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# Fusion Sub-System Design From an Integrated Command, Decision Support and ISR Perspective

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## Abstract

*What we have identified is a suite of technologies that together define a solution to fusion which captures a reasoning model that supports fusion. It is this approach that is needed if we are to capture the human capability of performing fusion which has at its core a reasoning function. It is a hybridization of formal and temporal concept reasoning, Peircean reasoning with an instantiation of Mills canons, Modal logic and coupled to an architecture based on Hawkins model of the neocortex. The solution concept will have significant impact on sensor development and a major impact on information architecture design. The effort supporting this effort is working towards a 70-80 percent solution to demonstrat the capabilities and the feasibility of linkage of the technologies.*

*Keywords: fusion, Peircean reasoning, co-evolution, formal concept analysis.*

## Introduction

This document provides information on the current state of a development effort at Sandia Labs that is taking an integrated systems engineering approach to the design of a data and information fusion engine for use in information intensive environments. The approach takes a step back to understand the requirements associated with this design from a higher perspective. In doing so we find a number of fundamental changes in approach that need to be made to identify solutions that are robust in the information domain. We need to recognize the dynamically chaotic environment these systems operate in, to understand decision making at a fundamental levels and then search the technological domains that may yield solutions to these problems. An engineering paradigm of divide, constrain and conquer can not be used to deal with the complex problems associated with combat and the information systems supporting command and control in this domain.

Information systems support command, control, fusion, decision support, as well as data and information collection. Vulnerability, is not failure of the "pipes" but it is the defeat, delay and disruption of the information itself. Design of these systems must be grounded in the theoretical foundations of logic, reasoning, an understanding of neural architecture and evolutionary mathematics. They cannot survive the rigors of their operational environment if constructed on a paradigm of layered failure mode and effects risk mitigation. The effort described herein, identifies a hybrid solution approach that folds Peircean reasoning and modal logic into an architecture based on a human neocortical model. That model of fusion is then integrated into a co-evolutionary game engine to begin the development of a predictive decision aid that interfaces to the command decision maker through his or her belief state.

## Command Paradigm

The first step in identifying the needs of a command decision support sub-system is to understand the decision making process. It is felt that we often neglect the cognitive load imposed on our commanders and as a result provide them with burdensome applications that take away from a fundamental task, one of survival. Systems engineering provides the means by which we can assess the larger context of the problem being addressed to ensure we solve the correct problem. One observation in the process is the need to understand the decision making process from a philosophically based perspective, and to approach the design in a manner that augments the decision making process and mitigates the impact on the tasks being addressed. Recognizing that decisions are based on a decision makers "belief state" enables us to design decision aids that simply modify that belief state.

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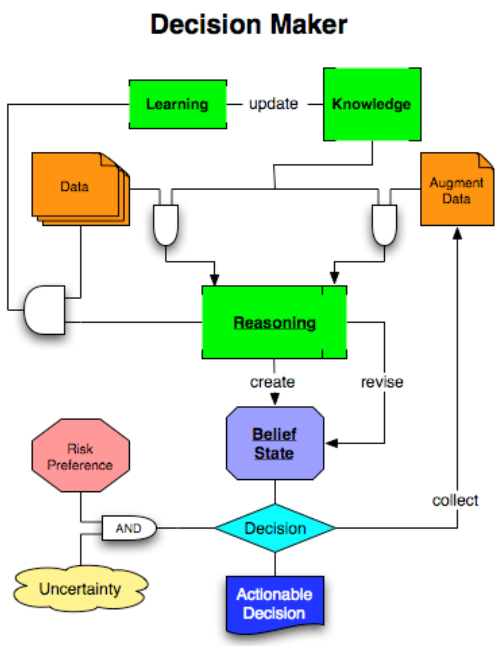


Figure 1. Decision making paradigm.

The model shows a system that collects data and convolves that with their collected knowledge to create an understanding of a situation, creating a belief state. The model permits the accretion of more data as well as updating the knowledge base, through learning or by adding to the command collective, individuals or systems with different skills. Once a belief state is generated decisions are made which are tempered by uncertainty, and risk aversion. This model also adds some insight into the concept of information deception. What can we do or what can an adversary do to corrupt the belief state of the decision maker?

Additionally, by approaching design from this perspective, we can develop solutions which enable the decision maker to employ their considerable problem solving skills to situations that may be novel, or were not recognized in the course of command activities. Basically, are attempting to augment a commanders skills rather than replacing them.

## Systems Considerations

The design of information systems are highly non-linear systems that operate in a domain in which the dynamics can be characterized as chaotic. As a result, the design of fusion systems information architectures, the command system, decision aids supporting command or the intelligence and sensor systems feeding the fusion systems are implicitly linked to each other and the requirements are a balance among them. This linkage between components makes design in an uncoupled manner, whether you optimize within the sub-domains or not, result in a sub-optimal system level performance. It is hoped that in the course of working through the elements of a fusion system we can see these intimate dependencies.

