Mental Models and Normal Errors

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1 Introduction

Perrow (1984) provided the following account of what he called a “normal” accident (see Figure 1):

> On a beautiful night in October 1978, in the Chesapeake Bay, two vessels sighted one another visually and on radar. On one of them, the Coast Guard cutter training vessel Cuyahoga, the captain (a chief warrant officer) saw the other ship up ahead as a small object on the radar, and visually he saw two lights, indicating that it was proceeding in the same direction as his own ship [Figure 1(t1), top panel]. He *thought* [italics added] it possibly was a fishing vessel. The first mate saw the lights, but saw three, and estimated (correctly) that it was a ship proceeding toward them [Figure 1(t1), bottom panel]. He had no responsibility to inform the captain, nor did he think he needed to. Since the two ships drew together so rapidly, the captain *decided* [italics added] that it must be a very slow fishing boat that he was about to overtake [Figure 1(t2), top panel]. This reinforced his incorrect interpretation. The lookout knew the captain was aware of the ship, so did not comment further as it got quite close and seemed to be nearly on a collision course. Since both ships were traveling full speed, the closing came fast. The other ship, a large cargo ship, did not establish any bridge-to-bridge communication, because the passing was routine. But at the last moment the captain of the Cuyahoga *realized* [italics added] that in overtaking the supposed fishing boat, which he assumed was on a near-parallel course, he would cut off that boat’s ability to turn as both of them approached the Potomac River [Figure 1(t3), top panel]. So he ordered a turn to the port [Figure 1(t4), top panel]. This brought him directly in the path of the oncoming freighter, which hit the cutter [Figure 1(t4), bottom panel]. Eleven coastguardsmen perished. (p. 215)

In retrospect, the question is (Perrow 1984), “Why would a ship in a safe passing situation suddenly turn and be impaled by a cargo ship four times its length?” (p. 217). Based on his analysis of this and other accidents in complex systems, Perrow concluded that the answer lies in the construction of a “faulty reality” (i.e., situation awareness; see Sarter and Woods 1991). In Perrow’s (1984) words: “… they [captains, operators, etc.] built perfectly reasonable *mental models* [italics added] of the world, which work almost all the time, but occasionally turn out to be almost an inversion of what really exist” (p. 230). This is a common theme among researchers of both human error (Reason 1990) and human power (Klein 1998) and has influenced numerous theories of human decision making (see Lipshitz 1993). My objective is to extend these theories with a more formal (computational) analysis of how (exactly) decision makers construct mental models to achieve situation awareness.

In this chapter, I outline a formal (Bayesian) framework and perform a detailed (computational) analysis of the Cuyahoga collision. The new contribution provided by my framework/analysis is to show that this prototypical “error” in situation awareness can be characterized as normal (normative) in a mathematical sense. I discuss the theoretical advantage of my framework in unifying the heuristics and biases proposed by previous researchers and the practical advantage of my framework in guiding the design of “decision support systems”.

