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Thomas Whalen

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Foreword

On behalf of the North American Fuzzy Information Processing Society, the Organizing Committee, the International Advisory Committee, and the International Program Committee, it is my pleasure to welcome you to the "Big Peach," and to the NAFIPS 2000 conference. We have had a gratifying response to our Call for Papers, and I envision a very exciting and stimulating conference. The meeting has a truly international flair, as there are 22 countries on six continents represented in this program, which includes about 100 papers in many different topics.

The single word "quality" as a theme of the conference covers both the methods of soft computing and fuzzy logic, which are qualitative rather than strictly quantitative or categorical, and its goal, which is to provide solutions that are excellent in quality rather than merely optimal in quantity. I think you will agree that the keynote addresses by Lotfi Zadeh and Michael Smithson, and the many contributed and invited papers, epitomize quality in both senses of the word.

Within this broad theme, papers will be presented in a spectrum of areas which include invited sessions in Optimization, Granular Computing , Intelligent Data Analysis, and Visualization, and contributed sessions in Decision Sciences, Learning, Image Processing, Mathematics, Clustering, Classification, Recognition, Biology & Medicine, Control Theory, Diffusion, Risk & Information, Information Networks, Linguistic Analysis, Hybrid & Hierarchical Systems, Psychology/Sociology, and Forecasting.

I would like to thank our honored keynote speakers, Prof. Zadeh and Prof. Smithson. I also thank my fellow members of the Organizing Committee: Brian Schott, Nancy Green Hall, and Augustine Esogbue. Brian, in particular, cheerfully put up with being the closest to me in proximity and thus the easiest one for me to pass along work to. Yanli Jiang has provided great assistance with the websites associated with the conference. Of course, the conference could never have happened without the work of the International Advisory Committee and International Program Committee, who reviewed the papers and provided numerous other kinds of assistance. Finally, to all the authors and presenters: this is your conference, and it has been a privilege to facilitate it for such a distinguished group!

Thomas Whalen, General Chair, PeachFuzz 2000

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Michael Smithson
The Australian National University
Canberra, Australia

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Uncertainty in the Physical, Social, and Virtual Worlds

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Overview

The Origins of Uncertainty Heuristics

A useful starting-point for an overview of human responses to uncertainty is that people seem to draw upon two primary sources of heuristics for dealing with uncertainty and commonsense theories about it. The first one is commonsense realism, and the second is commonsense sociality. Commonsense realism encompasses lay theories and intuitions about the physical world and how it works. Commonsense sociality, on the other hand, refers to lay psychology and sociology—our theories and intuitions about how the psycho-social world works. From these two sources spring most, if not all, of our heuristics, devices, formal methods, abstract theories, and frameworks for coping with an uncertain world. They overlap and may provide conflicting prescriptions. Perhaps the strongest and most obvious link between them is vicarious learning or second-hand knowledge. Nevertheless, I think the distinction is productive. It enables us to tell the "intuitive scientist-statistician" apart from the "intuitive psychologist-politician."

The relevance of this distinction for intelligent systems is twofold. First, insofar as such systems are to display human-like reasoning and behavior they must take account of the fact that human reasoning and behavior in social contexts may differ substantially from nonsocial contexts. Second, human interactions with intelligent systems raise the important issue of whether such interactions can (or should) be treated by humans as social or not.

Another important distinction to bring on board refers to the goals that people hold regarding what to do about uncertainty. At first glance it might seem that there is only one goal, namely to be rid of it. However, as Smithson (1989) has observed, there are at least four goals that can characterize people's desires about uncertainty:

- Banishment: avoiding or deleting uncertainties by declaring their sources out of bounds;
- Reduction: overcoming uncertainties by gaining relevant information;
- Management: ascertaining the nature of uncertainties as an aid to decision making; and
- Creation or maintenance: generating or otherwise contributing to uncertainty.

