Cognitive Aspects of Decision Making

Research Workshop
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<u>Responses to Charge Questions</u>

J.J. Anderson

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

The cognitive perspective of decision-making stands apart from the classical "game theoretic" perspective in which decision making is cast as a problem in optimization in terms of uncertainties, utilities and costs of the alternatives. From a "cognitive perspective" (C) decision-making is a dynamic process in which temporally varying noisy information is integrated across multiple time scales with a decision resulting when the information stream relevant of one of the alternative actions crosses a threshold. While the game theoretic approach will identify the optimum decision, the cognitive approach has a neurological basis but is often biased depending on the pattern in which the information is received. Thus, a cognitive perspective is the most realistic, if not essential, approach when studying animal and human decision-making in dynamic, real-time environments. Because the cognitive approach has a neurological basis it provides a route for comparing decision-making across and within taxa on the basis of differences in the neurological dynamics of the decision makers. Furthermore, because the cognitive perspective is dynamic it can address the biases and limitation in real-lime decision making where time dependencies may prematurely terminate the decision process externally.

In fisheries and ecology we need cognitive behavior models to better understand the life history strategies of animals. Models are needed to characterize how animals integrate sensory information and the physiological state when making essential life history decisions such as migration, mate choice, and foraging. A long-term goal is to understand and predict probabilistically animal behaviors in their natural environments. To date, we have developed a model for the movement behavior of fish in the complex flow fields of hydroelectric dams. We are also developing models to describe animal swarming and migration behavior of fish in oceans, plumes and in estuaries.

To explore further the cognitive decision making perspective consider a simplified example of the framework. A cognitive decision model, C, links the outcome (*O*) of an animal's behavior or decision (*D*) to the physical state of the environment (*E*) and the resources of the animal (*R*): $(E+R)\to D \Rightarrow O$. Because an animal has imperfect information (*I*) about the environment and outcomes are uncertain, it predicts the probable outcome $\left(\tilde{O}_i\right)$ of each decision (D_i): $(I+R)\to D_i \Rightarrow \tilde{O}_i$. The decision expected to produce the best outcome (D_{opt}) is selected in a statistical hypothesis test (*H*) that considers the predicted outcomes from all possible decisions: $H\left(\tilde{O}_1,\tilde{O}_2,...\right)\to D_{opt}$. The difference between the predicted and observed outcomes is a measure of the decision bias (*B*): $B=\left|O-\tilde{O}\right|$ and the animal can adjust to the bias in two fundamental ways. At the population level the animals' perceptual, cognitive and physiological states or abilities can change through natural selection. At the individual level, the animal learns, i.e. it adjusts the dynamic elements of the decision making process to remove the bias. When an animal's decision is optimal the bias approaches zero: $B\to 0$.
A goal in decision making studies is to understand the mechanisms that produce biased decisions. For example, studies show a tradeoff between the speed and accuracy in decisions (Bogacz et al. 2006). Also, bias may result from the experimental design itself and so not reflect real bias by the decision maker (Steel-Feldman 2006) and bias can occur because of rule of thumb associations used to judge the environment (Kahneman et al. 1982). As a general category, such biases involve errors in the perception of the environment: $I \neq E$. Alternatively, the coupling between the sensory information, decision and the

outcome may change because of physical changes in the environment. In this case the outcome of a decision becomes different than what was experienced in the past: $D \Rightarrow O'$ not the expected $D \Rightarrow O$. For example, migrating fish have evolved to interpret a change in the strain field (*I*) as an indication that the environment downstream (*E*) is unobstructed and consequently a decision (*D*) to move with the flow results in safe passage outcome (*O*). However, at a hydroelectric dam the flow field is so altered and unnatural that increasing strain occurs at turbine entrances and so the evolved response to strain results in the fish entering the turbine; a suboptimum outcome (O'). Because, the dam alters the decision-outcome coupling, $\left(D \rightarrow O\right)$ and the information-decision coupling $\left(I \rightarrow D\right)$ has evolved by natural selection evolved and does not quickly change, the task for successful fish diversion is to restructure the environment *E* so the fish experiences new information, I' , that directs it away from the turbine. Designing such a structure requires a cognitive model linked to a model of the flow field of the dam. The Numerical Fish Surrogate (Goodwin et al. 2006), makes this linkage and is now used to design dam bypass systems that successfully direct fish away from turbine entrances.

I propose that this cognitive paradigm is a powerful framework in which to view and study decision making in competition and combat environments of both animals and humans. In the paradigm, the contest between opposing forces, A and B, can be formulated in terms of the opponents' resources $\left(R_A, R_B\right)$, the accuracy of their sensory information $\left(I_A, I_B\right)$ and most importantly, their real-time outcome predictions: $\left(I+R\right) \rightarrow D \Rightarrow \tilde{O}$. Although this paradigm is highly abstracted and simplified it is a framework of decision making that has been adapted rather independently in the fields of ecology, psychology and economics. Most importantly, the shared concepts of these disciplines can be tracked to equivalent structures and functions neuroscientists have identified in animal and human brains. Thus, cognitive models of decision making are inherently interdisciplinary in nature and have the capability to explain group behaviors in terms of the neurodynamics of its members.

2. What are the main research gaps within you field/area of interest?
A main gap in ecology is in establishing the importance of describing animal behavior from the perspective of the animal. Thus, formulating how and why animals behave the way they do, we must base decision models in terms of the information available to the animals. It is neither realistic nor sufficient to simply assume animals make optimal decisions as defined by the scientist's omniscient perspective. A main gap in research is in developing experimental and mathematical tools to characterize the world as observed by the animals.

3. Which numerical methods and models are used to support/describe risk-based decision making?
Diffusion models of decision making are dominant in much of the literature I track. In these models information is perceived as noisy signals that are integrated over time. This is the decision variable and a decision emerges when a stream of information crosses a threshold. The integration processes has been described with numerous mathematical tools that share a Markovian quality but may have differing assumptions, some treating information discreetly while other treat information as a continuous variable. In our research, we have found exponential moving averages are a simple way to integrate information; for example Anderson (2004) and Goodwin et al. (2006).

While information for the decision variable is typically integrated with a Markov process, the criteria for stopping and actually making the decision seems to be more varied and depend on the experimental conditions. A two-alternative force choice task (TAFC) is common in psychological and neurological studies. In these cases Bayesian stopping rules are often used where the decision is made probabilistically depending on the ratio of the integrated decision variables. This model has been called the sequential probability ratio test (SPRT) (Gold and Shadlen, 2007). The SPRT seem well suited where the information collection and decision segments of the experiment are well defined as in the TAFC. In our studies with the Numerical Fish Surrogate, we deal with a less structured environment and the decisions are not well defined discrete as in TAFC studies: a fish decides to swim towards or away from a stimulus source for an amount of time determined by the state of the decision variables. As such, there is no clear demarcation between acquiring information and the decision and the decision is more akin to a reflex action rather than fixed choice. In our case, a SPRT stopping rule is not sufficient and we have used a more dynamic, but simpler process: continue with the behavior that has the highest level of the decision variable at the moment.

4. How spatial and temporal scales in decision making are addressed?
From my limited reading, it appears that mostly small spatial and temporal scales of decision making have been addressed. The impacts of large scales are probably understudied but clearly important to both tactical and strategic decision making. Research in animal perception of time is relevant to cognitive decision making. Time perception appears to decay hyperbolically, which may be of significance and worthy of additional consideration when using models that define decision

variables with exponentially moving averages that by their nature decay exponentially. Such issues might be important in the assignment of credit, which involves how a stimulus (*I*) is associated with an outcome (*O*). In my research group, we have addressed the issue of time by formulating decision variables with different time scales. This is discussed further in question 6 below.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

I suggest a valuable area of study is to explore decisions in real-time unstructured environments where the decision involves what we have referred to as change detection (CD). In this context, the subject continues in one mode of behavior until a significant change in the environment is detected and then it switches to an alternative behavior. For example, CD experiments have been applied to looming behavior, escape response and the detection of the direction of motion in a complex noisy visual environment. By studying CD across different experimental scales and taxa we might be able to determine if the discrete decision framework of the TAFS is applicable to continuous unstructured situation of the CD environment. It also might be possible to identify neurological time scales that underlie the dynamics of change detection.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

In our research we are investigating how concepts in time series forecasting can be applied to decision making with learning. The goal of this research is to develop computationally tractable algorithms for characterizing how organisms make decisions based on past experiences. A contribution of our effort may be described as follows: there are three important phenomena observed in classical and operant conditioning experiments: the partial reinforcement extinction effect, spontaneous recovery, and latent inhibition. Several models exist that capture one or two of these phenomena, but to our knowledge, no model yet exists that captures all three. We have developed an algorithm (Anderson et al. 2007) that not only captures all 3 phenomena but that is also computationally efficient and consistent with the neurological structure of organisms.

The model tracks estimates of future rewards by averaging the past rewards under different time horizons: specifically we characterize expected values of rewards computed from long- and short-term averages or learning rates. These decision variable streams are combined into a single estimate where the weight of each variable is defined by time-evolving uncertainties derived from the differences in past estimated and received rewards. These errors are also formulated as learning streams.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

To categorize the challenges in integrating cognitive decision support tools into tactical/strategic decision making I first restate the basic framework outlined above.

- Outcomes (*O*) of a decision (*D*) depend on the state of the environment (*E*) and the resources (*R*) of the decision maker: $(E+R) \to D \Rightarrow O$.
- To select an optimal decision the decision maker combines the available information (*I*) on the environment and its resource state to generate an expected outcome ($\tilde{O}_i$) for each alternative decision D_i: $(I+R) \to D_i \Rightarrow \tilde{O}_i$.
- The decision is the selection one of the possible set of alternative actions through a statistical hypothesis test (*H*): $H\left(\tilde{O}_1, \tilde{O}_2, \ldots\right) \to D$.
- A learning process adjusts the cognitive process C by tracking the bias (*B*) between the expected and actual outcome: $B = \left|O - \tilde{O}\right|$.