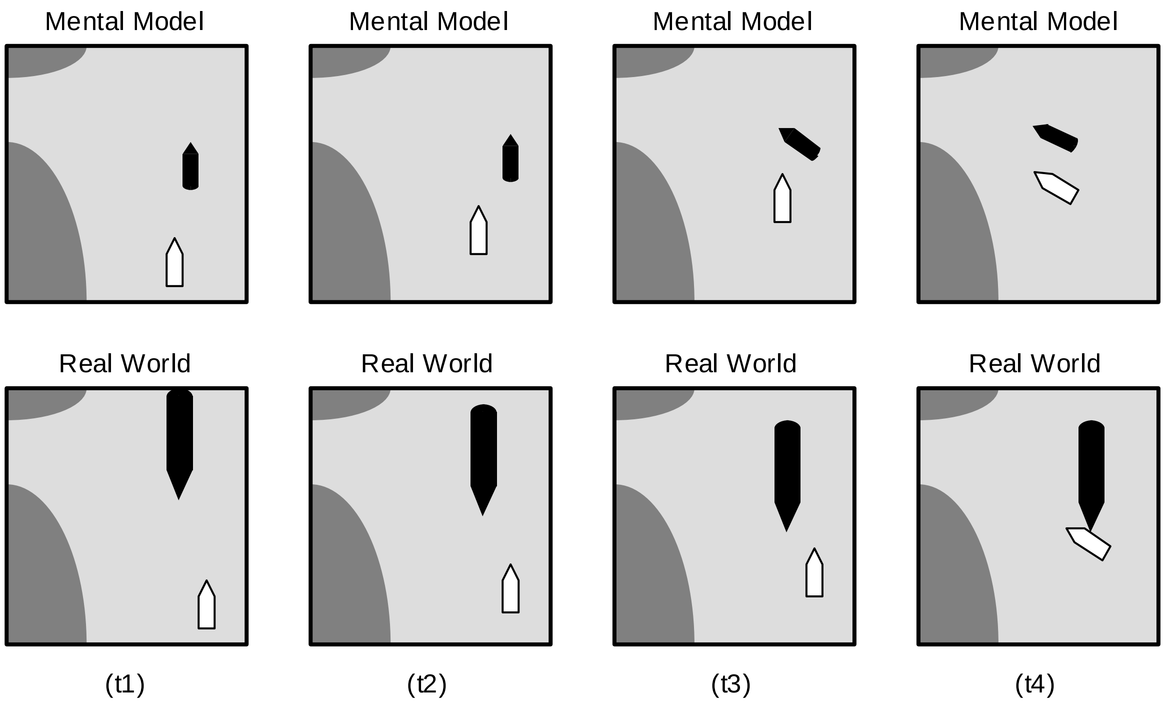

Figure 1: The Cuyahoga collision. Top panels depict captain's mental model and bottom panels depict real world. Small black boat (top panels) denotes fishing vessel and large black boat (bottom panels) denotes freighter. White boat denotes Cuyahoga in top and bottom panels. Time epochs are labeled (t1), (t2), (t3) and (t4).

2 Mental Models and Situation Awareness

The idea that human reasoning employs internal models is attributed to Craik (1943, see Johnson-Laird 1983) whose original theory highlighted three facets of these models. First, mental models are internal belief structures that represent an external reality. Second, mental models are constructed by computational processes to accomplish cognitive tasks. Third, mental models are adapted to the natural context of practical situations. Craik also highlighted three functions of mental models (also noted later by Rouse and Morris 1986), that is, to describe, explain and predict the world. Thus, influenced by Craik's original theory and informed by subsequent theories, I offer the following as a working definition: *Mental models are adaptive belief constructs used to describe, explain and predict situations.*

According to this definition, mental models are representational structures, not computational processes. However, it is vacuous to talk about representations without also talking about how these representations are used to accomplish specific tasks. Thus, my formal framework includes representational structures (which I call *models*) as well as the computational processes (which I call *modules*) that operate on these structures (Figure 2).

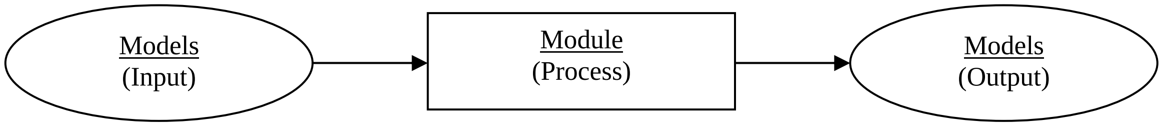

Figure 2: A mental module (process) operates on input models and generates output models.

Situation awareness can be characterized as the dynamic construction of mental models (via mental modules) to describe, explain and predict an evolving situation. This is in general agreement with the following definition proposed by Endsley (1988; also see Sarter and Woods 1991): "[Situation awareness is] the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and projection of their status in the near future." Note that Endsley's three facets of situation awareness correspond to the three functions of mental models identified by Rouse and Morris (1986) and others, namely describing (elements in the environment), explaining (their meaning) and predicting (their future status).