Banishment is preferred over reduction or management when people prefer clarity or simplicity to informativeness. While psychologists have had no luck in finding personality factors that are related to risk-taking or risk-aversion, they have found an apparent personality factor that can be characterized as a preference for banishment versus reduction of uncertainty. Sorrentino and his colleagues (cf. Sorrentino and Roney 1999) have developed a measure of "uncertainty orientation" whereby people range on a continuum from "uncertainty-oriented" (UO) to "certainty-oriented" (CO). Sorrentino and Short (1986) describe UOs as information-seekers in pursuit of uncertainty reduction (especially uncertainty about themselves), whereas COs prefer to seek clarity by avoiding information that would disconfirm or alter their established views. For instance in games of skill Sorrentino et al. (1992) found that UOs preferred playing at levels near the limits of their skill (i.e., moderate risk-levels) whereas COs preferred playing either at very easy or extremely difficult levels (i.e., where the outcomes were either certain success or certain failure).

Uncertainty-related goals also may be in thrall to 'higher-order' social goals, and it is here that we find the most obvious cases in which people are not interested in banishing or reducing uncertainty. Uncertainty creation or maintenance pervades social interaction and, far from being the bane and barrier that stereotypes would lead us to believe, often contributes fundamentally to peace and good order. To give just one example, conveying to someone that you trust them requires that you do not place them under constant surveillance or interrogation (i.e., you are not permitted to eliminate your uncertainty about them altogether). Privacy and politeness are two other examples of social order that require less than complete knowledge about one another.

Commonsense Realism

There is a large literature in psychology, behavioral economics, and related disciplines that investigates human intuitions and beliefs regarding uncertainty in the real world, i.e., the "intuitive scientist-statistician". In almost all of this research uncertainty arises from nonsocial sources such as random processes or events, and unobtainable information or knowledge. Most of this research is in the 'cognitive heuristics and biases' tradition made popular by behavioral decision researchers such as Kahneman and Tversky (1982). That tradition's successes have depended on an extensive elaboration of human judgmental and cognitive errors (i.e., deviations away from subjective expected utility theory, of which 27 were identified in Hogarth's 1980 book). The emphasis on error has garnered extensive criticism from various quarters. A complete review of this research is beyond the scope of this paper and unnecessary given the availability of both technical and introductory treatments (e.g. Dawes 1997 and Plous 1993). Instead, we will briefly examine some of the recent developments in theory and research that are attempts to progress beyond the heuristics and biases tradition.

Medin and Bazerman (1999) claim that recent research on decision making under uncertainty has exhibited three trends. I would add a fourth, which I call 'reverse-engineering'. The four trends are:

1. Incorporating more psychological influences and processes such as emotion, personality, and specific cognitive processes;
2. Taking into account the meanings that people derive from choices that they and others make as well as from the information provided;
3. Taking into account the social contexts in which judgments and decisions are made; and
4. Reverse-engineering heuristics with regard to environmental and/or biological functionality.

We will review examples of the second and third trends in later sections of this paper.

Perhaps the most interesting example in recent years of the first trend in research on subjective uncertainty stems from a theoretical distinction between two systems of information processing. Epstein (1990) calls them the rational and experiential systems, while Sloman (1996) labels them rule-based and associative (I will adopt Sloman's terminology here). Rule-based information processing represents information (and uncertainty) in abstract and formal (e.g., numerical) terms and tends to use logic and evidence-based reasoning. It is generally assumed to be slow and deliberate but also flexible, accessible to conscious appraisal, and generalizable. Associative processing is quick and spontaneous, but less flexible, not often consciously accessible, automatic, and context-specific.

In the same connection there is considerable evidence that we have two kinds of heuristics regarding categories, one treating categories as fuzzy clusters of similar things, and the other treating categories as crisp and having strict law-like criteria for membership (cf. Smithson and Oden 1999). Fuzzy clusters arise in associative processing, whereas crisp categories arise in rule-based processing. It appears all too easy to become ideological about crisp versus fuzzy categories. For instance, Pinker's (1997) treatment characterizes fuzzy categorization as "uninsightful" (pp. 127 & 309), whereas he sees crisp (rule-base) categories as "well-defined" and the basis of "real science". Much the same ideological battle-lines are drawn when it comes to associative versus rule-based processing.