In terms of this framework we are confronted with five challenges which listed without identifying their significance are:

1. Understand how the resource state (*R*) affects the actual and expected outcomes.
2. Understand the relationship between the environment (*E*) and the information (*I*) obtained from the environment.
3. Develop tractable algorithms to characterize outcome projections ($\tilde{O}$).
4. Develop tractable algorithms to characterize the decision process (*H*) for behavior selection for both structure (TAFC) and unstructured (CD) projections ($\tilde{O}$).
5. Develop tractable learning algorithms to characterize how outcome information *B* affects the cognitive model C.

For each of the five categories considerable information is available from controlled experimental and theoretical studies conducted in several fields. Therefore, perhaps a main and immediate challenge is to synthesize this vast literature and develop a decision support model that can be tested and improved in a more realistic environment setting.

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George Bonanno

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

Cognitive processes are of obvious centrality to decision making in the context of stress and trauma. For example, recent prospective research has born out the importance of cognitive capacities in relation to adjustment following potentially traumatic life events. Yet, there is a dearth of actual studies from which any further conclusions can be drawn.

2. What are the main research gaps within you field/area of interest?

Documentation of individual differences in response to potential trauma and the factors that inform those differences. Also, there is relatively little research on how various resilience factors might be promoted within at-risk populations.

3. Which numerical methods and models are used to support/describe risk-based decision making?

Latent class mixture modeling (LCMM) should be crucial

4. How spatial and temporal scales in decision making are addressed?

Attentional tasks may be of great use, as well as short cognitive skills batteries. These can be implemented in field studies using laptop computers

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Compare identify individuals who have exhibited a stable healthy trajectory of adjustment in the context of adversity (i.e., resilience; see below) with other individuals in various cognitive and decision making tasks. Learning how resilient individuals reason and make decisions will inform possible training programs to facilitate the development of similar skills in other individuals

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

My work revolves around the identification of core trajectories of adaptation in relation to either ongoing or maker life events. Although there may be variation within a class or trajectory, differences in trajectory membership are crucial. Individuals showing a stable trajectory of healthy adjustment or resilience tend to cope well, and show superior emotion regulation and cognitive regulation skills.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

1. Identification of individuals at-risk and individuals likely to be resilient
2. Identification of risk and resilience aspects of cognitive decision making that inform these group differences.
3. Identification of aspects of risk and resilience that are amenable to change or training.

V.A. Braithwaite

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

Animals are constantly faced with decisions; is this brightly colored insect safe to eat, which refuge or shelter is closest to me, which mate should I choose? To make the right decision the animals needs to compare the information they currently have with previously experienced, remembered events. In this way, animal cognition can be considered to underpin most forms of behavior. So to understand the choices animals make and to be able to manage natural populations we need to determine what circumstances change the decisions that are made and to find out how different environmental variables affect these choices. We will gain a better understanding of decisions-making processes in ourselves if we can resolve the mechanisms and processes used by animals.

Animal behavior spans from simple forms such as 'stimulus-response'; where the nervous system of the animal detects something in the environment and then responds to that specific stimulus. This is a reflex response that does not require cognition – given the same stimulus in similar situations the animal will produce the same response. Then there are more complex behaviors where the animal detects something, this information is internalized through a variety of sensory systems, these signals are then relayed to the brain where the information is processed before a response is generated. This second example requires cognitive input. I use cognition here to refer to three processes, (i) perception, (ii) learning and (iii) memory. Thus here, the decision that the animal makes is affected by the stimuli it currently perceives and how these compare with previous experiences, or with specific, given standards against which the animal assesses the new information. Some of these processes can be relatively simple; for example, a female weaver bird choosing a mate will assess the male's grass-woven nest to determine its quality, if the nest is not woven tightly enough she rejects it. She is able to make this decision based on a basic standard that she uses to measure nest quality. Other decisions demand that multiple pieces of information are integrated and so are necessarily more complex. Continuing with the theme of mate choice in birds; male sedge warblers have an extremely elaborate song that consists of many different syllables, females are remarkably good at listening to these songs and can discriminate between songs of different complexity based on syllable number and song duration. A male with a more complex song attracts her attention. Once the male has her attention he then performs an acrobatic flight that consists of multiple twists and turns. The female uses both the song and the 'flashy' flight to make a judgment on male quality. She needs to combine the auditory information about the song with the visual flight display and use these to generate an index or score for each male she observes. Clearly in this second example the female has a much more complicated suite of information to integrate to allow her to make her decision.
How she is able to do this, and how she can compare one male against a number of others are the types of question we try to address when we study animal cognition.

Given the variation in cognitive ability across the animal kingdom, we can select different animal models to study how cognition affects decision making in animals with relatively simple or with more complex brains. Such comparisons show us not just how complexity affects decision making capacity, but it also helps us determine how natural selection has shaped animal cognition in different environments and across different species. Studies of the evolution of cognition and decision making help us identify the factors that influence these processes in animals and humans.

2. What are the main research gaps within you field/area of interest?

Decision making in non-human animals has lagged a little behind studies of human cognition partly because there has been a general reluctance to acknowledge the fact that animals are capable of complex cognition. This has tended to hinder the field. In the last decade, however, a series of clever and elegant experiments have clearly demonstrated many animals are capable of far more cognitively demanding tasks than was once thought possible.

The study of animal decision making has until recently been the realm of the experimental psychologist, while this has taught us a great deal about the decisions rats and pigeons make inside Skinner boxes or enclosed arenas as the animal completes some form of learned foraging task, it has done little to explore the natural history of cognition and decision making. When we study individuals from a natural population of wild-caught animals we find there is often considerable variation in cognition and this affects the way these individuals behave and the choices that they make. What underlies this variation?

Another intriguing area that has recently started to attract attention is the study of when an individual decides to rely on its own private information to make a decision rather than utilizing public information that is available by socially learning, or copying others. The transition between when an animal prefers to use private rather than public information can reveal a great deal about how the animal values the information it is basing its decisions on. As this is an area we have only recently begun to work on many questions remain unsolved.

Finally, we still do not understand when a decision changes from being a routine, autonomous process to something that the animal is consciously aware of. For example, competing animals may go through a series of ritualized steps as their behavior escalates from an initial dispute over some sort of resource to a full-blown aggressive fight. At which point as the animal works its way through the various assessment rituals and then the decisions about whether to back down or to continue to escalate does the decision become a conscious one? Is it when the decisions begin to lead to different courses of action that the animal becomes consciously aware of what it is deciding? Can we determine whether an animal starts to 'mentally' play-out potentially difference scenarios before it makes its decision about how to behave? These issues remain unresolved.

3. Which numerical methods and models are used to support/describe risk-based decision making?

In the late seventies/early eighties a new research field began to emerge, this field was called behavioral ecology. The aim was to determine how the environment an animal exists in affects the choices that it makes. Using game theory and optimization models researchers began to explore what strategies animals adopted. Sometimes these were affected by an animal's state, its current internal motivations, but other factors also clearly play a role, for example whether the animal is isolated or in a group, and whether the environment the animal is in is stable and predictable or changing and variable.

The field has had an enormous impact on our understanding of behavior and decision making, but there have been a number of constraints along the way. In particular, we have been guilty of assuming that animals detect the environment in broadly similar ways to ourselves. About a decade ago, a number of researchers realized the need to combine studies of the function of decision making with the sensory mechanisms that the animal has available. This approach has been hugely beneficial and now allows us to generate more reliable models that use more realistic variables.

Within the last decade Individual Based Modeling has become one of the more popular approaches to make predictions about animal behavior and decisionmaking. These models provide us with an effective way to explore the mechanisms through which animals and populations use the ability to make decisions to exploit and operate within an environment. These models allow us to determine how individuals interact with each other and their environment, but they also allow us to scale-up so that we can see decision making at the group level. For some very coordinated group behaviors, for example fish schooling or swarming birds, these models have revealed how small changes in individual decisions can have large effects across a group.

4. How spatial and temporal scales in decision making are addressed?

Spatial scale can affect the way in which animals make decisions because of the amount of information that needs to be stored and for how long it must be remembered. For instance, an animal that is sampling and exploiting a food patch must at some point decide when it should leave the current patch it is foraging in to seek out a new patch. The factors that influence this decision include the frequency with which it encounters food items, the time since it arrived at the patch and some understanding of how far away alternative feeding patches are located. If the patch an animal is currently exploiting is large then it will deplete it more slowly and so it will spend a longer time at this patch compared to a smaller one. The ability of an animal to make decisions based on whether to stay foraging within one particular patch, or whether to leave and search for a new one will be affected by an animal's general ability to learn and remember.

Some animals may be predisposed to remembering details for long periods of time. For example, some food storing birds can decide to hide large numbers of seeds in many thousands of different locations. Then over the winter season they will return to these locations to collect the hidden food. The birds are much more accurate at remembering the locations of the hidden seeds and also at remembering which locations still have food and which are now empty compared with closely related bird species that choose not to store food items. Animals that are not used to operating over such long spatial and temporal scales often end up with inaccurate information on which they base their decisions.

