g., diseases) and data nodes, with *known, fixed* relations among them. In other words, a complete and static (probabilistic) model is available. Probabilistic inference in networks for such problems has been studied extensively. The conditional probability of nodes as well as the MPE can be determined by plugging the available data into evidence nodes and appropriately propagating its effects (Pearl 1988; Russell and Norvig 1995). While inference has been shown to be NP-hard for general network topologies (Cooper 1990; Shimony 1994), efficient exact and approximate techniques have been developed that can handle reasonable size problems.

Though interpretation problems seem fairly similar to "diagnosis problems," they differ in several important ways. The primary way they differ is that they lack complete and static models that connect the data with possible explanations. While interpretation problems have a fixed set of interpretation and data *types*, they can have an *indeterminate number* of *instances* of any of these types.[2] For example, in a vehicle monitoring system, an unknown number of vehicles will have been responsible for the overall data set and each vehicle will produce a "track" of an unknown number of sensor data points. The causal model used in the interpretation process identifies the connections between data types and explanation types, but not between *instances* of these types.

As a result, the associations between the individual pieces of data and individual interpretation hypotheses are a priori *unknown*. This leads to what is known in the *target tracking* literature as the *data association problem* (DAP) (Bar-Shalom and Fortmann 1988): which target should data be associated with? The DAP gives rise to what has been termed *correlation ambiguity* or *origin uncertainty*: it is ambiguous/uncertain which potential hypothesis each piece of data should be associated with (and provide evidence for). Diagnosis problems simply do not involve the DAP or correlation ambiguity.

The DAP and the possibility of an indeterminate number of event instances, can lead to a combinatorial explosion in the number of possible interpretations for a data set. For example, in a vehicle monitoring system, every single piece of data potentially could have come from: (1) any already hypothesized vehicle, (2) noise/clutter, or (3) a new (previously undetected) vehicle. Unless it is possible to *conclusively* rule out many of these interpretations, the number of hypotheses will grow exponentially with the amount of data examined.

To help understand the implications of the DAP, consider a medical diagnosis problem involving data association uncertainty: A doctor has a set of patients and a set of test results. However, the tests have not been labeled by patient and some may even be for patients that he has not seen yet (and knows nothing about). What is the diagnosis for each of the tested patients? This is clearly a much more difficult problem than conventional diagnosis problems since the doctor not only must diagnose the patients, he must figure out how many patients tests he has and associate tests with patients.[3]

Interpretation systems also face problems not faced by diagnosis systems that arise from the nature of their sensor data evidence. First, data from the same sensor over time may not be conditionally independent (given an interpretation hypothesis). Whether this is the case or not will depend on how much detail we represent in the interpretation hypotheses and the level of detail in the causal model. The second problem with sensor data is that there can be a massive amount of it when there are multiple passive sensors, continuously operating in a noisy environment; too much to completely process. On the other hand, in many interpretation problems we do not need to have explanations of every piece of data

[1] The MPE is also called the *maximum a posteriori probability* (MAP) interpretation.

[2] By indeterminate, we mean both that the number is a priori unknown and that it changes over time.

[3] To be fair, this example somewhat overstates the difficulties typically caused by the DAP. In problems like vehicle monitoring, basic consideration of the laws of physics can eliminate (or make extremely unlikely) many possible associations simply by virtue of position information, but this is less so for medical diagnosis (though some diseases are highly correlated to basic patient factors like age). Another reason is that in many interpretation problems, it is reasonable to assume that a single source was responsible for each piece of data—unlike medical diagnosis where the simultaneous occurrence of multiple diseases with overlapping symptoms is a key issue.

since we only care about certain events or interpretation types (e.g., platforms/targets vs. clutter).