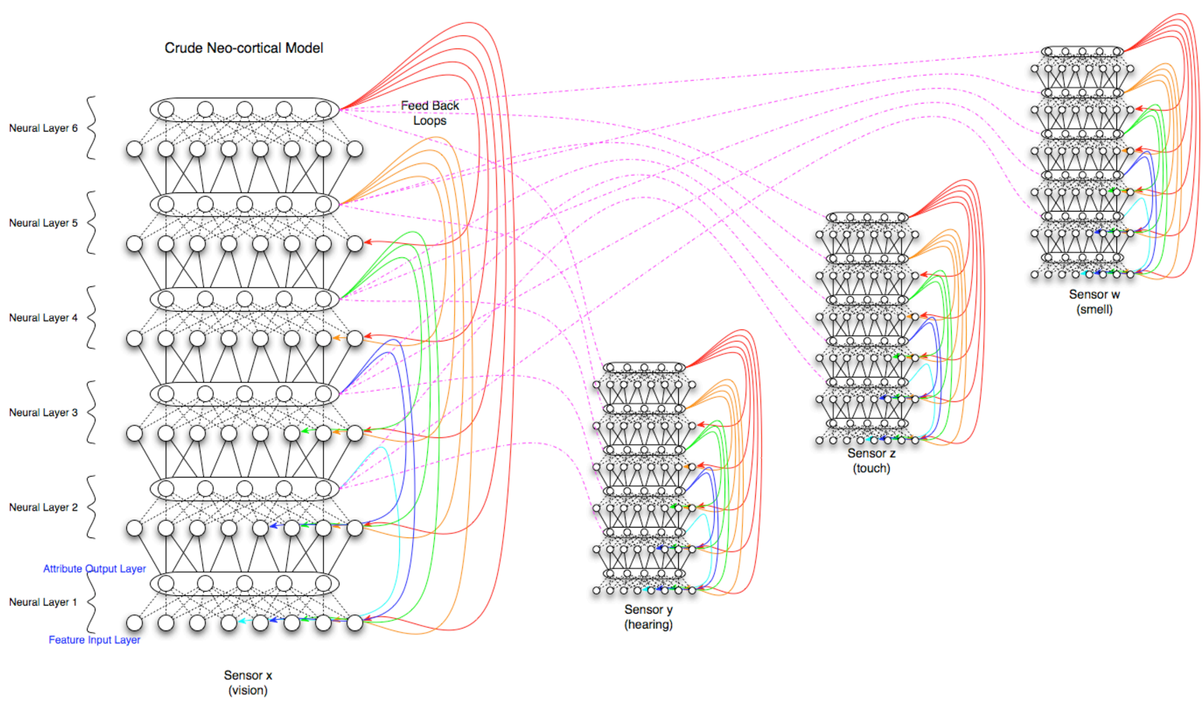


Figure 2. An interpretation of Hawkins neocortical model.

## Fusion Architecture

If we start with a fusion architecture, as a base of design the impacts on the other systems begin to emerge. In Hawkins book “On Intelligence” we see a model for the neocortex defined which ideally suites the needs of an information fusion paradigm that supports the essential elements of a reasoning based approach to fusion. In his model he articulates a layered system in which different levels of abstraction are realized at each of the six layers. Figure 2. takes a little liberty in representing the model Hawkins proposed and adds a technical solution to the representation of the layers of the neocortex. The points to capture from this construct is the comprehensive feedback loops between layers of the neocortex and the links to different sensors, like auditory, visual, smell, etc. The feedback loops activate an “expectation mechanism, when performing a similar function daily we expect things to be the same as the day before. Opening the door to your office, we expect to find a round smooth knob which must be turned. When that knob was changed overnight and we now discover a lever, we stop and have to adjust or discover a method for entering that door. We have effectively shifted from an inductive-deductive pattern matching system to an abductive based system.

In a similar way, the expectation crosses sensor boundaries such that not only do we expect a certain feel to the door knob but we expect to hear that familiar squeak, also a silver color and the knob to be at room temperature. When any of these conditions have changed we shift to an abductive problem solving paradigm.

In the model presented in figure 2, we have represented each layer as an ART neural network. The reason for selecting this initial technology is because of the classification capability of that design. We are looking for a system that correlates attributes with instances, a given set of attributes are possessed by a specific object. That object can in turn be a member of a higher level set of attributes which define a more complex abstraction. This abstraction mechanism becomes important for high level reasoning and fits into a knowledge representation technology that is based on formal concept analysis.

## Reasoning Engine

The reasoning engine is based on C.S. Peirce’s model of scientific inquiry. This philosophical construct provides the foundation for how we as humans reason about situations we new to us. This model consists of three reasoning capabilities; Abduction, deduction and induction. The logic associated with these forms of reasoning are captured in figure 3.

A crude way of looking at this suite of logic is abduction provides the hypotheses to possibly explain an observation, deduction is a means for selecting from that set of hypotheses, and induction is the means to validate the hypothesis selected. Induction can be viewed as a statistical collection of data that confirms or supports the hypothesis. This statistical validation must be tempered by maxims such as “severe” testing as defined by Mayo. A second nuance of this problem is the frequentist perspective that needs to be tempered by Bayesian statistics for many of the problem domains this solution is being proposed to address.

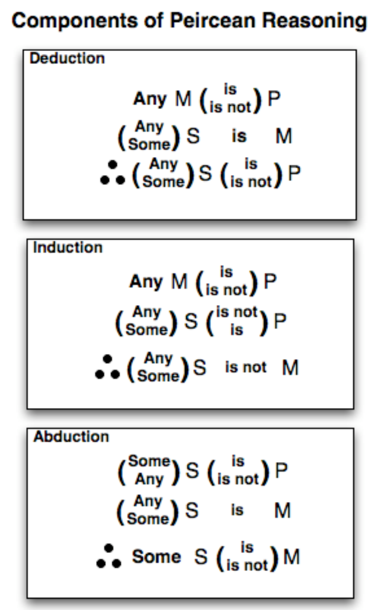


Figure 3. Formal representation of Peircean reasoning.

The architecture for the reasoning engine needed to support the fusion model being developed is provided in figure 4. This sub-system uses formal concept analysis technologies to capture the knowledge domains and for the foundation for conceptual and temporal reasoning. The component uses a contextual framework in order to narrow the potential domains of knowledge to search within. This aspect enables one to to recognize that “bullet items” is different if we are trying to understand the preparation of a presentation or if we are discussing weapon systems. This contextual information coupled with data being processed provides the basis for the construction of a working context that is used by the Peircean reasoning engine. Data is associated with attributes which is a gross screening process. The data must be processed via some form of logic operator, in this case the initial system will use a disjunctive logic filter to provide a degree of validation of the data.

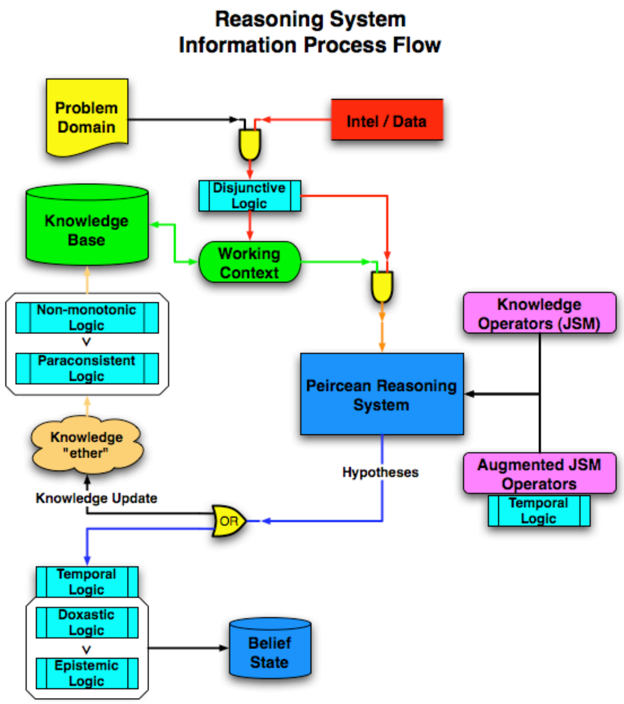


Figure 4. Peircean reasoning engine, temporally augmented.