Most researchers of mental models have suggested that the mind represents information at different levels of abstraction. For example, Johnson-Laird (1983) distinguished between different levels of linguistic information, Rasmussen (1983) distinguished between different levels of system representation and Moray (1990) distinguished between different levels of Aristotelian causation. However, the levels that have been proposed by these researchers are typically limited to deterministic representations and do not address the probabilistic representations that are required to reason under uncertainty (see Burns 2001, Gigerenzer et al. 1991, Johnson-Laird 1994).

Here I argue that cause and effect are fundamental concepts in human reasoning (also see Moray 1990, Pearl 2000, Rasmussen 1983) and that reasoning about causality requires both deterministic and probabilistic models. As such, I propose three fundamental levels of mental representation (Figure 3), which I characterize as Confidence (C), Hypothesis (H) and Evidence (E). I also propose (similar to other researchers; see previous) that more complex (domain-specific) representations are constructed by stacking this fundamental trio into strata (see Figure 3). In the remainder of this chapter, I focus on the three levels C, H and E within a single stratum.

To give an example for the case of the Cuyahoga, the captain's initial model of E was "two lights". This is a deterministic representation because there was no doubt in the captain's mind (by Perrow's 1984 account) about seeing two lights. One H (H_1) was that of a "fishing vessel moving in the same direction". The captain thought it was possibly a fishing vessel and "possibly" represents a measure of C in the H_1, $C(H_1)$. Although it is difficult to assign precise quantitative values to terms such as *possible* (see Zadeh 1996), I propose that people mentally represent at least rough probability estimates (see Burns 2001, Hertwig et al. 1999, Juslin and Olsson 1999). For example, in this analysis of the Cuyahoga collision, I assume that C can take on one of the following order-of-magnitude values: impossible (0), unlikely (ε), possible (η), likely (ρ) or certain (1).

3 Mental Modules and Bayesian Inference

Besides different levels of representation, situation awareness also involves different "stages" of computation (Figure 3). Here I use a Bayesian formalism to characterize the various stages (modules) that are needed to construct various levels (models). In the following, I outline the computational details of each stage (see Table 1), and later I use this formal framework to analyze the Cuyahoga collision.

Describing

The process of describing a situation can be characterized as representing information about the observed E (effect) and possible $\{H_1, H_2, H_3, \dots\}$ abbreviated to $\{H_i\}$ (causes) of this E. I propose that only those H_i with high $C(H_i)$ are active at a given time (due to attention/memory limitations), and that C in each H, $C(H_i)$ is represented in order-of-magnitude terms by probabilistic mental models (i.e., $C = 0, \varepsilon, \eta, \rho$ or 1). I also propose that E is represented by a deterministic mental model.

Explaining

The process of explaining a situation can be characterized as identifying the most likely cause (represented by H) of the observed effect E. I propose that this process is governed by Bayes Rule (see Burns 2001, Knill and Richards 1996):

$$C(H_i|E) \sim C(H_i) * C(E|H_i)$$

where each H_i is an active H, $C(H_i)$ is the *prior* (C in H_i before E is observed), $C(E|H_i)$ is the *likelihood* (of observing E, given H_i) and $C(H_i|E)$ is the *posterior* (C in H_i, given E). Note that the term $C(E|H_i)$ on the right hand side of this equation is "natural" in the sense that it models causality in the direction that nature works, from causes (represented by H) to effects (represented by E). Bayes Rule then specifies how this causal knowledge can be used to make the reverse inference of $C(H_i|E)$, that is, to explain the possible causes of E.