The temporal stability of information is also known to influence how that information is used by an animal. If the information is too variable it is unreliable and therefore is generally ignored. Experiments in which rats are given stable versus unstable spatial information, the rats quickly learn to ignore the unstable cues. In real world environments we see the same effect. Animals coming from an ecologically unstable environment will typically pay less attention to local environmental cues compared to animals from more stable environments. Animals can also learn to associate information about certain food types and an understanding of when those food items might go off / become unpalatable. For example, birds that store food can choose to store insects, that are perishable, or seeds that generally last many weeks. The order in which the animal decides to retrieve the hidden food items is dependent on how much time has passed since the food item was hidden. So the nature of the decision and the time scale over which the decision is made can affect what the animal chooses to do.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Many of the models we currently use in animal behavior are impeded because we do not know enough about the natural parameters that influence the decisions an animal makes. The only way to improve this gap in our understanding is to devise experiments, or to perform fieldwork that allow us to quantify the relevant parameters so that we can then use relevant estimates in the models.

By way of an example, scientists have recently been interested in determining the factors which affect whether juvenile coral reef fish return back to their natal reef or whether they actively choose to disperse to move away and colonize new reefs. To address this they have been out to coral reefs and measured recruitment rate as well as a number of other biotic and abiotic factors that could affect an individual's ability to return to a specific reef. They then used this natural data as different forms of parameter in Individual Based Models to determine what cues the fish use to help them decide whether to settle or whether to move on. Biotic factors, in particular the noise of other animals on the coral reefs, were found to have a significant effect on the decisions the juvenile reef fish were making.

The success of this approach stems from having a good understanding of the ecological system in which the fish exist, on being able to obtain accurate parameter information and using this with what is known about hearing in juvenile coral reef fish.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

I am specifically interested in how the environment an animal lives in affects the decisions that it makes. There are two ways in which the environment can have an effect. First as the animal grows and matures within an environment the nature of the environment will directly influence the animal's nervous system and brain development. If the environment is very predictable and constant the animal will not experience the value of learning - if everything is constant there is no need to learn. Such environments generally create animals that are not good at coping with change, that do not make good decisions and that often have trouble surviving if they find themselves in a naturally changeable habitat. A real example where this occurs is in captive rearing animals for later release associated with conservation or restocking programs. Particularly in fish reintroductions; fish hatcheries were designed to produce large numbers of juveniles. Little thought was given to what those fish will face once they are released into a naturally variable environment. The homogeneous, safe, constant hatchery environment does little to prepare these fish for life in the wild, and so not surprisingly when the fish are released there is a very high level of mortality among them. We have shown that adding just a basic amount of variability into the hatchery environment generates fish that have a much more flexible behavioral repertoire. The fish are better at making decisions based on what to forage on, which individuals to interact with, and at how closely they need to come together and school in a dangerous situation.

The second way in which the environment can play a role in decision making is in terms of the ecological factors that the animal has to encounter. We have been working on the role of predation pressure and habitat stability and the effects this has on the decision making abilities in individual fish. We have found a number of surprising results associated with these environmental variables and the choices fish make. For example, fish living in sites with predators show much more strongly lateralized brain responses than fish of the same species coming from sites with few or no predators. The fish from high predation sites will, for example, typically use their left eye to keep in visual contact with school mates, but when these same fish come across something dangerous such as a predator they turn their bodies so that they can view this through their right eye. In comparison fish from low predation sites show much lower levels of lateralization. Another difference is observed in the speed and accuracy of decisions that are taken. Fish coming from high predation sites tend to make rapid, inaccurate decisions compared to fish from low predation areas. We also know that living in a more stressful environment tends to select for individuals with certain personalities or suites of behavioral traits. For example, the more stressful the environment the more likely you are to find bold individuals. Bold, or risk-averse, individuals generally make more rapid decisions.

When we compare populations of fish from habitats that vary in their stability we find differences in what information the fish learn to help them spatially map their local environment. Fish from more stable sites show a strong preference for using local visual landmarks such as plants and rocks. Fish from less stable sites choose to ignore such cues and instead rely on turn direction and their position relative to more distant cues such as a bank or edge of a stream. We have found that these population differences arise partly through heritable behavior traits but also through exposure to the stable or unstable environments themselves.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

A. Determining how to identify the critical factors that affect the decision in question (i.e. internal motivation, external environmental factors, social factors)

B. When to copy versus when to rely on your own choice

C. When to switch from individual decision making strategies to group decision strategies

Roger Cooke

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

There are pervasive dysfunctionalities in deciding under uncertainty.

- People typically seize on (what they take to be) the most likely scenario and reason as if this were known with certainty to occur.
- People to not properly factor in the consequences of an intended action if the world is not in fact as they imagine.
- There is a tendency to conflate uncertainty (about what is the case) with indecision and weakness of will.
- Finally, the command and reward structures in many institutions tend to reward or at least condone overconfident decision strategies.

In public decision making, decision makers often fail to appreciate the diversity in the population of stake holders, and treat the public as if (s)he really were the 'representative consumer' or 'John Q Public'.

The same holds for the diversity in "expert advisors".

2. What are the main research gaps within you field/area of interest?

The theory is well articulated. We need outreach. It is not primarily a social science or psychology problem; we need good courses and good case studies, being a collaboration between decision analysts (good ones), educators and psychologists.

3. Which numerical methods and models are used to support/describe risk-based decision making?

See any textbook. I have developed and apply structured methods for expert judgment and stakeholder preference modeling.

4. How spatial and temporal scales in decision making are addressed?

These are criteria in a recent stakeholder preference exercise (see Linkov's new book).

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Validation is a very sore point in AHP and MCDM. New methods are specifically designed to provide external validation. Structured expert judgment methods treat experts as statistical hypotheses and subject these hypothesis to external validation. Similarly, what are called, ruefully, random utility models try to model a population of stakeholders as a distribution over utility functions. External validation is the main driver in these models. Its too much to explain here (see literature below).

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

This is best done by briefly describing recent publications.

Stakeholder Preference Modeling:

- *Arie H. Havelaar, Ángela Vargas Galindo, Dorotha Kurowicka, Roger M. Cooke Attribution of Foodborne Pathogens Using Structured Expert Elicitation, accepted for publication in Foodborne Pathogens and Disease.*
- *Rabin Neslo, Fiorenza Micheli, Carrie V. Kappel, Kimberly A. Selkoe, Benjamin S. Halpern Roger M. Cooke "Modeling Stakeholder Preferences with Probabilistic Inversion: Application to Prioritizing Marine ecosystem Vulnerabilities" appeaing in Linkov, I., Ferguson, E., Magar, V. (in press). Real Time and Deliberative Decision Making: Application to Risk Assessment for Non-chemical Stressors. Springer, Amsterdam, pp 248-271.*
- *Cooke, R.M. "Obtaining distributions from Groups for Decisions under Uncertainty", Appearing in Making decisions with scant information - front-end decision-making in major projects, T. Williams, K. Samset and K. Sunnevag*

Regulating under uncertainty:

- *Cooke, R.M. and MacDonell, M. (2008) "Regulating under Uncertainty: Newsboy for exposure limits" Risk Analysis vol. 28 no. 1.*

Sensitvity analysis

- *Lewandowski, D. Cooke, R.M. and Duintjer Tebbens, R.J. "Sample Based Estimation of Correlation Ratio with Polynomial Approximation" Transactions on Modeling and Computer Simulation, vol. 18 no.1, article 3, 2007.*
- *Radboud J. Duintjer Tebbens, Kimberly M. Thompson, M.G. Myriam Hunink, M.D., Thomas M Mazzuchi, Daniel Lewandowski, Dorota Kurowicka, Roger M. Cooke, "Uncertainty And Sensitivity Analyses Of A Dynamic Economic Evaluation Model For Vaccination 3 Programs" Medical Decision Making 2008 .*

Expert Judgment

- *Cooke, R.M. (2008) Special issue on expert judgment, Editor's Introduction Reliability Engineering & System Safety, 93, Available online 12 March 2007,*
- *ElSaadany, S. Cooke, R.M., Xinzheng Huang, X. (2008) On the Performance of Social Network and Likelihood Based Expert Weighting Schemes, Special issue on expert judgment Reliability Engineering & System Safety, 93, 745-756, Available online 12 March 2007.*
- *Cooke, R.M., Goossens, L.H.J. (2008) TU Delft Expert Judgment Data Base, Special issue on expert judgment Reliability Engineering & System Safety, 93, 657-674, Available online 12 March 2007.*

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

Real time decision making requires good heuristics. The following are examples that a well trained decision maker should automatically tick off in his / her deliberative process

- What is the best/worst that could plausibly happen, how would my choice play out in these cases?
- Does one decision dominate all other alternatives in every conceivable situation? If so, am I wasting time deciding which comes in second place?
- How surprised would I be if the 'implausible' happened? What would I do?
- Am I deciding for myself, or for others?
    - If for others, what are the interests and beliefs of other stakeholders? How should they be consulted? Will they buy in?
- Are there observations that could be performed prior to deciding, are they worthwhile? Are there experts who could be consulted?

RENAE DITMER

1. Why do we need to study cognitive aspects of decision making?

Chemical, biological, and radiological/nuclear (CBRN) events present significant challenges to the Department of Defense (DOD) decision makers at strategic, operational, and tactical levels. Incomplete information and competing political and military objectives following a CBRN event further complicate the decision process for the individual decision maker, magnifying the risk to mission execution inherent in an already complex decision environment.

More specifically, while much work has been done to develop CBRN plans, policies, guidance, education, training, exercise, and decision support tools in accordance with current defensive technologies and knowledge on CBRN agent fate, almost no effort has been expended to methodically characterize the CBRN decision maker's intent and motivation as it pertains to decision making in this highly complex and often ambiguous decision environment. Both anecdotal evidence from lessons learned during real world CBRN events and CBRN exercises has repeatedly demonstrated that decision makers consistently and repeatedly "default" to other and heretofore unexplored decision processes that override the benefits that the investment in CBRN defense plans, policy, guidance, education, training, decision supports tools, and technology bring them.