The knowledge operators which are being designed on principle identified by J.S. Mills provides the basis for the conceptual reasoning. The augmented operators will reflect the need to fold temporal aspects of into the reasoning process in order to operate on process reasoning issues. The result of this set of process steps is a viable hypothesis to explain a set of observations or provide a means for processing a task. Should the existing knowledge base prove insufficient in establishing a solution the system needs to be able to expand its knowledge base to augment its deficiencies. The successful result will provide the basis for establishing or updating the belief state. Again it is the belief state, human or machine that forms the basis for decision or actions.

### Logic Infusion

Figure 4 shows a number of instances in which logic systems are being introduced into the reasoning architecture. The set identified is a baseline that needs to be assessed and expanded based on the needs / domains of application. Modal logic, which folds the concepts of possibility and plausibility into the reasoning landscape, must play a key role in the processing of data, information, knowledge and belief. The ambiguity of language results in situations that have the potential of producing contradictions that can be ameliorated to varying degree through the application of logics. In the knowledge domain, the update of knowledge or the addition of new knowledge domains, can produce examples of these conflicts that need to be resolved. The bird paradigm is a simple example; birds have feathers, lay eggs and fly. Consideration of penguins creates conflict in this knowledge domain because penguins can not fly. This problem is studied in a number of logical research domains associated with non-monotonic and paraconsistent logics.

We are attempting to address some the issues of knowledge generation, and update through the functional application of non-monotonic and / or paraconsistent logic. We recognize the need to integrate logics into the system some of the focused research / applicability of a particular modal logic needs to be pursued in follow-on efforts.

Similarly, belief generation and revision is the domain of doxastic and epistemic logic. What is very obvious in developing an architectural solution to the larger problem of fusion and decision aid design is the overriding dependence of these systems on temporal logic. Temporal logic provides a framework enabling one to reason about change. This technology addresses issues of truth associated with timeliness, duration and order of events and information. Simplistically, a target location in a database that is 2 weeks old is not a good candidate for prosecution in maneuver warfare. The architecture being instanciated is helping to identify process points where the various modal logics naturally fit into the system.

## Knowledge representation

The representation of knowledge has a number of requirements that enable us to apply a number of technologies to produce the hybrid solution being sought. We need a technology that enables the construction of knowledge bases, that minimize transformations between conceptual reasoning and process reasoning systems, and augment a Peircean based abductive reasoning architecture. The most difficult of these requirements involves the transformation between conceptual and process reasoning. In conceptual reasoning we are attempting to identify some object or concept while in process reasoning we are having to recognize the concept but and additionally the state and the allowable transitions in state.

### Formal Concept Analysis (FCA)

Formal concept analysis is a knowledge representation development effort initiated by Ganter & Wille based on ordered set theory. The mathematics of FCA lend themselves to lattice theory and the rich representation capabilities of that domain. FCA is based on the idea of a formal context, $\mathcal{K}_{FC}$, defined by a "triple" as the one in equation 1.

$$\mathcal{K}_{FC} = (G,M,I) \qquad \text{Eqn 1}$$

In this equation G and M are sets of objects and attributes respectively and I is a binary relation between the two sets. There is an operator defined, $(\cdot)'$ which aids in the definition of formal concepts from the formal context.

$$(A)' := \{m \in M \mid (g,m) \in I \ for\,all\, g \in A\}$$
$$(B)' := \{g \in G \mid (g,m) \in I \ for\,all\, m \in B\} \qquad \text{Eqn 2}$$

In this expression, the operator action on the object set A produces the set of attributes common to objects within that set. Likewise, application of the operator on the set of attributes B produces the set of objects which posses those attributes. The interesting application of this operator, which has very practical operational implications, is shown in equations 3.

$$A \subseteq ((A)')'$$
$$(A)' = (((A)')')' \qquad \text{Eqn 3}$$

Operationally, this operator permits us to efficiently construct a working context based on data being processed to produce a complete object / attribute context. The first application of the operator identifies common attributes while the second application identifies objects possessing the attributes which were common to the original set of objects. The result of this operation can potentially be a larger object set than the original object set based on the formal context on which the operator is being applied. This is a very powerful tool for use in knowledge / data search.

The linkage to lattice theory provides avenues into a robust representation domain that can aid an analyst in developing an understanding of the collected data. The technologies use the "Begriff" of an identified context as the basis for the construction of that lattice. The Begriff, $\mathcal{B}$(G,M,I), is the ordered set of all concepts within a context. A concept is defined by the conditions in equation 4.

$$(A,B) \xrightarrow{fc} (G,M,I)$$
$$\Leftrightarrow \qquad \text{Eqn 4}$$
$$A \subseteq G, B \subseteq M, (A)' = B \ \& \ (B)' = A$$

The ordering of the concepts in $\mathcal{B}$(G,M,I) is defined in the next expression.

$$(A_1,B_1) \le (A_2,B_2) \Leftrightarrow A_1 \subseteq A_2 \vee B_2 \subseteq B_1 \qquad \text{Eqn 5}$$

An example of a lattice is given in from information developed by K. Wolff for his FCA tutorial. This example is a simple model capturing aspects of a knowledge base dealing with animals. In matrix representation the information is the following.

| Animals | Preying | Flying | Bird | mammal |
|---|---|---|---|---|
| Lion | x | | | x |
| Finch | | x | x | |
| Eagle | x | x | x | |
| Hare | | | | x |
| Ostrich | | | x | |
| Bee | | x | | |

Table 1. Matrix representation of an animal context.

The lattice representation of this information is shown in figure 5.

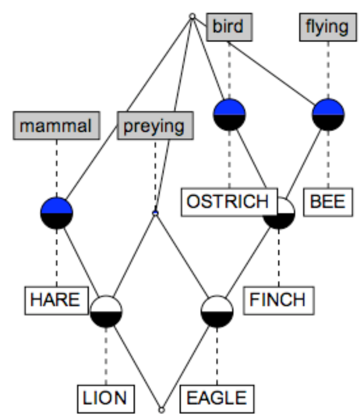


Figure 5. Lattice of animal domain.

The expansion capability of this technology is captured by the "Bee" entry in the matrix. The lattice prior to the addition of the information related to the bee consists of information in figure 5 with the upper right node (BEE) removed. Expanding a knowledge base is a simple task in this technology. Likewise, the parsing of a lattice can be accomplished nearly as easily. What this does is give us the ability to structure the lattice at varying levels of knowledge abstraction and then when additional detailed information is of interest we can "zoom" into an object node to see the additional structure of the knowledge base under the selected node. This mechanical process adds to the potential understanding of knowledge and data being worked with.