To deal with the characteristics just discussed, interpretation systems must be *constructive* (Carver and Lesser 1991; Clancey 1985) and they also must usually make use of *approximate strategies* to determine solutions. For example, they may construct only some of the possible interpretations for the data they process and they may process only part of the available data. There are five basic approximation techniques that can be used by interpretation systems:

1. process only part of the available data;
2. construct only some of the possible interpretation hypotheses for the processed data;
3. compute approximate belief ratings (conditional probabilities) for the hypotheses (perform limited "evidence propagation")[4];
4. compute beliefs only for certain types of interpretation hypotheses (e.g., those from the explanation corpus);
5. consider only some of the possible interpretations (hypothesis combinations);
6. use criteria other than the MPE to select the solution (e.g., assemble solutions from hypotheses whose belief ratings surpass some *acceptance threshold*).

Obviously, these techniques are not independent. If a system does not process all of the data then it cannot in general create all possible interpretations of the complete data set nor compute the true conditional probabilities of the hypotheses. If a system does not create every possible interpretation hypothesis for some data, this not only limits the interpretations that can be considered, it also results in approximate belief ratings since it results in incomplete propagation of the effects of evidence. The bottom line is that these approaches will result in interpretation solutions that are only approximations of the optimal, MPE interpretation: they may be incomplete or they may not be the most probable composite interpretation.

The Blackboard Model

This section introduces the blackboard model of problem solving. Since we are focusing on the application of blackboard systems to interpretation, our discussion of general characteristics will be limited. More complete introductions to the blackboard model can be found in (Carver and Lesser 1992; Carver and Lesser 1994; Engelmore and Morgan 1988). (Carver and Lesser 1992) concentrates on blackboard-based SI and other recent examples can be found in (Hayes-Roth 1995; Lesser et al. 1993).

The blackboard model is based on the following idealized model of problem solving: a group of experts sits watching solutions being developed on a blackboard and whenever an expert feels that he can make a contribution toward finding the correct solution, he goes to the blackboard and makes appropriate changes or additions. Among the key ideas behind this model are that problem solving should be both *incremental* and *opportunistic*. That is, solutions should be constructed piece by piece and at different levels of abstraction, working where the available data and intermediate state of possible solutions suggest the most progress can be made.

In the basic HSII model, a blackboard system is composed of three main components: the *blackboard*, a set of *knowledge sources* (*KSs*), and a control mechanism. The blackboard is a global database (i.e., shared by all the KSs) that contains the (sensor) data and interpretation *hypotheses*. The KSs embody the problem solving knowledge of the system: they examine the blackboard and can add, modify, or even delete hypotheses when appropriate. KSs are intended to be independent, interacting only by making changes to the blackboard. The blackboard itself is typically structured as a set of *levels*. For interpretation problems, the blackboard levels are basically organized as a partial order, with data levels at the "bottom" and abstract explanation levels at the "top." Levels are themselves structured in terms of a set of *dimensions*. Dimensions are used to define the "location" of a hypothesis within a level. This makes it possible to provide efficient *associative retrieval* of hypotheses.

The network of hypotheses and data on a blackboard is analogous to the structure that would be created for a belief net model of an interpretation problem. The data objects and hypotheses correspond to belief net evidence and explanation nodes, respectively. Inter-hypothesis links correspond to belief net causal/evidential links. As we have said, a key issue for interpretation is being able to evaluate the strength of the evidence for hypotheses and possible interpretations. Blackboard systems have almost invariably used ad-hoc representations of belief. As they are created or modified, blackboard hypotheses are assigned belief "ratings," representing how likely they are to be correct. However, even in a blackboard-based interpretation framework like RESUN (Carver and Lesser 1991) that computes probabilistic belief ratings, these ratings are not (exact) conditional probabilities.

Dynamic Belief Networks

As we have shown, interpretation forces a system to deal with issues that are not raised by diagnosis problems. For example, since the number of possible data and interpretation instances are a priori unknown, interpretation problem solving is necessarily constructive. With a belief net, this means growing the network as data arrives and is processed. As each piece of data is processed, a corresponding evidence node could be created (with appropriate conditional probablity information), new explanation nodes may need to be created, and evidential links added to connect the evidence node to nodes the data directly supports.