2. What are the main research gaps within you field/area of interest?

- Need to understand how the **severity** of CBRN events impacts various missions at different levels (tactical, operational, and strategic). At present, the severity of the impact is assumed to be the same on all.
- Need to determine **probability** of CBRN events in order to determine risk. Right now our models in DOD only deal with the probability of the severity of contamination or exposure to CBRN agents, not the actual probability of the CBRN event over time. Thus current CBRN models describe probable severity only, assuming that probability of an event is 100% due to the lack of statistical evidence that would allow probability of CBRN events to be estimated.
- Need to develop contamination and exposure **standards** for operations and for public health in order to establish level of risk decision makers *can* take with regard to various mission priorities, etc. At this point none have been established even though we know any increasing amount of the severity of contamination and exposure to CBRN.
- Need to agree upon **terms of reference** for integrating all aspects of risk analysis into DOD doctrine, policy, guidance, and TTPs. At this point, DOD uses "risk," "risk analysis," "risk assessment," "hazard assessment," and "hazard" interchangeably. DOD needs to align with industry on use of terms of reference and with acceptable RA methodology in order to come up to industry and government standards as defined by OMB and others.
- Need to understand the **linkage** between risk analysis and military decision making, including understanding how cognitive frameworks impact decision making.
- Need to **identify** operational decisions required following a CBRN event have not methodically identified and the optimal timeline(s) for their implementation.
- Need to **integrate** the unique risks CBRN poses into decision policy, guidance, and tools.
- Need to **invert our approach** to developing risk-based decision frameworks by starting with identifying the decisions that need to be made and what feeds them rather than the outcomes sought.
- Need to **study the CBRN event decision process** so that we can understand what the process is and how individual cognitive factors, group social factors, and competing military – political priorities increase/decrease risk to the decision process itself.

3. Which numerical methods and models are used to support/describe risk-based decision making?

No peer-reviewed models exist at present for complex operational-strategic level decision making (e.g., launch sorties). At this point, due to the research gaps identified above, the only tools available to support risk-based decision making are tactical level tools that model agent dispersion, agent fate, and medical logistics requirements (HPAC, EXPEDITER, STAFFS, etc.). JOEF, which is/was intended to reduce operational risk by integrating ("fusing") input from multiple similar sources so that the individual decision maker or functional group could analyze them in order to inform post-CBRN event decisions has stalled out in development because there are no criteria by which to filter (assign risk) inputs, leaving the individual decision maker to do this on his/her own.

4. How are spatial and temporal scales in decision making addressed?

The models identified above in #3 account for both the spatial and temporal "severity" of the risk equation for CBRN for DOD, although without contamination and exposure standards, there is currently no threshold limit for severity. The *probability of the severity of contamination or exposure* on human health over time can be estimated by these models to some degree,

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

- Study to determine the **probability** of CBRN events in order to determine overall risk of CBRN events and the subsequent priorities in portfolio management. Current probability of CBRN events has been determined using a highly subjective approach based on interviews with subject matter experts which was developed by DHS. This approach has extraordinary bias built into it which can be overcome by identifying valid and reliable indicators (materiel and nonmateriel) associated with offensive CBRN use.
- Studies to model the actual materiel and nonmateriel **severity** of CBRN events impacts on various military missions at different levels (tactical, operational, and strategic).
- Determine and codify acceptable **standards** for CBRN contamination and exposure so that risk tolerances and risk-based decision criteria can be identified. For example, at the tactical level, there are no standards for safe levels of contamination or exposure, so even though severity of contamination or exposure to many agents has been determined, without identifying the level of risk we are willing to take in various operational environments (wartime v. peacetime, CONUS v. OCONUS, etc.), it is impossible to develop risk-based decision criteria.
- Study to determine how **cognitive issues** impact CBRN decision making and whether that differs from decision making following other contingencies.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

I have worked for DOD since Amerithrax. My own specific research has centered around the following:

1. The development of guidelines for commanders for sustaining military operations following an attack with a biological agent on a military installation
2. The development of risk-based policy, guidelines, TTPs, training, and tools for tactical, operational, and strategic level commanders and their support staffs for chemical, biological, and radiological/nuclear events.
3. The development of risk-based standards for contamination or exposure of military equipment, materiel, facilities, and operational areas to CBRN agents.
4. The development of risk-based decision criteria for military and government decision makers following a CBRN event.

Decision science as a whole has been haphazardly addressed across DOD, with little credence given to the need to do so. The role of psychological or sociological frameworks has not been methodically considered in DOD decision analysis, and thus is not integrated into current decision frameworks. The complexity of the CBRN decision process has elevated the need for both although senior leadership support and funding has not been forthcoming. DOD's continued emphasis on technological solutions to decision making has furthered hampered our understanding of the role of the individual and the group in the decision process in the military. Until there is recognition that there is a need for inclusion of decision science in DOD and funding to match it, little will change.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

- **Failure to understand what a rigorous, methodologically sound risk-based decision process and support tools mean to deliberative tactical, operational, and/or strategic decision making.** In my opinion, we have thus far failed to completely achieve these objectives, with my most severe criticism reserved for the absence of genuinely risk-based outputs as outlined above. My observation is that this is primarily due to the dearth of well-trained methodologists within DOD who are either trained risk analysts or who are familiar enough with risk analysis as a discipline to know whether we are actually producing risk-based outputs. Attempts by risk analysts and practitioners to inject a more scientific risk-based approach into CBRN decision making over the past seven years has been largely dismissed by ill-informed DOD decision makers and program managers at all levels.

  In addition, much of the funding for counter-CBRN, including risk management, has gone to the development of agent dispersion models, the understanding of agent fate (although there are huge research deficits of agent fate studies for many operational environments and surfaces), and to the development of equipment to detect CBRN events and to estimate their severity. Funding for studies on the social and psychological (including cognitive) aspects of decision making, specifically with regard to CBRN which we believe is managed differently than other military decisions due to its novelty and complexity, has been nonexistent. Taken together, the research gaps and funding priorities have created a situation where we have put ourselves at high risk were we to have a CBRN event simply because we would be relying on the cumulative knowledge of subject matter experts being interpreted by leadership ill-versed and unfamiliar with the notion and application of risk-based decision making.
- **Poor if well-intended investments in science and technology.** Although DOD has invested a significant amount of funding in counter-CBRN technology and technically-based tactical solution sets for CBRN, little if any investment has been made to deliberately, methodically, scientifically investigate the human cognitive aspect of the

process itself. Curiously, in spite of evidence from lessons learned and exercises of the disproportionate impact of the individual decision maker in the post-CBRN event environment, given the low level of funding for the issue, one might effectively argue that DOD has methodically dismissed or eschewed the importance of the cognitive decision process in complex operational environments.

- **Lack of genuine risk-based policy, guidance, and technology and a deficit of information sharing required to integrate a rigorous decision process.** As the result of the above, we have created and implemented various kinds of policy that is simply not methodologically sound, thereby endangering the community that implements it while increasing DOD's liability in distributing it. Addressing the deficits identified above will go a long way to achieving the goal of "risk-based" policy and tools for DOD.

Joshua I. Gold

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

Work in my laboratory at the University of Pennsylvania focuses on the neurobiological underpinnings of decision making. We study simple decisions about sensory input (e.g., is a visual stimulus present or absent? Which direction is it moving?) because we can carefully control the sensory input and quantify its effects on the decision process. However, we strive to identify even in these simple decision processes computational and neurophysiological principles that seem likely to contribute to more flexible, nuanced and cognitive aspects of decision making. We believe these are issues worth studying because our understanding of them is still in its infancy. For example, we know very little about how and where in the brain information about goals and expectations is used to help weigh the alternatives under consideration for decisions about a future course of action.

Our work is basic research that is motivated by a desire to better understand mechanisms of decision making in a healthy primate brain. Therefore, our short-term (less than approximately five years) goals are focused on designing and executing experiments that elucidate those mechanisms. We do not currently work on translating these results into practical applications. Nevertheless, in the longer term we hope that this basic research will benefit at least two kinds of application. The first is clinical: to combat the many devastating clinical disorders that can interfere with the brain's ability to process and interpret information for perception, cognition and decision making. Treating such disorders, like schizophrenia, will require a better understanding of how decision making is accomplished in a healthy brain. The second application is likely to have more direct relevance to the military: to train or provide tools to help humans make better (faster and/or more accurate) decisions. This application also will require a better understanding of the underlying neural mechanisms, including identifying the strengths and limitations of those mechanisms and how they are shaped by experience.

2. What are the main research gaps within you field/area of interest?

As noted above, I believe our understanding of the neural mechanisms of decision making is still in its infancy – the gaps are everywhere. Studies that combine decision-making behavior and neural recordings in monkeys or behavior and non-invasive brain imaging like functional magnetic imaging (fMRI) in human subjects are beginning to identify brain regions where activity is correlated with particular aspects of the decision-making process, including acquisition of new sensory information, accumulation of that information to support or oppose the alternatives under consideration and commitment to a course of action (for reviews, see Gold and Shadlen, 2007, *Ann Rev Neurosci*; Heekeren et al, 2008, *Nat Review Neurosci*). However, these studies are only a first step, as numerous critical questions remain unanswered. Which of these brain regions play causal roles in the decision process? How do these different components work together as a unified decision process? What are the critical computations they perform? How do these computations take into account the diversity of information – including sensory input, prior expectations, predicted outcomes, goals and values – needed to make decisions?