The reality of the situation is that attributes are often defined by continuous real variables and / or may be probabilistic. Formal concept analysis deals with attributes with continuous variables by defining a special construct called a "many valued context". They are defined in the next expression.

$$\mathcal{K}_{mv} = (G, M, W, I) \qquad \text{Eqn 6}$$

As before, G is the set of objects, M is a set of attributes with values from the set W, defined by a ternary relational operator I. In this extension, the set of all values an attribute may assume is defined by the domain of that attribute.

$$dom(m) := g \in G \big| (g, m, w) \in I, w \in W \qquad \text{Eqn 7}$$

To use many-valued contexts in formal concept analyses these attributes must go through a scaling process in order to generate a formal context that identifies the presence or absence of an attribute. Scaling can be considered as a construction of a special context that defines the relations of the many-valued attributes with new attribute sets and then 'joining' the original context and the new scale context. The new scaling context can be represent in equation 8.

$$\mathcal{S}_m := (G_m, M_m, I_m) \qquad \text{Eqn 8}$$

$M_m$ is a set of new attributes to represent the many-valued attribute in G and $I_m$ is the binary relationship between the attribute sets. An example from Tam involves book prices.

| | Price | | | >$0 | >$25 |
|---|---|---|---|---|---|
| Book A | $25.95 | | $25.95 | | x |
| Book B | $19.95 | | $19.95 | x | |
| Book C | $74.95 | | $74.95 | | x |

Table 2. Initial book price context and scaling context.

This results in a new context defined below.

| | Price > $0 | Price >$25 |
|---|---|---|
| Book A | | x |
| Book B | x | |
| Book C | | x |

Table 3. Scale context of book prices.

This process of scaling is import in the extension Wolff takes in extending formal concept analysis into the temporal domain.

Dealing with uncertainty and probabilities of attribute associations has been treated in a more mechanistic fashion by the author. The Attribute sets carry a probability of association with an object into the lattice construction domain which is converted to a binary relationship based on a 'threshold' value identified by an analyst. This approach simplifies treatment of information uncertainty and lends itself to use by Finn's instantiation of Mills first canon which requires the construction of 3 exemplar lattices.

**Temporal Logic**

Temporal concept analysis is an extension of FCA in which the evolutions of the system or object are considered in conjunction with the conceptual aspects of the object. The principle researchers in the area, Wolff and Neouchi, approach the problem by adding directed edges to the lattice to capture the evolutionary behaviors of the attributes. Wolff's efforts have resulted in a very formal representation of the temporal extensions of FCA while Neouchi has focused on the development / definition of sets of operators that focus on issues associated with temporal concepts.

Wolff has approached temporal concept analysis be scaling the time and event space and adding directed edges to the concept lattice of the context. The potential difficulty of this approach can be seen in the simple example in the next figure.

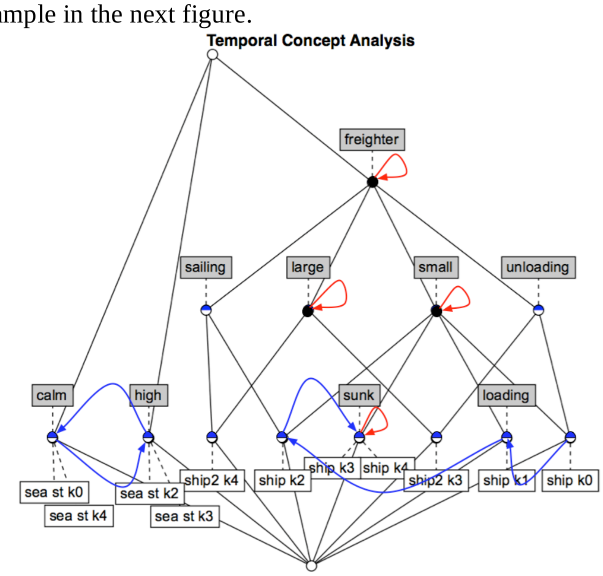


Figure 6. Example of lattice with directed edge overlay.

The blue vectors on the lattice in figure 6 indicate the temporal evolution of the objects in the formal context. The red vectors show persistent states of objects in that context. What I think becomes clear is the complexity of the display for even so simple an example. Complex information bases will rapidly overwhelm an advantages lattice representation bring to formal concept analyses.

A way around this complexity issue is to redefine how we think about systems / objects and the states of those systems. Traditionally, we view a system in a specific state as a unique object, so we are force in a FCA paradigm to replicate an object as many times as we have states for it. If we instead view the system as being unique with sets of constant or time dependent attributes we can reduce the complexity of the lattice.

The paradigm we are working to develop is a 'zoomable' model in which we can zoom into an object to flesh out greater detail of the object at lower levels of conceptual abstraction. We can perform a similar function when approaching issues of systems state or the time dependent attributes. We can zoom into the special attribute and use the mathematics or technology that is better suited for the problem being solved. For example we can use FCA to move us into a conceptual neighborhood and focus on a temporal attribute and use Bayesian, Markov, or the temporally extended formal concept analysis to refine our understanding of a situation.

We might be able to see these possibilities in more detail by considering the information in the next figure. The notional example considers different temporal traces for the 4 attributes and a different set of attributes for two objects. We can see that taking a snapshot of these systems or objects at different points in time produces different collects of attributes for the objects. This can also change with different threshold levels. At point 'a', object 1 is characterized by attributes A while object 2 by attributes A and D. If D was not in the data set the correct hypothesis could not be identified. Using a process of temporal matching could refine the hypothesis since A is present in object 1 at all three states while it is only present at state 'a' in object 2.

Knowing the Markov transition matrix could aid in the proper identification of a temporally dependent hypothesis. Likewise temporal extensions of formal concept analysis could also be used to refine the selection mechanisms. The second approach may require additional computational overhead, but should be just as effective.

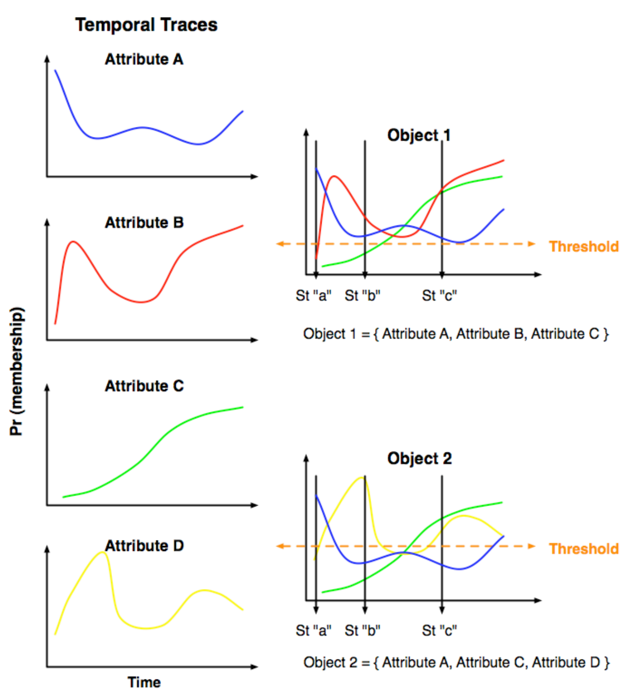


Figure 7. Temporal traces of four attributes and two objects with a mix of attributes.