Instead of this approach, however, the belief net community has focused on *dynamic belief nets* (DBNs) to

[4] We are using "evidence propagation" in the same basic sense that (Pearl 1988) refers to "belief propagation."

deal with the temporal issues raised by interpretation. The basic idea behind DBNs is to construct new instances of the dynamically changing portions of the belief net for each *time slice*,[5] but make use of the *Markov Property* to eliminate all but the latest two time slices of information by doing a *rollup* of all previous sensor information. Instead of having, say, *a single* vehicle hypothesis with supporting data/evidence nodes being added over time, a DBN would have a time t vehicle hypothesis, a time $t+1$ vehicle hypothesis, and so on. Each such vehicle hypothesis would be supported by data from its time slice plus by the previous *vehicle hypothesis*—not (directly) from all the accumulated data. Introductions to DBNs can be found in (Dean and Wellman 1991; Nicholson and Brady 1994; Russell and Norvig 1995).

Blackboard-based Interpretation vs. DBN-based Interpretation

Blackboard-based interpretation systems can be extremely flexible. The blackboard model has emphasized the need for an intelligent *search* process and *approximation* techniques to solve complex interpretation problems. Interpretation hypotheses can be constructed and refined incrementally, as part of a search process driven by "sophisticated control architectures." A variety of approximate knowledge sources can be defined and applied. Blackboard systems do not have to work time slice by time slice, forward in time; they do not have to create all interpretations of the data they process; and they do not have to process all the available data.

For example, blackboard-based systems can examine the data abstractly, looking for likely "targets," and then *selectively* process data over a range of times to confirm/deny and refine their hypotheses (e.g., (Durfee and Lesser 1988)). Likewise, they can focus their activities on pursuing only interpretation hypotheses of most value—as in possible attacking aircraft vs. friendly aircraft. Because they incrementally develop hypotheses, blackboard systems can also work at multiple levels of abstraction—they need not immediately explain all data in terms of the ultimate (explanation corpus) interpretation types. This is one mechanism for dealing with the combinatorics of the DAP: implicitly representing uncertainty about higher level associations by not creating links representing those associations until sufficient data is acquired.

The blackboard model has also emphasized the need to dynamically and opportunistically adjust strategies in response to the developing state of problem solving. By this we mean that blackboard systems can adapt their problem-solving strategies as data loads, ambiguity, system goals, and available time change. Decisions about what hypotheses should be pursued and how they should be pursued are based on the intermediate state of problem solving (the current hypotheses, data, goals, and so forth). This allows blackboard-based interpretation systems to deal with resource limitations by reasoning about appropriate solution quality vs. processing time trade-offs.

In contrast to the blackboard model, the DBN approach to interpretation is quite *in*flexible. A DBN works time slice by time slice, doing complete and exact interpretation—i.e., determining all possible interpretations of the new data and computing exact probabilities. There is no ability to selectively and opportunistically search. Russell and Norvig (Russell and Norvig 1995) (p. 518) state that "probably the most important defect of DDNs [dynamic decision networks] is that they retain the property of forward search through concrete [i.e., complete] states...." If we compare the DBN approach to the blackboard approach, we see that this is a key way that blackboards get their flexibility and power: they are not limited to forward search and can deal with partial states rather than complete states.