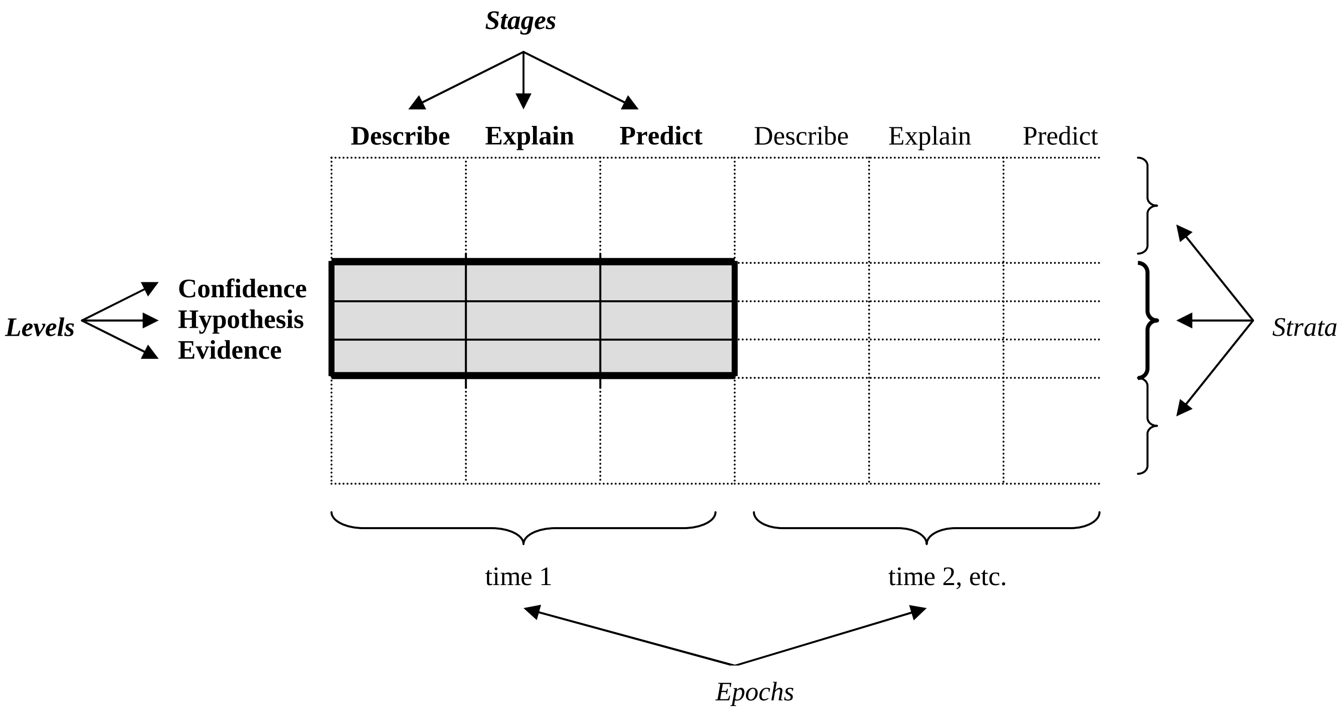

Figure 3: In my framework, the *levels* refer to different types of mental *models* (i.e., representations) and the *stages* refer to different types of mental *modules* (i.e., computations). The *levels* are further grouped into *strata* (of domain abstraction) and the *stages* are further grouped into *epochs* (of scenario evolution).

When E and H_i are familiar to a decision maker, an estimate of $C(E|H_i)$ may be stored in memory and therefore be available for recall (see Tversky and Kahneman 1974). In other cases, a decision maker must estimate $C(E|H_i)$ by a process commonly referred to as *mental simulation* (see Biel and Montgomery 1986, Dougherty et al. 1997, Hendrickx et al. 1989, Johnson-Laird 1994, Jungermann and Thüring 1987, Kahneman and Tversky 1982, Kahneman and Varey 1982, Klein, 1998, Klein and Crandall 1995, Klein and Hoffman 1993, Thüring and Jungermann 1986, Tversky and Kahneman 1982). Similarly, a decision maker may need to change the "frame of discernment" as a situation unfolds by generating new hypotheses (i.e., "stories", see Klein 1998, Pennington and Hastie 1993). For example, if the posteriors do not adequately distinguish between C in different Hs, then the decision maker may generate a new (more discriminating) set of Hs $\{H'_i\}$ and corresponding Cs $\{C(H'_i)\}$.