**"Belief State"**

Referring back to the architecture diagram in figure 4, there is a belief state cache identified. This cache can be viewed as the tagged collection of validated hypotheses generated by the reasoning system. This cache contains the understanding up to the current point in time, of data being collected and assesed. The structure of this cache is defined in the next equation.

$$Bk_j = \left\langle \begin{array}{c} t_j, Active_j \\ \{h_{j,0}, d_1, \ldots d_n, d_1^v, \ldots d_m^v\} \\ \{h_{j,k}, d_1, \ldots d_n, d_1^v, \ldots d_m^v, h_{j,k-1}, \ldots h_{j,k-t}\} \\ \{h_{j,r}, d_1, \ldots d_n, d_1^v, \ldots d_m^v, h_{j,r-1}, \ldots h_{j,r-s}\} \end{array} \right\rangle \quad \text{Eqn 9}$$

These belief kernels consist of a time tag, $t_j$ an activation flag, $Acitve_j$, a hypothesis, $h_j$, data collected that results in the hypothesis, $d_n$ and data collected to validate the hypothesis, $d^v_m$. The next two notional inclusions consist of hypotheses from higher levels of abstraction that may depend on hypotheses generated at sets of lower abstraction. This construct is needed to trace the impact of changes or updates to information at lower levels of abstraction.

## Conclusion

What we have identified in this short note is a suite of technologies that together define a solution to fusion which captures a reasoning model that supports fusion. It is this approach that is needed if we are to capture the human capability of performing fusion which has at its core a reasoning function. The solution we are working towards is a 70-80 percent solution, to demonstrate the synergistic functioning of the major technologies we have identified as integral to that solution.

Significant additional work needs to be performed to ensure the optimal identification of the modal logics required by the solution. There may be a better mix, or alternatives that have not been realized. Logic has implications on the information security, on its timeliness, on its validity, and its quality. Modal logics also aid in the management of knowledge and the belief. The effort here has only scratched the surface, but the importance of this integration can not be missed or ignored.

The knowledge representation technology of formal concept analysis is in my opinion the best suited to support logic, reasoning, and the neocortical architecture identified as the real time fusion engine. It also seems to support the two major forms of reasoning that we need in decision aid problems were we need to be able to perform concept reasoning as well as process or temporal reasoning.

Finally, a fusion solution requires a core reasoning capability. When the inductive – deductive functioning of the system cannot identify a situation you need to be able to switch into an abductive hypothesis generating function in the effort to find a solution to this new situation. Working in a very tightly coupled manner is Hawkins neocortical model, this structure supports pPeircean reasoning, is a natural for multi-sensor fusion, and the feedback mechanisms are a very powerful approach for prediction / expectation functionality.

**Implications**

I think the most significant implication of this approach to solving fusion lies in its impact on information system architectures. There seems to be a belief that we need huge information conduits to move data from the sensor to the decision maker. This approach results in smaller conduits to the higher decision making functionaries, with only slightly larger conduits near the data collection assets. This is because we abstract the data into multiple levels of information. This permits us to communicate ideas rather than 'bits' of data.

A second implication concerns the impact on the design of sensors. If we build a robust fusion system, we can optimize the function of the sensor systems to maximize the effectiveness of the sensors. We may not want to collect raw acoustic data but capture data related to a higher level of abstraction the will lead to more effective detection capabilities.

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# Fusion Sub-System Design

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# Briefing Topics

- Relationship of Reasoning & Cognition
  - Decision Making Paradigm
- Data / Information Fusion
  - Architecture (Hawkins Neocortical Paradigm)
- Supporting Technologies:
  - Formal Concept Analysis (FCA)
  - Temporal Concept Analysis
  - Peircean Reasoning
  - Modal Logic
- Status

# Cognition vs. Reasoning

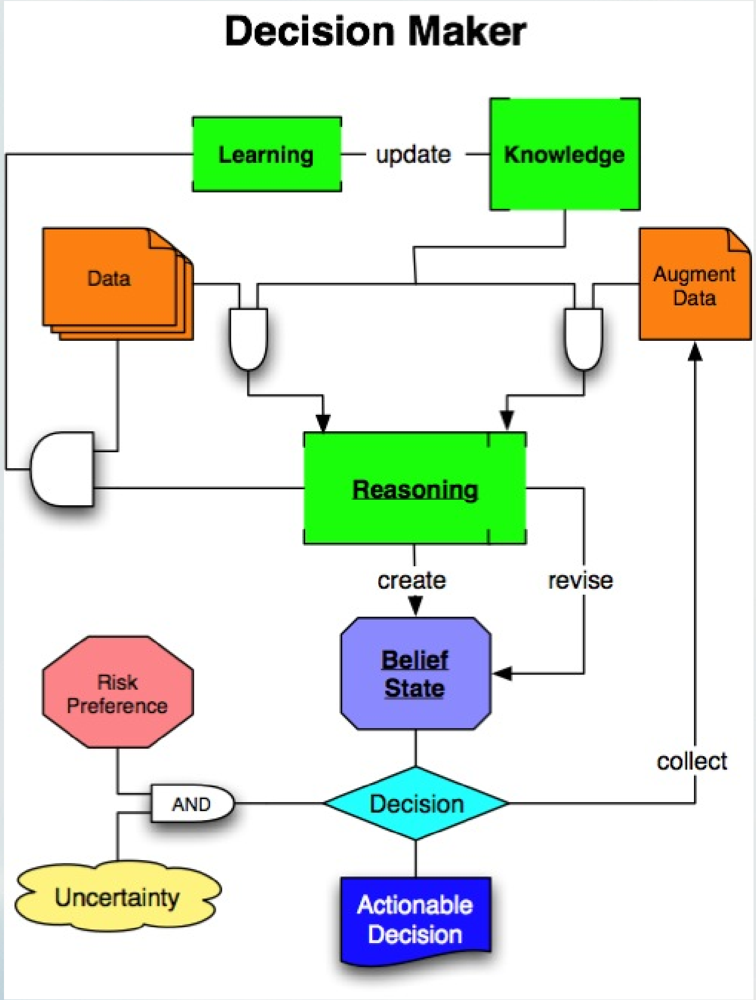
- Cognition:
  - Is the function associated with the acquisition, storage, representation and utilization of information.
- Reasoning:
  - Is the function to discern what is unknown from a position of what is known.
    - Reasoning is fundamental to human decision making, it is endemic in everything we do.
      - Reasoning can be a skilled application of the scientific method or a process flawed in its method, and/or data. (Peirce's fixation of belief; tenacity, authority, …)
- Reasoning is a product of Cognition.