One of the key proposals in the Epstein-Sloman framework is that the rule-based and associative systems operate rather independently of one another, and therefore may yield conflicting responses to the same inputs and likewise may be affected by different influences. Windschitl and Wells (1998) have pointed out that little is known about associative processing of uncertainty mainly because the prevalence of numerical representations of uncertainty-related information in psychological research is likely to have invoked rule-based processing in most research subjects (see also the following section on "Words versus Numbers"). However, their experiments point to at least one important influence on associative processing, namely the alternative-outcomes effect.

Windschitl and Wells (1998: 2) suggest that "the associative system is sensitive to relative differences between the chances for the focal outcome and the chances for other *individual* outcomes." For instance, the rule-based system 'knows' that holding 10 out of 100 tickets in a raffle gives you the same chance of winning regardless of whether only one other person holds the remaining 90 tickets or 90 people each hold one of those tickets. But their studies found that associative reasoning distinguishes these two situations on a comparison basis. The first situation is dispreferred because the focal resource of 10 tickets is compared with the other person holding 90, whereas the second situation yields a comparison between you holding 10 tickets and each other person holding just one. Windschitl and Wells found that people preferred the second kind of situation and reported a greater certainty of winning even though their subjective probability estimates did not differ between the situations.

While much more research on associative information processing is needed, clearly there are ramifications here for intelligent systems design. Systems intended to mimic human decision making under uncertainty may need to incorporate at least some of the characteristics of associative information processing and permit those to operate semi-independently of rule-based processing. Systems that involve interactions with people will require considerations about whether (or when) they should invoke associative or rule-based processes.

The fourth trend, reverse-engineering, manifests itself in two guises. One involves asking in what kind(s) of environments or on what performance criteria human heuristics 'pay off' or are functional, at least in the short run. The most common argument is that many heuristics are efficient, satisficing short-cuts (for an early example, see Thorngate 1980). An example of an argument that points to environmental suitability is Smithson's (1997) claim that Gambler's Fallacy arises from a tendency for people to mistake a random process for an anti-persistent process, and likewise conservatism in anchoring-and-adjustment processes stems from mistaking a random process for a persistent one. Smithson found that naïve subjects are quite accurate and relatively unbiased in making next-turn predictions of persistent and anti-persistent chaotic processes, and argued that both Gambler's Fallacy and conservatism pay off in natural environments where persistent and anti-persistent processes predominate rather than random ones.

The second version of reverse-engineering produces evolutionary arguments concerning the inclusive fitness functions of particular heuristics. Cosmides and Tooby (1994) find, for instance, that the confirmation bias (the tendency to attend more to instances that confirm rather than those that disconfirm one's expectations) does not seem to operate when the rule is a contract involving an exchange of benefits, of the form "If you get that benefit, you must fulfill this requirement." Cheaters take the benefit without fulfilling the requirement, and humans are good at detecting cheaters. Cosmides and Tooby suggest that this particular algorithm is one that is part of our evolutionary inheritance, as a check against having our altruism taken advantage of.

The take-home lesson from reverse-engineering is one that already informs some intelligent systems designs (but not all of them!). We may happily hand over to such systems tasks in which humans do not excel, but we do not want to design virtual environments that are ill-suited to or militate against human heuristics, especially 'hard-wired' heuristics.

Commonsense Sociality

Now let us turn to the investigation of human intuitions and beliefs regarding uncertainty as it arises in the <u>social</u> world, i.e., the "intuitive psychologist-politician". In this domain uncertainty arises from social sources and therefore is produced by agents that have intentions and strategies. At first glance it might seem that a consideration of socially produced or mediated uncertainty is not directly relevant to intelligent system design (except perhaps in group-ware). In fact, it is of central importance for three reasons.

First, much of what we think we know is really second- or third-hand knowledge, and the same is true of what we think we do not know. Uncertainties associated with second-hand messages stem from attributions that we make about the source (e.g., their trustworthiness and credibility) as much as those we make about the contents of the message. As a result, source characteristics themselves can determine levels of uncertainty almost independently of what the source communicates.