Predicting

The process of predicting a situation can be characterized as identifying what E is most likely to be observed in the future. Mental simulation (see previously) also plays a key role in this stage of situation awareness. That is, to predict future E, a decision maker must project (i.e., via mental simulation or perhaps via recall from memory) how a hypothesized state i at time t, $H_{i(t)}$, will evolve to a new state j at time t+1, $H_{j(t+1)}$. Next, the decision maker must simulate (or recall) what E_k at time t+1 is likely to be caused by this new state, that is, to estimate $C(E_{k(t+1)}|H_{j(t+1)})$. Finally, the decision maker can estimate C in the expected E, $E_{k(t+1)}$ by summing over all Hs that can possibly give rise to that E:

$$C(E_{k(t+1)}) = \Sigma_j [C(H_{j(t+1)}) * C(E_{k(t+1)}|H_{j(t+1)})]$$

Repeat

The previously mentioned stages (i.e., describing, explaining and predicting) are repeated at each epoch (time step) as new evidence is acquired from an evolving situation. Thus, in this formal framework (Table 1), situation awareness is characterized as the dynamic construction of mental models via iterative application of mental modules.

Table 1: Mental Models and Mental Modules in Situation Awareness

Stage	Module	Input Models	Output Models
Describing			
	Represent Evidence	{E}	E
	Activate Hypotheses	{H}	$\{H_i\}$
	Estimate Confidence	{C(H)}	$\{C(H_i)\}$
Explaining			
	Estimate Likelihood	E, H_i	$C(E\|H_i)$
	Update Confidence	$C(H_i), C(E\|H_i)$	$C(H_i\|E)$
	Generate Hypotheses	$H_i, C(H_i)$	$H'_i, C(H'_i)$
Predicting			
	Project Hypotheses	$H_{i(t)}, C(H_{i(t)})$	$H_{j(t+1)}, C(H_{j(t+1)}), E_{k(t+1)}$
	Estimate Likelihood	$E_{k(t+1)}, H_{j(t+1)}$	$C(E_{k(t+1)}\|H_{j(t+1)})$
	Anticipate Evidence	$C(H_{j(t+1)}), C(E_{k(t+1)}\|H_{j(t+1)})$	$C(E_{k(t+1)})$

4 Analyzing the Cuyahoga Collision

Here I use this formal framework (Table 1) to analyze the Cuyahoga collision. I focus on the captain's mental models and step through the scenario illustrated in Figure 1. Each step of the analysis corresponds to a single stage of situation awareness (i.e., describing, explaining or predicting) at a given time epoch, that is, (t1), (t2) and so forth.

Describing (t1): The captain sees two lights. At (t1), the captain's mental model of the E can be characterized as $E_{(t1)}$ = "two lights". Based on Perrow's (1984) account, I assume that the captain entertained the following four Hs:

$H_{1(t1)}$ = "fishing vessel moving in same direction"
$H_{2(t1)}$ = "fishing vessel moving in opposite direction"
$H_{3(t1)}$ = "other vessel moving in same direction"
$H_{4(t1)}$ = "other vessel moving in opposite direction"

Assuming that the captain considered all $H_{i(t1)}$ roughly equally likely (prior to observing any evidence), then $C(H_{1(t1)}) = C(H_{2(t1)}) = C(H_{3(t1)}) = C(H_{4(t1)}) \sim \eta$.