# Belief and Decision Making

- Beliefs "…guide our desires and shape our actions." C.S. Peirce
  - Peirce believes "doubt" in the fuel that drives the engine of inquiry.
- Inquiry employs the mechanisms of reasoning to mitigate doubt.
- These perspectives on belief and reasoning provide the basis for a "decision making" paradigm.

# Decision Making

- The convolution of data and knowledge form the basis of a belief state.
- Belief may be revised by assimilating new data, or updating the knowledge base.
- Given a belief state, actions taken are conditioned by the decision makers degree of risk aversion and uncertainty or doubt at the time of the decision.



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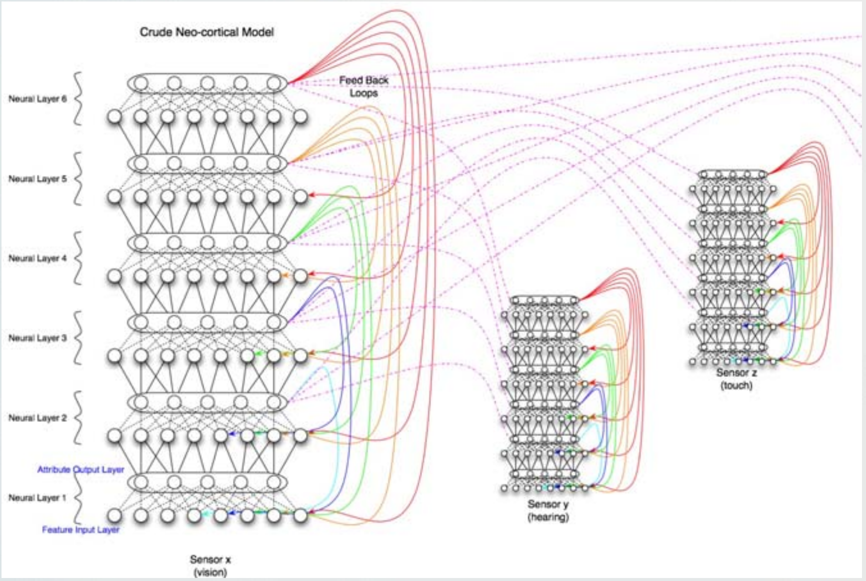
# Data / Information Fusion

- The decision making model has an intrinsic fusion functionality.
- This functionality is founded on the mechanics to reasoning.
- Design of virtual fusion systems must consider reasoning as a fundamental function of fusion.
  - Failure to include this in the design is a major design failure.

# Architecture

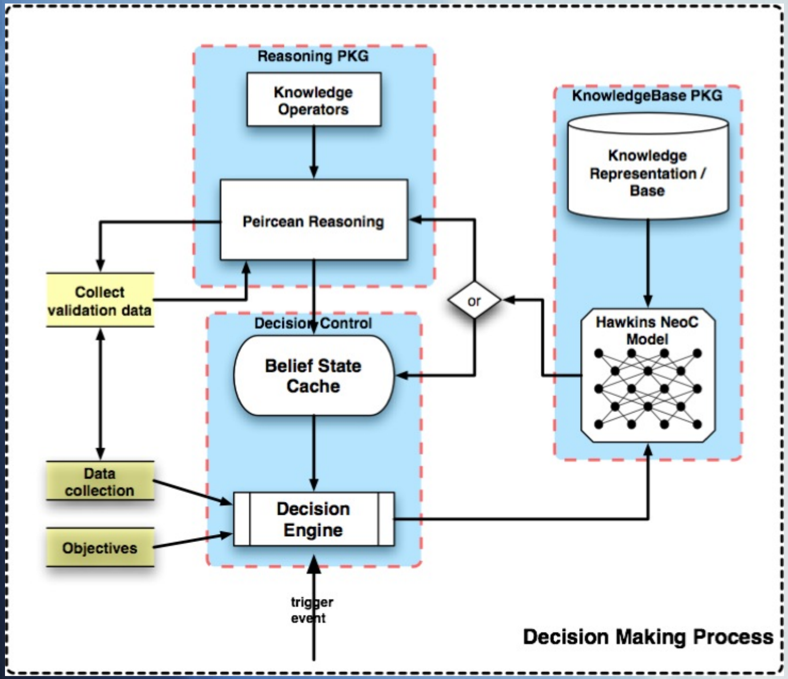
The intersection of philosophy and engineering

- Hawkins neocortical model
  - 6 neural layers.
    - Provides an abstraction mechanism.
  - Feedback loops between all layers.
    - Activate “expectation” mechanisms (prediction)
  - Linkage between functional regions.
    - Multi-sensor capabilities.
- A physical manifestation of Peircean reasoning.