3. Which numerical methods and models are used to support/describe risk-based decision making?

Our work on perceptual decisions relies on two related computational frameworks. The first is signal detection theory (SDT; see Green and Swets, 1966, *Signal Detection Theory and Psychophysics*). STD describes a process for converting observations of noisy evidence into a categorical choice. It uses Bayesian logic to combine incoming evidence, prior probabilities and value into a quantity called a decision variable that is used with a decision rule to determine the choice, thereby achieving certain goals like maximize the percentage of correct responses. Early uses of SDT in decision making centered on modeling and understanding performance on perceptual tasks, treating the brain as a "black box" and the decision variable as a conceptual quantity. More recently, SDT has been used to understand neurophysiological data, including identifying correlates of decision variables in the activity of neurons in the brains of subjects performing decision-making tasks.

The second computational framework is sequential analysis (SA), an extension of SDT that deals with multiple pieces of evidence observed over time. As an interesting historical footnote relevant to the discussion of military applications, among the first examples of SA was a scheme called "Banburismus" developed by Alan Turing and his team of British codebreakers in their efforts to crack the "Enigma" code used by the Germans during World War II (Gold and Shadlen, 2002, *Neuron*). Their scheme, later formalized into a key component of statistical decision theory called the sequential probability ratio test, includes three key components: 1) express incoming information as a "weight of evidence" that is based on likelihood ratios; 2) accumulate the weight of evidence over time; and 3) stop at a pre-defined threshold. This basic scheme, which has been implemented in numerous forms including recruitment or race models and accumulator models that mirror the mathematical description of a random-walk or diffusion process, are particularly successful at describing the trade-off between speed and accuracy that is a hallmark of many cognitive and perceptual decisions. Moreover, like SDT, SA has more recently been used to analyze the underlying brain activity.

The application of SA and SDT to decisions that emphasize risks and rewards ("value based") as oppose to perceptual judgments has only just begun (see, for example, Corrado et al, 2005, *J Exp Anal Behav*). One important, unresolved issue is the role of randomness in these models of decision making. SA and SDT typically assume that the decision variable includes all information relevant to the decision, and that the decision rule attempts to use that information to make a "best guess" at the answer that will achieve a particular goal, like maximize the percentage of correct responses. In contrast, many models of value-based decisions assume that randomness is inherent to the decision process itself, which uses a probabilistic decision rule based on subjective measures like utility to generate behavior that on average achieves certain goals like maximizing utility but at any given time can appear to be random. It remains to be seen how this kind of randomness might be incorporated into the SDT and SA frameworks.

4. How spatial and temporal scales in decision making are addressed?

Issues of spatial and temporal scales are central to perceptual decision making. My work focuses on vision. A fundamental feature of the primate visual system is the spatial tuning of the underlying neurons. That is, visually responsive neurons tend to have spatially restricted receptive fields, meaning that they only respond to stimuli that appear in a restricted region of (typically retinotopically defined) space. Therefore it is imperative that we characterize the spatial tuning of every neuron that we record from. In general, receptive field size increases in brain regions further along the visual processing stream, but little is yet known about how these spatial scales affect the mechanisms of decision making.

The SA framework emphasizes the spatial scales of decision making. In particular, evidence accumulation over tens to hundreds of milliseconds appears to be a central feature of simple decisions about sensory stimuli. Accordingly, this evidence accumulation is a key feature of the neural activity we study in the context of decision making: we tend to search for neurons with activity that can not only persist over these relatively long (in neurophysiological terms) timescales but also tend to increase as new evidence arrives. A primary reason we use single-unit recordings in monkeys, as opposed to non-invasive imaging in humans, is that the former and not the latter can give us access to neural signals on these timescales.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

My work focuses on experimental studies to help validate models of decision making. We work with non-human primates (rhesus monkeys) because we believe that they are currently the best model system for studying both complex decision-making behavior and its neural underpinnings. We train the monkeys to perform demanding sensory-motor tasks that typically involve making a categorical judgment about the presence or identity of a sensory stimulus. We can manipulate a large range of task characteristics, including the strength, duration, complexity or other features of the stimuli presented; their relative frequencies of occurrence; and the probability, magnitude and quality of reward received. We can then quantify how each of these manipulations affects behavior, using over a century's worth of psychophysical methods. Moreover, we can record or manipulate (e.g., using electrical microstimulation) the activity of individual neurons while the monkeys are performing these tasks to try to understand how neural activity relates to particular aspects of decision-making behavior.

As a specific example, we are currently conducting experiments to better understand how and where in the brain information from vision is combined with information about reward expectation to help guide simple perceptual decisions. We are training monkeys (typically two monkeys are used for each experiment) on a reaction-time version of a visual motion direction-discrimination task: they are required to view a random-dot motion stimulus moving coherently in one of two directions and, once they have decided the direction of motion, make a saccadic eye movement to a visual choice target located in that direction. The monkey is then given a juice reward for a correct response, but in an asymmetric manner: one drop of juice for a correct rightward decision, two drops of juice for a correct leftward decision. We therefore can quantify the effects of signal strength and reward expectation on the speed and accuracy of decisions, which we expect to model using SA. In addition, we will be recording neural activity in both the frontal eye field and caudate, two brain regions known to reflect reward expectation and sensory-motor processing in the context of saccadic eye movements. We will test whether activity measured in these brain areas reflects specific aspects of SA, such as the accumulation of sensory input and commitment of the decision.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

As described elsewhere in this document, my research focuses on neural mechanisms that underlie simple decisions about sensory stimuli. We combine electrophysiology and psychophysics in monkeys, psychophysics in human subjects and computational modeling to better understand the basic principles that govern how the brain converts variable sensory input into categorical judgments that guide behavior. We study these simple decisions because they are experimentally tractable but believe that we are uncovering mechanisms that have direct relevance to more complex perceptual and cognitive decisions.

A particular emphasis in my lab is the role of experience in shaping the neural mechanisms of decision making. Training can cause long lasting improvements in the ability to detect, discriminate or identify sensory stimuli. Our goal is to identify how and where in the brain training exerts its influence to improve perceptual processing. One intriguing, recent result from our lab (Law and Gold, 2008, *Nat Neurosci*) is that improved performance on a visual motion direction-discrimination task corresponds to changes in how the brain forms the categorical direction judgment but not how the brain represents the motion evidence used to form that judgment. This result is relevant to the workshop theme and the broader context of decision making because it implies that even for simple perceptual decisions, the decision process itself is highly plastic and can be shaped by the experience of the individual. A better understanding of how, exactly, these mechanisms are shaped by experience might help to design more effective methods for training decision-making abilities.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

1. Which stages of decision formation are more and less likely to be helped by support tools? One lesson we can learn from our understanding of the neurobiology of perceptual decision making is that there appears to be a continuous flow of information in the brain from sensory input to motor output that includes multiple processing stages, carried out both sequentially and in parallel, that all contribute to the decision. Thus, it is unlikely that "decision formation" represents a unitary, identifiable process in the brain. Accordingly, for which of this set of processes is a support tool most effective? Pre-processing (e.g., improving signal-to-noise) of the inputs? Accumulating evidence? Applying the accumulated evidence to a decision rule? Acting on the rule once a commitment has been reached?

2. How should information from multiple sources be presented or combined? One remarkable feature of the brain's ability to make decisions is the capacity to incorporate information that comes from dramatically different sources, such as visual input and reward expectation. One critical issue for a support tool would be the units in which information from such disparate sources is presented. How much evidence is provided by one source relative to another? How can evidence from different sources be weighed to support or oppose the alternatives? A closely related question is whether a support tool can or should try to itself combine information from multiple sources, or merely present such information separately (but in comparable units) to the decision maker for further processing.

3. Can tools be designed that have sufficient flexibility to deal with multiple forms of uncertainty and different goals? Uncertainty presents the fundamental challenge to a decision maker, implying that errors are inevitable. The question is how to minimize those errors and, perhaps most importantly, how to avoid particular kinds of errors (possibly at the expense of accruing other kinds of errors). Unfortunately, "there is no universal measure of whether an error is large or small" (Scheidman et al, 2003, *J Neurosci*) or particularly undesirable. Therefore, it is critical for a decision process to take into account the particular goals of the decision maker when determining how to deal with uncertainty. How can such goals be specified in the support tools? Once specified, how do those goals shape the support or decision process?

Lev Ginzburg and Scott Ferson

1. Why do we need to study cognitive aspects of decision-making?

We need to study the cognitive aspects of decision making for at least three general reasons: (i) to be able to make better decisions, (ii) to improve communication about our decisions, and (iii) to anticipate the decisions of others.

By 'better decisions', we mean decisions that are more defensible and comprehensive, and that are less likely to be contradictory or self-defeating in contexts where multiple decisions have to be made. It is well known that expected utility theory does not describe how human beings actually make their decisions in practice, but it is often offered as a normative theory, that is, as the way we should be making decisions. However, the presumption that expected utility theory prescribes optimal decision making is contingent on many assumptions about decision making that may often not be true, including the availability of perfect information about probabilities, a single self-interested decision maker, multiplicity of decisions, a closed world whose possible future states can be known in advance, among several others. In many situations, therefore, better decisions may require relaxing these constrictive assumptions and generalizing the decision theory we use.

Improving communication about decisions to stake holders and the public can be intended to foster understanding in them about how and why a decision has been made. Of course, it can also be intended to manipulate public opinion in a way favorable to the decision maker. In fact, these two intentions are really indistinguishable, and failing to recognize this may be part of the problem that inhibits effective communication efforts. Disastrous public relations debacles are surprisingly common, for instance, in risk assessment when high-profile decisions are made. It may not matter whether the decision itself is high-consequence or about a relatively minor or local issue. In the past, botched communication efforts about both important and minor decisions have flared up into major affairs embarrassing to decision makers and their institutions. Among analysts, it is widely presumed that the primary reason for controversies and backlash from the public is that the lay citizenry are poorly educated about the sources of the risks, and poorly equipped with quantitative tools by which they might understand the important underlying issues. In fact, there is now compelling evidence to believe that, in many of these situations, it is not the public that is deficient or at fault, but the risk assessment itself that is deficient and thus the experts who constructed it who are at fault. The deficiencies are that the risk assessment fails to address certain kinds of exterior risks such as, for example, the risk that the assessment does not include important factors or agents of harm, the risk that the analysts are incompetent, or that they are in league with decision makers or others to mislead the public. Such exterior risks are certainly real and important to the public, and neglecting them can result in wasted efforts or even explosive mistakes. The clear pathway to developing effective communication strategies is to understand the underlying cognitive issues and mental mechanisms by which trust is established. Substantial advances have been made recently in these research areas.