Explaining (t1): The captain infers that the other ship is proceeding in the same direction. Based on domain causality (i.e., same direction causes "two lights", different direction causes "three lights"), I assume the following likelihood for each H:

$$C(E_{(t1)}|H_{1(t1)}) \sim \rho; \quad C(E_{(t1)}|H_{2(t1)}) \sim \varepsilon; \quad C(E_{(t1)}|H_{3(t1)}) \sim \rho; \quad C(E_{(t1)}|H_{4(t1)}) \sim \varepsilon;$$

where ρ means "likely" and ε means "unlikely". Applying Bayes Rule, I use these likelihoods to update the priors $C(H_{i(t1)})$ from *Describing (t1)* previously and compute the posteriors $C(H_{i(t1)}|E_{(t1)})$:

$$C(H_{1(t1)}|E_{(t1)}) \sim \eta*\rho; \quad C(H_{2(t1)}|E_{(t1)}) \sim \eta*\varepsilon; \quad C(H_{3(t1)}|E_{(t1)}) \sim \eta*\rho; \quad C(H_{4(t1)}|E_{(t1)}) \sim \eta*\varepsilon.$$

Thus, the two most likely (posterior) explanations at time (t1) are $H_{1(t1)}$ and $H_{3(t1)}$. In words, the most plausible explanation is that the other ship is moving in the same direction. Because the posteriors at (t1) will act as priors at (t2), I now set the following:

$$C(H_{1(t2)}) \sim \eta*\rho; \quad C(H_{2(t2)}) \sim \eta*\varepsilon; \quad C(H_{3(t2)}) \sim \eta*\rho; \quad C(H_{4(t2)}) \sim \eta*\varepsilon.$$

Predicting (t1): The captain expects that the ships will draw together rapidly. At this point, the captain mentally simulates (or recalls from memory) what will happen in the next epoch (t2) and constructs mental models of the resulting (expected) E. I summarize the possible E at (t2) as the following:

$E_{rapidly(t2)}$ = "ships appear to draw together rapidly"
$E_{slowly(t2)}$ = "ships appear to draw together slowly (or not at all)"

I then characterize the likelihood of observing each $E_{k(t2)}$ given each $H_{j(t2)}$:

$$C(E_{rapidly(t2)}|H_{1(t2)}) \sim \rho; \quad C(E_{rapidly(t2)}|H_{2(t2)}) \sim \rho; \quad C(E_{rapidly(t2)}|H_{3(t2)}) \sim \varepsilon; \quad C(E_{rapidly(t2)}|H_{4(t2)}) \sim \rho;$$
$$C(E_{slowly(t2)}|H_{1(t2)}) \sim \varepsilon; \quad C(E_{slowly(t2)}|H_{2(t2)}) \sim \varepsilon; \quad C(E_{slowly(t2)}|H_{3(t2)}) \sim \rho; \quad C(E_{slowly(t2)}|H_{4(t2)}) \sim \varepsilon.$$

In words, the expectation for H_1, H_2 and H_4 is that the ships will draw together rapidly, and the expectation for H_3 is that the ships will draw together slowly (or not at all). Combining these likelihoods with the priors $C(H_{j(t2)})$ from *Explaining (t1)* previously and summing over all active Hs, yields the following:

$$C(E_{rapidly(t2)}) = \Sigma_j \; [\; C(H_{j(t2)})* C(E_{rapidly(t2)}|H_{j(t2)}) \;] \sim \; \eta * [\; (\rho*\rho)+(\varepsilon*\rho)+(\rho*\varepsilon)+(\varepsilon*\rho) \;]$$
$$C(E_{slowly(t2)}) = \Sigma_j \; [\; C(H_{j(t2)})* C(E_{slowly(t2)}|H_{j(t2)}) \;] \sim \; \eta * [\; (\rho*\varepsilon)+(\varepsilon*\varepsilon)+(\rho*\rho)+(\varepsilon*\varepsilon) \;]$$

Because $C(E_{rapidly(t2)}) > C(E_{slowly(t2)})$, the most likely expectation for (t2) is that the ships will draw together rapidly.