Another thing to note about DBNs is that they do not completely address the DAP and the resulting possibility of exponential growth in the number of interpretations and thus network structure. DBN's do reduce growth in the network that would come from adding numerous data/evidence nodes. *Rollup nodes* (Russell and Norvig 1995) are used to compactly represent previous sensor data, so that only the last time slice of the network needs to be maintained. This does not address the potential for exponential growth in the number of interpretation hypotheses over time, however. In general, approximation techniques will be required to deal with this issue. Furthermore, while the rollup approach works for simple interpretation problems (e.g., (Huang et al. 1994; Nicholson and Brady 1994)), it may not be practical for interpretation problems involving sensor data with multiple, continuous-valued attributes. For example, suppose that environmental characteristics in some region are causing particular distortions in the signal received from a target vehicle (e.g., certain frequencies shifted by x Hz.). Expectations about the continued appearance of this distortion need to be maintained between time slices. Doing this could require extremely complex, infinite-valued rollup nodes, which are not going to be practical in belief network computations.

While the DBN approach lacks flexiblity, it does have the ability to determine the optimal, MPE interpretation of a data set (in those problems that stay small enough). Blackboard-based interpretation systems can apply many approximation techniques, but the formal properties of the resulting solutions currently cannot be determined, except perhaps empirically. This drawback is not limited to blackboard-based interpretation systems, though. While target tracking algorithms (Bar-Shalom and Fortmann 1988) are often based on formal techniques like the Kalman filter, they resort to approximations outside of the formal system in order to deal with the DAP. For example, they may consider only the most likely of the possible interpretations on

[5] Each discrete time when new sensor data arrives.

each sensor cycle (Bar-Shalom and Fortmann 1988) or may periodically prune less likely hypotheses (resulting in later conditional probabilities being only approximations) (Cox and Leonard 1994).

Conclusion

A wide range of important tasks can be viewed as interpretation problems: vehicle monitoring and tracking, robot map making, sound understanding for robotic hearing, speech understanding, and so forth. This comparison of blackboard-based and DBN-based approaches makes it clear why one might still want or need to use a blackboard system. In spite of recent advances in formal techniques like belief nets, these techniques still lack the flexibility to handle complex interpretation problems.

Still, blackboard-based interpretation systems have some serious problems. Because they lack formal underpinnings for their belief computations and their decisions about actions, it is impossible to assess the quality of their solutions except through empirical means. By contrast, DBNs can potentially compute exact conditional probabilities and determine the most probable explanations. DBNs also have the potential to make use of decision-theoretic control methods.

One of the reviewers stated that he thought the blackboards were being talked about less today not because of the emphasis on formal techniques, but because there is "not much more to say" about them and "no place for them to go." We do not agree. This paper makes it clear that there are significant limitations in the current AI approaches to complex interpretation problems. Clearly, there are opportunities here to synthesize systems with the best characteristics of these approaches.

For example, we are currently exploring methods for developing formal statements about the properties of solutions based on certain approximate interpretation strategies. These results would be applicable to blackboard-based systems. In purusing this research, we are considering research on approximation methods for probabilistic inference in belief nets. This research has largely assumed that a complete network model is available and the problem is that exact evaluation is not tractable. As we have discussed here, this assumption is often invalid for interpretation because of the potential exponential growth of the network. We are exploring the use of models of the domain such as near monotonicity (Carver and Lesser 1996), to deal with evaluation of incomplete networks.

Another explanation for the appeal of the blackboard involves the characteristics of search algorithms. Whitehair and Lesser (Whitehair 1996) have examined how the blackboard architecture supports "sophisticated control" strategies that are necessary for "complex domains." Complex domains do not exhibit *monotone* properties, and have highly interrelated search paths. The *Interpretation Decision Problem* (IDP) formalism (Whitehair 1996) has been used to represent complex domains and analyze the behavior of blackboard-based interpretation systems. In the IDP formalism, the structure of both problem domains and problem solvers is represented in terms of context free attribute grammars and functions associated with the production rules of the grammars. This framework shows that it is possible to develop analytic models of the behavior of "ad-hoc" AI architectures like blackboard systems.

References

Yaakov Bar-Shalom and Thomas Fortmann, *Tracking and Data Association*, Academic Press, 1988.