Understanding the decisions and decision making processes of others is obviously critical in many endeavors ranging from public relations to land use planning to conducting war. This must include understanding how groups come to decisions or consensuses in practice, and determining how well-functioning groups should come to better decisions is part of the challenge. It will involve understanding not only the motivations of others that might be described by their utility functions, but also the perspectives and prejudices they have with respect to extant uncertainty. For instance, our recent research has shown how different groups can see a single data set very differently through the mist of its uncertainty that arises from small samples, imprecise measurements, and equivocal interpretations of impact. For example, pharmaceutical companies, individual doctors and their patients, patient rights groups, drug advocates urgently seeking new treatments, public interest advocacy groups, and the main decision maker, the FDA, infer sometimes surprisingly different conclusions about a drug from the evidence in a single data set. In fact, the FDA would have two entirely different perspectives from the same data set, depending on whether it was encountered before or after the drug had been formally approved for use.

2. What are the main research gaps within you field/area of interest?

The main research gap involving cognitive aspects of decision making in our area of interest concerns the two kinds of uncertainty and how they interact in the human brain when unique decisions are chosen. The two kinds are incertitude (also called epistemic uncertainty) which is a lack of knowledge such as arising from poor or incomplete measurements, small sample sizes, or model uncertainty, and variability (also called aleatory uncertainty) which is the actual stochastic fluctuation in a quantity though time, across space, or among individuals or components. Recognition of these two kinds of uncertainty is in fact quite old in decision theory. Ninety years ago, Knight distinguished between decisions under risk, which were based on known probabilities and maximizing expected utility, and decisions under uncertainty, which cannot be based on expected utility because the probabilities are unknown on account of epistemic uncertainty.

As mentioned above, humans are known to routinely violate the norms of expected utility theory embodying Bayesian rationality. Hsu et al. reported in Science recently that there are some humans that actually do behave as though they maximize expected payoff using probabilities evaluated as Bayesian theory prescribes. These humans are observed to have lesions in areas of their brains associated with perception of and decision making under incertitude. Thus, it may turn out to be true that the traditional purely probabilistic approach to decision making is simply an incomplete model of the process in unimpaired human brains. It seems to us that completing the model of human decision making will require a scheme that integrates the two kinds of Knightian decisions in a single theory that respects both aleatory and epistemic uncertainties.

Current research at Applied Biomathematics supported by Sandia and NASA has focused on how the two forms of uncertainty should be wrangled together in engineering calculations and decisions such as those required for the construction of bridges and the design of spacecraft.

3. Which numerical methods and models are used to support/describe risk-based decision making?

3) The numerical methods currently used to support risk-based decision making include several techniques ranging from back-of-the-envelope cost-benefit calculations to fully elaborated formal decision analyses involving the selection of the decision that optimizes the expected value of distributional payoff (or cost) matrices over possible futures. (Note, however, that Monte Carlo simulation is not one of these techniques; it is a method for uncertainty propagation, but not an optimization method.) When epistemic uncertainty is present rather than (probabilistic) risk, then various methods such as maximin, maximax, minimax regret, or the Hurwicz criterion are employed instead of maximizing expected value of the decision.

When epistemic and aleatory uncertainties are *both* present in a decision context, one would like to generalize the maximizing of expected value to handle imprecise probabilities and payoffs. The best method to use in this case is still under debate in the literature, but a consensus appears to be forming around E-admissibility, although various other strategies that are simpler to compute may be almost as good as E-admissibility. Some of these strategies can identify a single decision to choose no matter how great the imprecision of inputs. E-admissibility, however, typically identifies a class of decisions that are each possibly the best decision (in the sense of maximizing expected value), unless the imprecision is small enough to isolate a single decision as optimal.

Information-gap decision theory is also sometimes used when both kinds of uncertainty are present. It is the proper decision theory for use when fuzzy arithmetic is used as the calculus for uncertainty propagation. In addition to specifying the best decision, info-gap theory can also provide characterizations of its robustness and opportuneness. A recent paper from Applied Biomathematics describes how epistemic uncertainty about probability distributions can be expressed as probability boxes for an info-gap analysis.

4. How spatial and temporal scales in decision making are addressed?

When data are expressed over spatial or temporal scales, decision making can become complicated, sometimes substantially. The first question to ask about such data is whether there are differences across space or time that merit special attention. If there are, then decisions appropriate at one place or time may not be appropriate elsewhere or at another time. On the other hand, if the data are essentially homogeneous, then it makes sense to ignore space and time to make a decision for the aggregate. We think that an important part of this problem is that humans are wired to perceive patterns, even when they do not actually exist. For instance, it is well known that humans will readily perceive noteworthy clustering, gradients, and swaths of structure among points that were randomly assigned positions on a geographic map. Likewise, pulses arranged randomly in time will seem to humans to contain significant temporal patterns.

In fact, the methods of inferential statistics had to be invented to discern patternless datasets from datasets with real patterns that are different enough in some respect from randomness to be very unlikely to have arisen by chance. The traditional statistical methods used for this purpose assume asymptotically large sample sizes. Of course, in practice, sample sizes are sometimes fairly small. Paucity of samples means that the detection of clusters and other nonrandom patterns across space or time is made considerably more difficult. Sometimes real patterns are missed; sometimes randomness is misclassified as pattern. We believe that, when data sizes are very small, it will be important to use—or develop if necessary—*exact* statistical tests that can reliably detect nonrandomness across space or time that is worthy of focusing decision making. A growing corpus of such tests is now available for practical use.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

There are two central cognitive issues pertaining to decision making that we feel are essential to explore experimentally. The first is how humans discount epistemic information, which we know from Ellsberg's original work can cause human decision making to departure significant from 'rationality'. Can this discounting be quantified in a way that is analogous to risk discounting? Risk discounting is the effect by which humans pay less (or more) for a gamble than they do for a guaranteed payment of the expected value of that gamble. Is the Ellsberg discount rate consistent in different settings and for different kinds of decisions? Are different discounting rates used for potential gains versus losses as is true for risk discounting? Does its size depend on the magnitude of the gamble? How can the Ellsberg discount be combined with the risk discount to understand how humans make decisions in the face of the two kinds of uncertainty?

The second central issue needing experimental study is which kind of visualization techniques work best to communicate uncertain risks to humans, i.e., how do humans most efficiently perceive information that contains both aleatory and epistemic uncertainty in a way that appreciates both. We have explored various visualization techniques, including depicting density gray shading, defocusing (dithering), animation, and bounding interval ranges about probabilities. The problem is to find the scheme that will be natively understandable to viewers without much or any instruction. Can visualization techniques appropriate for conveying uncertainty about scalar quantities be extended to convey uncertainty about multivariate quantities and spatial maps of quantities?

Both of these experimental questions are currently the focus of our Homeland Security project mentioned below, but additional and more wide ranging experimental work should be conducted.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

Our research at Applied Biomathematics has addressed many of the fundamental issues of decision making under risk and uncertainty. Most of these projects have produced reports and/or software packages encapsulating the findings and methodologies developed. The most relevant recent projects include:

Funding	*Project*
NIH	Detecting nonrandom clustering among rare events in small data sets
USDA	Forest pest risk in dynamic landscapes
Sandia	Methods for accounting for and propagating epistemic uncertainty
NASA	Methods for aleatory and epistemic uncertainty in early spacecraft design
Pfizer	Perspective visualization of data through uncertainty
BRGM	Bayesian methods in risk assessment
Homeland Security	Developing spatial risk maps from sparse and imperfect incidence data

The Sandia project has extended over many years and has involved developing methods to aggregate disparate information from multiple sources, accounting for dependencies among variables, meta-level sensitivity analysis, validation (comparing predictions to data), and basic descriptive and inferential statistics for imprecise information.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

7) We believe that the three main challenges facing the practical use of quantitative decision analysis in real-time or deliberative decision making are (*i*) correctly handling incertitude (epistemic uncertainty) which may imply there is no optimal answer in some cases, (*ii*) understanding how humans can or should use risk discounting and Ellsberg discounting to come to unique decisions, and (*iii*) the need for suitably general software that handles incertitude, accounts for the two kinds of discounting, and has good visualization capabilities.

Cleotilde Gonzalez

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

In military situations, the outcome of combat is often determined by the decisions made and by the actions in the battlefield. From the decision to fight or avoid conflict through the decisions that define the planning and execution of combat, making the *right* decisions is the key to mission success and the preservation of our forces.
By definition, individual decision making is essentially a cognitive activity. Good decisions are made by an individual having the right information available in the right form at the right time, but all these requirements are accompanied by the appropriate processing of that information. Awareness of the current situation, the options available, and the risks and opportunities associated with the courses of action.

Much progress has been made in the development of technology that provides an individual with a wealth of information. However, the availability of this information and the application of the tools to process the information do not guarantee that the *needed* information will get to the right people in the right manner to facilitate a better and more timely decision. Clearly, there is a significant opportunity to enhance the battlefield decision making environment by continuing to define and support the philosophy of *decision centered design*, which starts by understanding the cognitive processing of information.