Describing (t2): The ships appear to draw together rapidly. At (t2), the new E (which confirms the captain's expectation; see previously) is that the ships indeed appear to draw together rapidly. That is, $E_{(t2)} = E_{rapidly(t2)}$.

Explaining (t2): The captain infers that it is a fishing vessel moving in the same direction. Given the new E, $E_{(t2)}$ = "ships appear to draw together rapidly", the likelihoods $C(E_{rapidly(t2)}|H_{j(t2)})$ from *Predicting (t1)* previously can be used in Bayes Rule to update the $C(H_{j(t2)})$ from *Explaining (t1)* previously:

$$C(H_{1(t2)}|E_{(t2)}) \sim (\eta\rho)*\rho;\quad C(H_{2(t2)}|E_{(t2)}) \sim (\eta\varepsilon)*\rho;\quad C(H_{3(t2)}|E_{(t2)}) \sim (\eta\rho)*\varepsilon;\quad C(H_{4(t2)}|E_{(t2)}) \sim (\eta\varepsilon)*\rho.$$

In words, the only likely H at this time is that of a "fishing vessel moving in same direction", $H_{1(t2)}$. Note that although Perrow (1984) called this "reinforcing the incorrect interpretation", and Hutchins (1995) called it *Confirmation Bias*, my analysis shows it is actually a normative (Bayesian) result of updating the modeled Hs with the modeled E.

Predicting (t2): The captain expects the other ship to turn and cause a collision. Focusing on the only likely H, $H_{1(t2)}$, the captain uses his domain knowledge of fishing boats to mentally project (i.e., simulate or recall) a new model at time (t3), $H_{1(t3)}$. This new model represents a scenario in which the Cuyahoga will cut off the fishing vessel's ability to turn as it approaches the river (Figure 1(t3), top panel).

Acting: The captain turns his ship to avoid a collision. Based on his situation awareness (see previously), the captain decides to take action to prevent a collision. Note that this decision is reasonable in light of the captain's mental models (as analyzed here), including his mental simulation of how fishing boats behave in this part of the Chesapeake Bay (i.e., his projected model $H_{1(t3)}$). The fundamental problem was that the most likely H at time (t2), $H_{1(t2),}$ did not match reality in a significant way. The unfortunate consequence was a collision, which was exactly what the captain's action was intended to prevent!

5 Discussion

The case of the Cuyahoga is a classic example of what is often called a *decision error*. However, contrary to this label, my analysis shows that the captain's decision was rational in the context of his perception of the situation (i.e., his mental models). This is similar to the conclusion reached by Perrow (1984) and others. However, my analysis goes further in demonstrating that the computational processes (i.e., mental modules) underlying the construction of these mental models were also rational. That is, the captain's probabilistic perception of the situation was also consistent with the norms of Bayesian inference, given his deterministic models of H and E. This is an important insight because *Confirmation Bias* is one of the most commonly cited causes of human error in the command and control of complex systems (see Perrow 1984 for more examples in transportation systems, nuclear power and other domains; see Klein's 1998 account of the Vincennes shootdown of an Iranian airbus for an example in the domain of air defense).

Normal Errors

Perrow (1984) called such accidents normal because he believed that they are inevitable (although not necessarily anticipated; also see Wagenaar and Groeneweg 1987) in complex human-machine systems. My analysis suggests that the associated errors are also normal in a mathematical sense because the underling computations can be characterized as normative (Bayesian). The catch, of course, is that these Bayesian computations operate within the bounded context of the decision makers' mental models.

For example, a perfect (unbounded) Bayesian would have considered at least two things that a human (bounded) Bayesian like the captain of the Cuyahoga apparently did not. First, unbounded Bayesians would have considered the possibility that their original model of the E (i.e., "two lights") was incomplete. That is, the E at one stratum of abstraction (see Figure 3) is actually one of several (perhaps many) Hs (with associated Cs) at a lower stratum of abstraction. Second, unbounded Bayesians would have retained all Hs about the other ship and used this information in their subsequent decision to act.