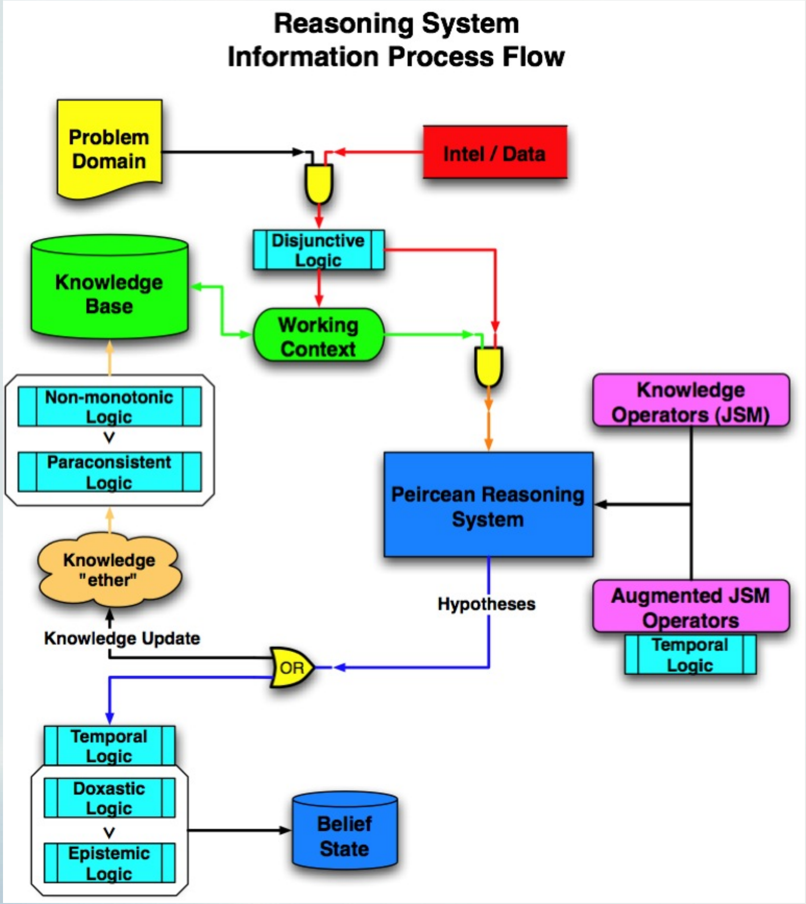


# Design Implementation

Automated & Deliberate Processes




Detail of the Deliberate Processes



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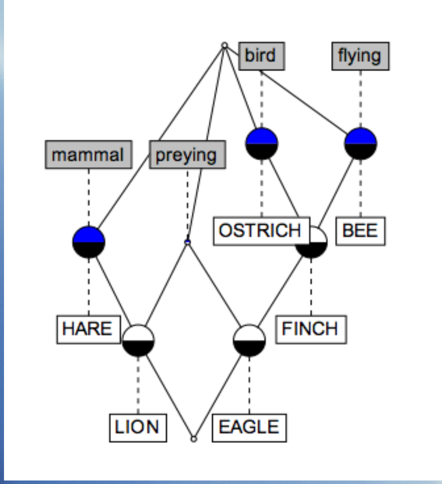
# Briefing Topics

- Relationship of Reasoning & Cognition
  - Decision Making Paradigm
- Data / Information Fusion
  - Architecture (Hawkins Neocortical Paradigm)
- Supporting Technologies:
  - Formal Concept Analysis (FCA)
    - Knowledge representation
  - Temporal Concept Analysis
    - Knowledge representation in a temporal domain
  - Peircean Reasoning
    - Belief state generation/revision
    - Hypothesis generation
  - Modal Logic
    - Belief revision, knowledge update, temporal reasoning, etc.
- Status

# Formal Concept Analysis (FCA)

| Animals | Preying | Flying | Bird | mammal |
|---|---|---|---|---|
| Lion | x | | | x |
| Finch | | x | x | |
| Eagle | x | x | x | |
| Hare | | | | x |
| Ostrich | | | x | |
| Bee | | x | | |




Based on Ordered Set Theory

$$\mathcal{K}_{FC} = (G, M, I)$$

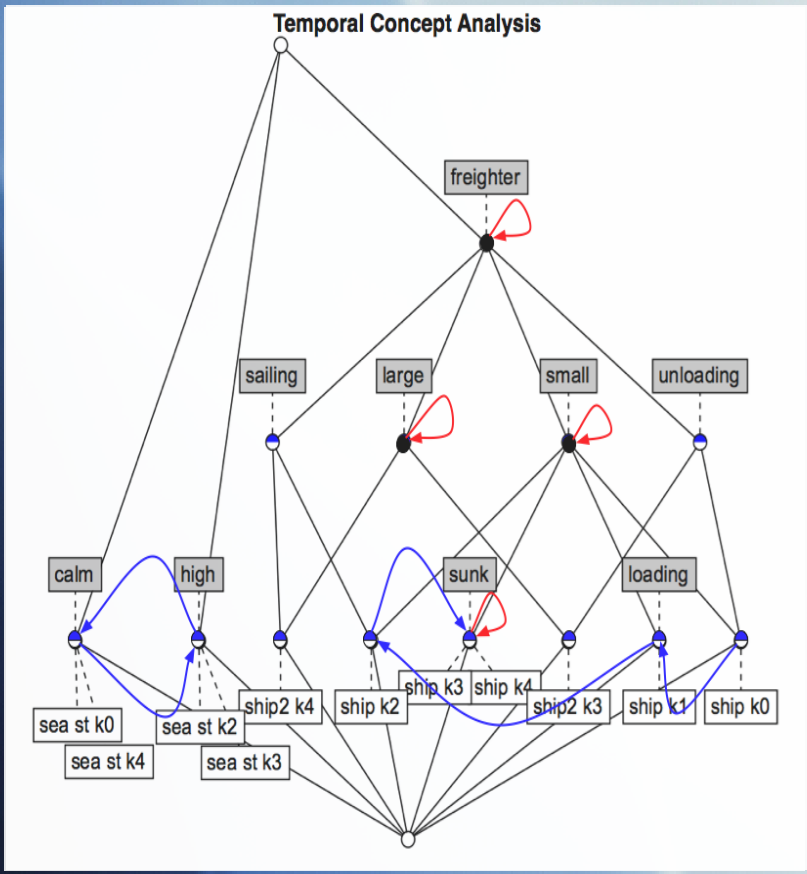
G & M represent sets of “objects” and “attributes”
I is a binary relation between sets G & M

Fundamental operator ( )’

$$(A)' \coloneqq \{m \in M \mid (g,m) \in I \ \ for\, all\, g \in A\}$$
$$(B)' \coloneqq \{g \in G \mid (g,m) \in I \ \ for\, all\, m \in B\}$$

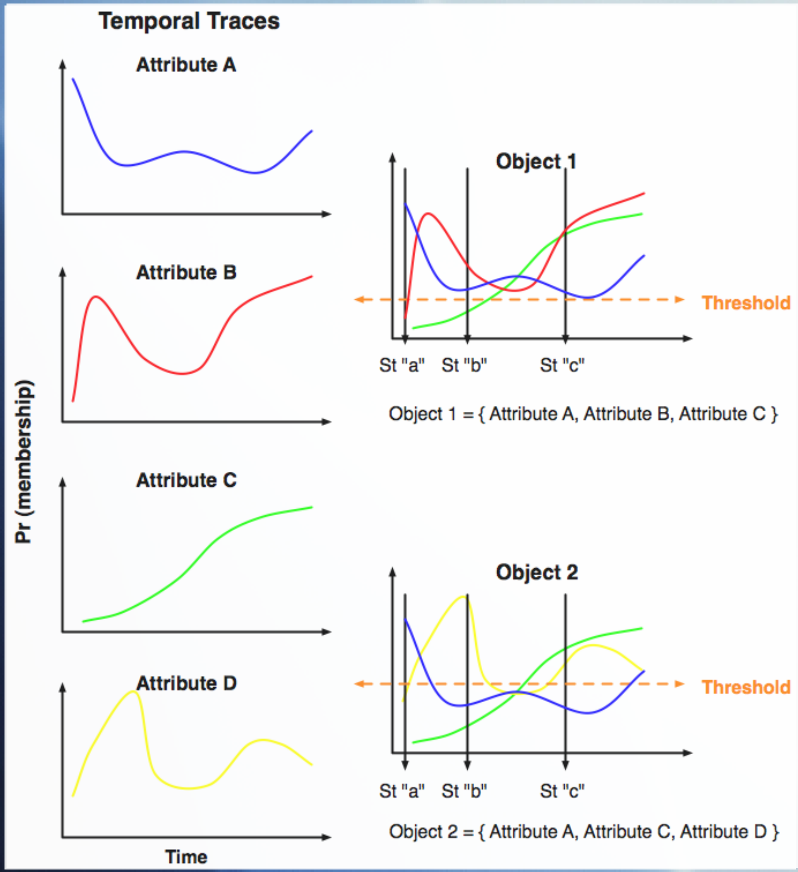
Natural extension of attributes into a real valued domain.
Fuzzy set theory provides the mathematical transformation.