2. What are the main research gaps within you field/area of interest?

Dynamic Decision Making (DDM) is a research field in much need of theories and development. DDM studies how people make decisions in environments that change while the decision maker is collecting information about it. In contrast with the wide research programs available on judgment and decision making in static tasks, dynamic tasks are not used often in strong research. In general, these are tasks that are much more challenging to study than traditional laboratory tasks. For example, in the dynamic decision making laboratory (www.cmu.edu/ddmlab) we study military command and control, medical diagnosis, luggage screening, and conflict and peace.

A common finding in DDM research is that decision makers remain sub-optimal even with extended practice, unlimited time, and performance incentives. However up to this point it has been difficult to explain why is so challenging to learn in these environments. Research is needed to understand learning in dynamic tasks, understand human cognitive processes involved in performing generic basic and complex dynamic tasks, such as accumulation and flows, and global warming.

3. Which numerical methods and models are used to support/describe risk-based decision making?

For risk-based decision making there is a wealth of literature. In general, Risk Analyses and computational cognitive modeling are interesting methods in this case.

4. How spatial and temporal scales in decision making are addressed?

These are rare research topics. Time is a pervasive dimension of decision making. All our decisions take time, develop over time, and result in consequences that are not immediate, but rather are develop over time. Not much research exists currently regarding the spatial and temporal scales in decision making.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Some experiments may be aimed at the investigation of the effectiveness of feedback on learning in dynamic tasks: (1) tests of the efficacy of different types of feedback, (2) examination of the timing of the feedback and the feedback delay, and (3) tests of the type of cause-effect relationships, such as self-reinforcing, self-correcting loops and their interrelationships. Here are some examples on the efficacy of feedback on learning in dynamic tasks:

Tests of the efficacy of different types of feedback

Three possible types of feedback have been identified from the literature: outcome feedback, cognitive feedback and feedforward. Surprisingly, outcome feedback has been found to be largely ineffective to improve decision making in dynamic tasks. Cognitive feedback and feedforward seem to be more effective in helping improve DDM, although their effectiveness seems to depend on the presence of outcome feedback. According to previous results, we would expect that providing explicit understanding of the dynamics of the environment rather than implicit knowledge will improve performance in this task. We also expect that providing individuals with a way to foresee the status of the environment before decisions are made will also help. Thus, any of two types, cognitive feedback or feedforward, would be more effective than outcome feedback.

Initially, the independent contribution of each type of feedback to learning in DDM needs to be established while controlling for the timing or feedback delays. We can run an experiment in which individuals are assigned to a group receiving either no feedback at all, outcome feedback only, cognitive feedback only or feedforward only.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

I study DDM in a wide range of dynamic systems, from the simplest, repeated binary choice tasks to the more complex, real-time dynamic resource allocation tasks under time constraints and dynamic complexity (interrelationships among decisions and environmental variables over time). I also study DDM in a wide diversity of contexts. Some of the dynamic contexts I study include military command and control, supply-chain management, air-traffic radar control, medical diagnosis, and dynamic resource-allocation tasks. I develop simulations that represent realistic tasks in these contexts and use those simulations as research data collection tools (Gonzalez, Vanyukov, & Martin, 2005). Finally, I use a wide variety of research methods including laboratory experiments with complex simulations, computational cognitive modeling, field data collection, and functional magnetic resonance imaging (fMRI).

I view human decision making in dynamic environments as a learning process (Gonzalez, Lerch, & Lebiere, 2003). Essentially, this learning process involves an accumulation of situation-action-outcome links through the interaction with an environment and the refinement of those links over time. In this learning process individuals rely on their accumulated experience to make decisions by retrieving solutions to similar situations stored in their memory (Gonzalez & Quesada, 2003). This theory of learning has been instantiated and tested against human data (Gonzalez et al., 2003) using ACT-R computational models (Anderson & Lebiere, 1998).

Herb Simon explained bounded rationality as the match between mind and environment; he used the analogy of a pair of scissors to express this concept (Simon, 1990). In DDM, both, the computational abilities of the decision maker and the structure of the task environment play a key role the choices made. I have directed a great deal of my research efforts toward investigating these two factors and their interaction. This work, mostly sponsored by the ARL ("Learning and adaptation in complex battle situations"), has generated a set of empirical results that suggest not only the independent effects of each blade but also the interaction of the two blades.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

1) the complexity of the situations studied may make the tools obsolete, insufficient.
2) the individual differences of the decision makers.
3) the adaptation of the tools to the status of the individual.

Greg Kiker

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

Within complex environmental challenges, there has been a distinct lack of integration between model development/execution and its concomitant linkage with practical decision making. Cognizance of any socio-political factors is usually assumed into static irrelevance or ignored entirely in the interests of getting “the best possible science.” Often there seems to be a prevailing idea on the part of scientists and engineers that decision-makers and stakeholders will be able to recognize and appreciate the power, nuance and uncertainty contained in a set of “best possible science” results. An interesting paradox to the “best science” narrative is that if scientists and engineers are overly confident in their results, any changes or modifications to their conclusions may cause them to lose face or status in their role in providing relevant data to decision making. Alternately, if they are overly hesitant in their results concerning the lack of information, its variability or its inherent uncertainty, they are accused of being evasive, opaque, or even incompetent.

In the last twenty years of research, most efforts in my field towards integration of information into decisions has been in the design and implementation of specific “decision support systems” or “expert systems” that attempt to reduce human judgment into manageable and predictable tree structures. Often the result of these tools are interesting in an academic sense but are usually not accepted by decision-makers in reality. As a result, in practice most model results are fed into more *ad hoc* decision-making approaches (Kiker *et al.*, 2005).

Adaptive management (Walters and Holling, 1990; NRC 2004) has been increasingly adopted (at least in abstract principle) by many resource management agencies. With respect to actual adaptive management implementation within natural systems, the role of uncertainty has created a critical point of human/model interface where the models are now providing higher levels of uncertainty analysis (in terms of both model sensitivity and variation of simulated results) while humans are seemingly static in their ability to comprehend and thus manage these disparate streams of incoming information.

Anderson *et al.* (2003) presented a useful description of adaptive decision making and its relationship with uncertainty. In addition, the authors highlight the linkage of decision heuristics with internal and external social contexts to help select the most appropriate form of adaptive management. A significant challenge to advocates of adaptive management is the accounting of various social and institutional drivers that create unstable and uncertain foundations upon which adaptive framework can unwittingly be constructed. Within environmental simulation, we are facing a decision point as to make more detailed and complex decision tree structures to auto-manage complex systems or to simplify the incoming system data into a few heavily tested/analyzed metrics for a set of decision heuristics. In other spheres, this conflict is mirrored by the “Heuristics and Biases” approach (Kahneman and Tversky, 1974; 1996;) and the “Fast and Frugal Heuristics” framework (Gigerenzer et al., 1999; Gigerenzer, 2000).

2. What are the main research gaps within your field/area of interest?

The primary research gap that we face in Biological/Environment/BioResource modeling is the linkage and combination of mathematical models over temporal, spatial and disciplinary scales. Most of our funding and real world challenges tend to stretch over biogeochemical processes with functional integrative aspects in ecology and/or hydrology. Recently, as the demand for more coupled human/natural system models has emerged, we are attempting to incorporate human management, perception and action within the computational realm of modeling.

A current gap with some considerable current effort being leveraged towards it is in the development of functional tools for analyzing model sensitivity and the inherent uncertainty of model results. (Muñoz-Carpena *et al.*, 2007; Saltelli *et al.*, 2005; Saltelli *et al.*, 2000, 2004). In almost all our new model construction and execution projects, we are beginning to link decision analysis with uncertainty methods provides a basic analytical framework for systematic adaptive management. Our research group has designed a conceptual, integrated plan that is being tested in the Okavango River Basin (Botswana, Namibia and Angola) (Kiker *et al.*, 2008 in press). Often responsive management is seen within a passive adaptive management concept instead of an experimental learning context. Institutional learning pedagogies are rarely included into adaptive decision-making frameworks with groups usually opting for a reactive problem fixing methodology rather than a proactive problem/solution visualizing scenarios. Walters (2007) viewed the institutional failure of adaptive management efforts in fisheries management as “ *i) lack of management resources for the expanded monitoring needed to carry out large-scale experiments; ii) unwillingness by decision makers to admit and embrace uncertainty in making policy choices; and iii)* *lack of leadership in the form of individuals willing to do all the hard work needed to plan and implement new and complex management programs. (p. 304)"*

3. Which numerical methods and models are used to support/describe risk-based decision making?

There often seems to be large disconnect between the "state of the art" in environmental world and the "state of practice" where fundamental decisions are constructed, tested and implemented. Within the hydrological and ecological world, large scale, computationally complex and spatially explicit models dominate the landscape. Discrete and mechanistic simulation of both hydrological and ecological processes require literally thousands of parameters many spatially and temporally varying. Within the Everglades restoration, several large teams of modelers at many academic and governmental institutions are simulating high detail spatial elements and temporal elements of the biogeochemical system. In hydrology, watershed scale models linked with Geographic Information Systems are usually executed at daily or sub-daily time steps to simulate basic hydrographs and time/space varying water management. Monte Carlo Analysis and stochastic simulation are well established in the BioEnvironmental modeling field. In the ecological modeling field, more progress towards agent-based and individual-based models is evident (Grimm and Railsback, 2005). Any direct linkage with risk-based decision-making is usually focused with "soft" model linkage (where one model's output forms another model's input) to simplified decision tree or multi-criteria methods.