Norman Carver and Victor Lesser, "A New Framework for Sensor Interpretation: Planning to Resolve Sources of Uncertainty," *Proceedings of AAAI-91*, 724–731, 1991.[1]

Norman Carver and Victor Lesser, "Blackboard Systems for Knowledge-Based Signal Understanding," in *Symbolic and Knowledge-Based Signal Processing*, Alan Oppenheim and Hamid Nawab, editors, Prentice Hall, 205–250, 1992.

Norman Carver and Victor Lesser, "The Evolution of Blackboard Control," *Expert Systems with Applications*, special issue on The Blackboard Paradigm and Its Applications, vol 7, no. 1, 1–30, 1994.[1]

Norman Carver, Victor Lesser, and Robert Whitehair, "Nearly Monotonic Problems: A Key to Effective FA/C Distributed Sensor Interpretation?," *Proceedings of AAAI-96*, 88–95, 1996.

William Clancey, "Heuristic Classification," *Artificial Intelligence*, vol. 27, 289–350, 1985.

G.F. Cooper, "The Computational Complexity of Probabilistic Inference using Bayesian Belief Networks," *Artificial Intelligence*, vol. 42, 393–405, 1990.

Ingemar Cox and John Leonard, "Modeling a Dynamic Environment using a Bayesian Multiple Hypothesis Approach," *Artificial Intelligence*, vol. 66, 311–344, 1994.

Thomas Dean and Michael Wellman, *Planning and Control*, Morgan Kaufmann, 1991.

Edmund Durfee and Victor Lesser, "Incremental Planning to Control a Time-Constrained, Blackboard-Based Problem Solver," *IEEE Transactions on Aerospace and Electronic Systems*, vol. 24, no. 5, 647–662, 1988.

Robert Engelmore and Tony Morgan, editors, *Blackboard Systems*, Addison-Wesley, 1988.

Lee Erman, Frederick Hayes-Roth, Victor Lesser, and D. Raj Reddy, "The Hearsay-II Speech-Understanding System: Integrating Knowledge to Resolve Uncertainty," *Computing Surveys*, vol. 12, no. 2, 213–253, 1980 (also in *Blackboard Systems*, Robert Engelmore

[1] Can be obtained from: "http://www/cs.siu.edu/~carver/".

and Tony Morgan, editors, Addison-Wesley, 31–86, 1988).

Barbara Hayes-Roth, "An Architecture for Adaptive Intelligent Systems," *Artificial Intelligence*, Special Issue on Agents and Interactivity, vol 72, 329–365, 1995.

T. Huang, D. Koller, J. Malik, G. Ogasawara, B. Rao, S. Russell, and J. Weber, "Automatic Symbolic Traffic Scene Analysis Using Belief Networks," *Proceedings of AAAI-94*, 1994.

Victor Lesser, Hamid Nawab, Izaskun Gallastegi, and Frank Klassner, "IPUS: An Architecture for Integrated Signal Processing and Signal Interpretation in Complex Environments," *Proceedings of AAAI-93*, 249–255, 1993.

Ann Nicholson and Michael Brady, "Dynamic Belief Networks for Discrete Monitoring," *IEEE Transactions on Systems, Man, and Cybernetics*, special issue on Knowledge-Based Construction of Probabilistic and Decision Models, vol. 24, no. 11, 1593–1610, 1994.

Judea Pearl, *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, Morgan Kaufmann, 1988.

Yun Peng and James Reggia, *Abductive Inference Models for Diagnostic Problem-Solving*, Springer-Verlag, 1990.

Stuart Russell and Peter Norvig, *Artificial Intelligence: A Modern Approach*, Prentice Hall, 1995.

Solomon Shimony, "Finding MAPs for Belief Networks is NP-Hard," *Artificial Intelligence*, vol. 68, 399–410, 1994.

Whitehair, R. 1996. A Framework for the Analysis of Sophisticated Control. Ph.D. diss., Computer Science Department, University of Massachusetts.