# Temporal Concept Analysis



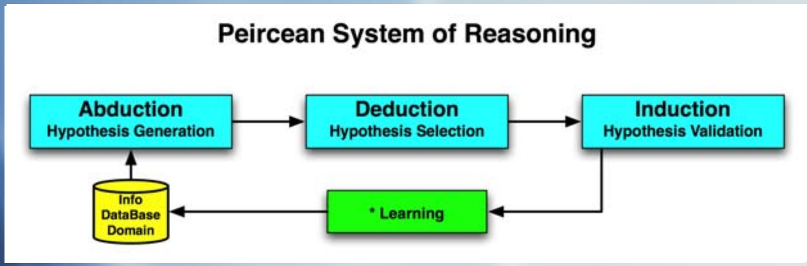

- Natural extension of FCA (Wolff, Neouchi)
  - Approach adds second set of edges (directed)
  - Identify state trajectories and terminal states.
- Our approach takes a modified view of systems / states.
  - Systems possess temporally dependent attributes.
  - Permits robust application of the most effective technology.
  - Potentially enables “reuse” of Mill’s operators.

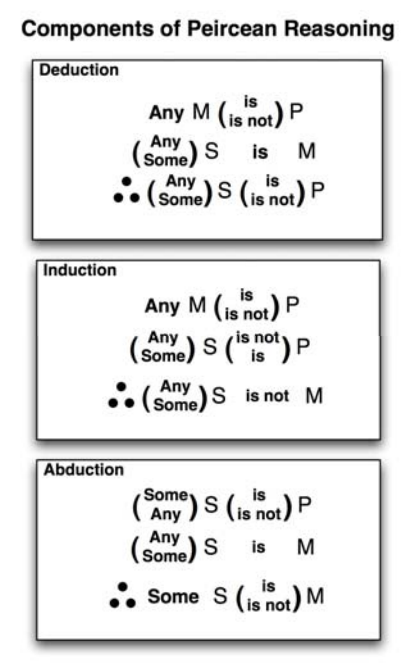
# Modified “state” Perspective




- “snapshots” provide different views of included attributes.
  - FCA identifies 2 hypotheses.
  - Temporal matching narrows the hypotheses
- Potential temporal technologies:
  - Markov techniques
  - Bayesian technologies
  - Temporal extension of FCA

# Peircean Reasoning




- Peirce's "method of scientific inquiry".
  - Abductive component adds unique capabilities.
- Initial set of knowledge operators based on "Mill's Canons".
  - Method of Agreement
  - Method of Differences
  - Indirect Method
  - Method of Residues
  - Method of Concomitant Variations

# Peirce’s Reasoning Model

- Deduction
  - The argument which shows a necessary connection between premises and the conclusion.
    - Logical deduction has its basis in mathematical reasoning.
- Induction
  - Draws a rule from the results of sample cases.
    - Three types: crude, quantitative, and qualitative.
      - Crude: Denying an event because it seldom happens.
      - Quantitative: Arguments based on a random sample.
      - Qualitative: Involves the verification or confirmation of a hypothesis.
- Abduction
  - The formulation of hypotheses, the process by which we arrive at plausible explanations of unique events.
  - Analogic
    - The formulation of hypotheses through analogy.

# Modal Logics

- Modal logic is the calculus of information processing
  - Address many dimensions of information operations.
    - Knowledge, belief, morality, time
- Epistemic Logic
  - Basis for treatment of Knowledge
    - Tactical, Operational, Strategic skills
- Doxastic Logic
  - Basis for treatment of Belief
    - Decision making
- Deontic Logic
  - Basis for the handling of moral issues
    - ROEs
- Temporal Logic
  - Dealing with temporal aspects of information

# Status

- We have:
  - Defined a model of fusion.
    - Uses a human based fusion construct.
  - Validation of the hybrid technology integration is progressing.
    - Shooting for a 70% solution.
  - A non-traditional view of system states is being employed to maximize technology effectiveness.
- We must:
  - Explore modal logics in greater detail.
  - Assess and expand the knowledge operator sets.
    - Consider; process reasoning, conceptual reasoning, causal reasoning, …
- Implications:
  - Changes the information architecture, inverted conduit sizing.
  - Impact on sensor design, potentially focus sensing on higher level abstractions.

# Backup Slides

# Logic / Reasoning

- Logic foundations
  - K ~ Knowledge
  - B ~ Belief
  - $\models$ ~ "logically valid"
  - α,β represent blocks of information/knowledge
  - ⊥ ~ logical contradiction
- Update and Revision
  - Principles 7-11
  - Contraction & expansion operators
    - " - ", " + ", " * "
    - " * " expansion under consistency

**Veridicality of Knowledge**

(1) $\models K(\alpha \to \beta) \to (K\alpha \to K\beta)$

(2) $\models B(\alpha \to \beta) \to (B\alpha \to B\beta)$

(3) $\models K\alpha \to \alpha$

(4) $\models K\alpha \to B\alpha$

(5) $if \models \alpha, then \models K\alpha$

(6) $if \models \alpha, then \models B\alpha$

$(Consistency)$ (7) $\neg B\perp$

$(Veridicality\ of\ Positive\ Introspection)$ (8) $BB\alpha \to B\alpha$

$(Veridicality\ of\ Negative\ Introspection)$ (9) $\neg B\perp \to (B\neg B\alpha \to \neg B\alpha)$

$(Positive\ Introspection)$ (10) $B\alpha \to BB\alpha$

$(Negative\ Introspection)$ (11) $\neg B\alpha \to B\neg B\alpha$

Ref. Lindstroem & Rabinowicz



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