That is, they would have retained the unlikely H that the other ship might be moving in the opposite direction and they would have considered the high cost of their contemplated action (to turn) in light of this possibility.

Because of these limitations, some might characterize the captain as non-normative (biased) relative to an unbounded Bayesian. However, given the finite resources available to naturalistic decision makers, I suggest that it is more accurate (and more useful) to characterize the captain as a Bayesian bounded by mental models.

Heuristics and Biases

At first glance, my claims about the normative nature of human reasoning (previously) may appear to be at odds with the vast literature on non-normative heuristics and biases (see Kahneman et al. 1982, Sage 1981). It is not. For example, the widely cited heuristics known as *Anchoring/Adjustment*, *Availability*, *Representativeness* and *Simulation* (see Tversky and Kahneman 1974) are all implicitly captured by my computational modules (Table 1). *Anchoring/Adjustment* is inherent in the module ***Update Confidence*** in which a prior anchor is updated with a likelihood adjustment. *Availability* is inherent in the module ***Activate Hypotheses*** in which $C(H_i)$ is a formal measure of availability used to determine which H_i are active at a given time. The *Simulation* heuristic is inherent in the modules ***Generate Hypotheses*** and ***Project Hypotheses***, which consider the deterministic construction of new models (H'_i and $H_{j(t+1)}$) via mental simulation. Finally, *Representativeness* is inherent in the module ***Estimate Likelihood*** in which $C(E|H)$ is a formal measure of how representative E is of H. Thus, rather than being in disagreement with previous findings, I believe that the formal framework (Table 1) can clarify and unify many of the isolated heuristics proposed by previous research.

I also believe that this approach can shed new light on the biases that result from these heuristics. In particular, the main finding of my analysis is that a prototypical case of *Confirmation Bias* (i.e., the Cuyahoga collision) can be explained in terms of normative computations operating on cognitive representations. Gigerenzer et al. (1991) made a similar claim with regard to two other widely cited biases, that is, the *Overconfidence Effect* and the *Hard-Easy Effect*. Here I stress that my results stem from an integrated analysis of computational modules and representational models in a naturalistic context (see Burns 2001, Richards 1988, Richards et al. 1996). This is an important shift in emphasis because research on heuristics and biases has typically focused on computations (i.e., heuristics) while making nonnatural assumptions about representations (i.e., not adequately characterizing the participants' tacit assumptions; see Nickerson 1996). My approach focuses on mental models in a natural context simply because the performance of any computation (module) is bounded by the representations (models) available to it.

Decision Support Systems

As discussed previously, models in the mind (i.e., mental models) are used by decision makers to describe, explain and predict situations. Similarly, models of the mind are needed by decision scientists to describe, explain and predict cognitive competence. Thus far, most theories of naturalistic decision making (see Lipshitz 1993) have been limited to qualitative models that only describe human performance. My goal is to develop more quantitative models (also see Miao et al. 1997) that can go further to explain and predict human performance in naturalistic decision making.

My work is motivated by a desire to improve the design of computer systems that support human decision making in practical applications. My claim is that the design of external systems provided to decision makers must consider the internal models used by these decision makers.

That is, computational models of how decisions should be made (optimally, in support systems) must be developed in concert with computational models of how decisions are made (actually, in human minds). I believe that the formal framework presented in this chapter can help bridge this gap and thereby improve both the scientific understanding of human decision making and the engineering development of computer support systems.

6 Conclusion

My objective was to specify, in computational terms, how decision makers construct mental models to achieve situation awareness. I began by outlining a formal framework comprising three levels of mental representation and three stages of mental computation. I then used this framework to analyze a case study in naturalistic decision making. My main insight is that prototypical decision errors can be attributed to normal (Bayesian) mental modules operating on natural (bounded) mental models.

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