Second, we make judgments and decisions not just in isolation, but most commonly in comparison with others' judgments and decisions. In social psychology the notion that social reality testing is secondary to physical reality testing has been largely overturned. Turner and Oakes (1997: 359-360) put this most forcefully when they claim that the "individual always acts as a member of a group, society or culture, applying established norms even when physically alone, interpreting the physical world in light of how similar others in the same situation would be expected to respond...". For Turner and Oakes, it is disagreement with or between those similar others that invokes uncertainty because people take for granted a shared orientation towards a common reality among those in their group, society, or culture.

Third, uncertainties are used in communicative practices for a variety of purposes. Examples of such practices include leaving things unsaid, referring to them indirectly, and using linguistic hedges or qualifiers. These practices form part of the basis for social arrangements such as privacy and secrecy, trust-building, politeness and tact, quotidian conversation, many social rituals, and the maintenance of status hierarchies (Smithson 1989). As a result, when we encounter unsaid matters, missing information that we know could be made available, indirection, hedging or the like, we make inferences about what intentions lie behind them (Are they hiding something? Trying to be polite?...).

A shortcut to appreciating the difference between coping with uncertainty under commonsense realism and commonsense sociality is to imagine being wakened in the middle of the night by the sound of something thudding repeatedly on the roof of your house. If you believe that this is a 'natural' phenomenon of some kind then it calls for a physical explanation (What is hitting my roof? Where is it coming from? How can I stop it? Do I have the physical means?). On the other hand, if you believe that this is being done intentionally by an intelligent agent then the questions become psychological and social (Who is doing this? Why are they doing it to me? How can I get them to stop? What can I bargain with?).

A key difference between the orientations just described is that in the social orientation understanding the physics of what is happening becomes largely irrelevant. Dennett (1995: 229-231) refers to the design stance and intention stance in his account of reverse-engineering, and both stances are observable in ordinary people's interactions with systems (intelligent or otherwise). When faced with a system that is behaving oddly, we usually do not limit ourselves to asking what physical causes lie behind its behavior. Instead, we are quite likely to ask ourselves whether it was designed or meant to behave this way, and what its designers intended it to do (e.g., "bug or feature?"). When faced with a human (or human-like or god-like) agent, we adopt the intentional stance immediately and ask ourselves what the agent intends to do.

Research on judgment and decision making under uncertainty has only just begun to take commonsense sociality seriously, and with some interesting results. In connection with communicative practice norms and their impact on how we react to uncertainty, Slugoski and his colleagues (Hilton and Slugoski 1999, Slugoski and Wilson 1998) have provided experimental demonstrations that at least some of the 'biases' from the cognitive heuristics and biases literature are explicable in terms of inferences that subjects in those experiments made about the intentions of the experimenters. They begin with Grice's (1975) claim that to understand the full meaning of a message the receiver must both understand the content of the message and what it conveys in a given context (which he calls an implicature).

Grice claims that receivers make *default assumptions about communicators* that amount to an overall assumption of cooperative intentions. He proposes four maxims that underlie this cooperative principle.

1. Quality: Do not say what you believe to be false. Do not say that for which you lack adequate evidence.
2. Quantity: Do not provide too little or too much information than is required.
3. Relation: Make your contribution relevant.
4. Manner: Avoid obscurity and ambiguity. Be brief, and orderly.

Consider, for instance, students reading a problem on an examination paper. Their default expectation is for the information provided in the problem to be accurate, no more nor less than they need to solve the problem, relevant to solving it, clear, and unambiguous. They not only become upset when they believe that any of these criteria are violated, but will also make inferences about the intentions of the examiner (e.g., the examiner is out to deceive or trick the student).

Hilton (1995) claims that the student in this situation makes two judgments under uncertainty. The first is a judgment about what task is set before them (e.g., this is a problem in integral calculus), and this is based on their knowledge about exams, teachers, and Grice-like fairness norms regarding exams. The second is a judgment about how best to perform the task (e.g., how to solve the integral calculus problem).

An example of this issue in research on human inferences is the card task first studied by Wason (1968) to see whether laypeople would correctly use modus tollens in reasoning about a rule. Subjects were presented with four cards with one