4. How spatial and temporal scales in decision making are addressed?

Many decision tradeoffs are constructed on simplified assumptions or heuristics that are either set by customers or left to researchers to suggest. The result is often scale combinations that are too prescriptive or inconsistent among different research efforts. Multidisciplinary teams often spend much of their time designing and implementing ephemeral, *ad hoc* interfaces that serve to link two sets of model code in an often brittle and limiting fashion. Hard linked, multi-scale models are slow to construct, hard to run and often terminal in subsequent expansion possibilities. Frequently, when detailed, computationally complex models are combined to give a unified or synchronous scale response, the overall transparency or understandability of the results are lost.

The numerous assumptions required for multi-scale modeling must be collected and clearly articulated for decision-makers and stakeholders. When higher order interactions are evident in the results, caused by either varying driver inputs or assumed parameter values, linked models become quite opaque and black box issues and procedures become the main operating feature of the linked system. Attributing specific consistent cause and effect relationships to specific model outputs, a component that decision-makers often desire, can be a daunting and time-consuming task for technical teams. Surprises in the model results are even more difficult to attribute specifically to different inputs or internal calculations of the model. When decision teams begin to doubt the efficacy of linked, multi-scale systems, they tend to fall back on simpler, understandable and historical analysis techniques which may provide simplicity at the cost of assuming to irrelevance most of the factors that led to their initial drive to commission the linked, multi-scale methods.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Currently within the BioEnvironmental modeling field, there are few experimental studies that analyze humans directly in environmental decision-making. Simulations are developed mostly in the total absence of decision-makers or stakeholders and then modified upon review or some iteration with technical representatives of decision making groups. As a result, we are attempting to construct simulation/scenario/gaming scenarios in both central and de-centralized mechanisms. Current NSF and related proposals in conjunction with our ***UF Digital Worlds Institute*** (http://www.digitalworlds.ufl.edu) aim to create novel virtual environments and decision/scenario simulations with respect to natural resource and security challenges. In addition, we have developed a portable ***DecisionPlace*** system to provide visualization, calculation and interaction tools to local groups with specific interest in bioenvironmental decision challenges.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

My own research has been spent in two primary areas, hydrological and ecological model development and their application to environmental decision analysis. As I have worked to institute these tools within adaptive management contexts, I have become quite interested in the themes of cognitive psychology and its linkage with risk-based decision making. As an engineer, my role is to create functional tools that integrate relevant theories into practical, on-site tools and methods. Increasingly, I am working within multi- or trans- disciplinary teams to provide technical integration for different sets of information and results provided by social and scientific partners. In conjunction with the US Army Corps of Engineers – Engineering Research and Development Center, we have developed additional tools and methods that aid in these efforts (Kiker et al., 2006; Kiker and Linkov, 2006).

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

Challenge 1. Finding theories and practice of integrating multi-scale and multi-disciplinary environmental knowledge in real time, adaptive contexts. *What theories are comparable so that we have confidence in combining "apples, oranges and springboks"?*

Challenge 2. Constructing active decision simulation in both immersive and remote context for environmental planners and managers that mirror their institutional situation. *How can managers and interested parties practice real-time decision making in a place that is "safe" to error and learn for later application in reality?*

Challenge 3. Constructing tested and confident decision heuristics in both real-time and adaptive learning contexts. *What are the most important and powerful rules of thumb that can guide us (and our constituencies) without locking us into rigid group-think ideas and practices?*

Challenge 4. Minimizing or mitigating delays and uncertainties in gaining real-time, trustworthy environmental data. *What is the most appropriate data and at what certainty will help us to move forward in an effective (yet adaptive) execution plan?*

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Irving Lachow

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

1. Why do we need to study decision making in the military, at the IRM College, and in the field of policy analysis?

The importance of decision making in a military context is clear: military decisions affect the lives of huge number of people and the fate of nation states. In the nuclear context, military decisions can even affect the future of our planet. At a more tactical level, military decisions decide the outcomes of battles. On the business side of the military, decisions affect the allocation of resources on a huge scale and can impact cities, communities, and companies.

The Information Resources Management (IRM) College is part of the professional military education system. Therefore it supports the improvement of decision making in the military context. More specifically, it prepares leaders to direct the information component of national power by leveraging information and information technology (IT) for strategic advantage. Its primary areas of expertise include leadership; process management; information technology, policy, and security; transformation; and management of acquisition processes and reform. These areas are relevant for both the operational and business side of military affairs. As the information component of national power grows in importance, the role of information leaders will increase, and the value of good decision making regarding information and IT will do so as well.

Decision making is what policy analysis is all about. In fact, policy analysis can be defined as "a real-world decision-making tool."[1] More formally, one can view policy analysis as the process of determining "which of various alternative policies will most achieve a given set of goals in light of the relations between the policies and the goals."[2] Thus, it impossible to perform policy analysis without explicitly addressing the human decision making process.

2. What are the main research gaps within you field/area of interest?

I do not track the field in sufficient detail to provide a definitive answer. However, I can postulate that one possible gap is the application of decision making research to senior national security leaders. Senior executives face a particularly difficult set of challenges due to a variety of constraints: heavy workloads, political pressures, cultural constraints, and bureaucratic factors, to name a few. Making good decisions on complex and sensitive issues is hard enough in the abstract, but the additional constraints faced by senior government officials compound the problem. It is not clear if sufficient attention has been paid to helping these officials make better decisions. Many of prescriptions found in books and articles are simply not realistic or practical for these executives.

3. Which numerical methods and models are used to support/describe risk-based decision making?

It depends on the specific application one is examining. For example, there are highly rigorous and quantitative risk models for financial decision making (e.g. portfolio theory). I am sure that there are numerical methods and models for risk-based decision making in a military context, but I am not familiar enough with that field to comment on those models. Two good sources of information on this topic are MORS and the CCRTS Conferences.

4. How spatial and temporal scales in decision making are addressed?

I do not have sufficient information to answer this question in detail. I can say that long time frames (and great distances) lend themselves formal methods of decision making (i.e., decision analysis tools based on rational thinking). Short time frames (and short distances) often focus on the use of heuristics, biases, and intuition (e.g. Gary Klein's Recognition-Primed Model of decision making).

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

It depends on the particular aspect of decision making that one is trying to analyze with a given model. In the case of military decision making, one can conduct experiments with troops in the field (e.g. live-fire exercises), one can use

[1] http://www3.interscience.wiley.com/journal/112758221/abstract?CRETRY=1&SRETRY=0
[2] http://en.wikipedia.org/wiki/Policy_analysis

simulations with live users to observe their behavior, one can conduct decision making exercises and/or table-top games, or can try to capture data from people in the field without creating a formal experiment (that is, one can observe user behavior without the people knowing that they are being observed). As before, MORS and CCRTS are good sources for papers on this topic.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

I have done secondary research (not direct experimentation) on two aspects of decision making, both of which are relevant for the workshop. First, I looked at decision making in network-centric warfare.[3] In particular, I analyzed the use of rational and intuitive methods, weighed their advantages and disadvantages, assessed when each should be used (and when each method usually was used), and made recommendations for improving decision making in networked environments. These recommendations looked at a wide range of elements, including recruitment and retention, training and education, and the use of technologies such as simulations.

Second, I examined decision making by senior leaders in the Pentagon (most notably, the Secretary of Defense).[4] I again focused on the use rational and intuitive methods and developed recommendations for improving the ability of senior leaders to use both approaches. For example, I suggested the use of decision-making exercises to improve intuition about matters that are difficult to analyze rationally.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

I think that the challenges are somewhat different for tactical and strategic decisions. Generally speaking, tactical decisions are conducted in short time frames (real time or near real time) and focus on limited objectives. While these decisions may involve important trade-offs, they often do not involve complex trade-offs among a wide range of competing interests. In contrast, strategic decisions often involve long time frames (possibly years) and focus on high-level objectives. These decisions can involve trade-offs among a wide range of incomparable factors and a large number of stakeholders. While there are exceptions to these two characterizations (for example, a decision about responding to a nuclear attack would be strategic but could involve a short time frame), they are true often enough that I will base my analysis on these assumptions.

The three main challenges in the tactical context might be: time constraints, cultural factors, and quality of information. The first challenges is self-explanatory: one may simply not have enough time to use a rigorous decision making tool. For example, if someone is shooting at you, you may respond intuitively, often without conscious thought. Even if one has a few minutes to make a decision, and formal tools could be used (in theory), there are often cultural factors that mitigate against their use. Decisiveness is a highly valued trait in many situations. How would soldiers respond if their leader pulled out a laptop and started to run a formal model in order to make a decision about a military situation? Would that be acceptable? Would the leader be seen as wise or as someone who was unsure about what to do?

Finally, a potential challenge in tactical situations is that one may not know whether they can trust the data used in the decision making model. There may not be enough time to validate the data or to run parametric analyses on the model's output. If users are unsure about the input (and output) of a decision making tool, they may be reluctant to rely on it, especially if time is short.

In a strategic context, the three main challenges may be: time constraints, cultural factors, and political factors. The first challenge, time constraints, has less to do with the time frame that exists for the decision to be made and more to do with the amount of time that the decision maker has (or thinks they have) to run a model. As noted above, senior leaders are often extremely busy. They can work very long days and juggle incredible schedules. Such people may not feel that they can devote the time necessary to use, or support the use of, formal decision tools.

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[3] This research resulted in a book called *Battle-Wise* (2006) and a presentation given at the 10th Annual ICCRTS Conference in 2005. I worked with David Gompert and Justin Perkins on these efforts.
[4] This research resulted in an NDU White Paper and two presentations: one to the Director of Program Analysis and Evaluation at the Pentagon, the other to a class of civilian and military leaders at the George Washington University.

The second constraint, culture factors, is similar here to the tactical situation. Leaders may feel reluctant to rely on decision tools if they feel that it makes them look weak or unsure. Unless there is a tradition of using these models in a particular organization, leaders may not be willing to be the first to use such models and risk their careers.

Finally, strategic decisions often involve political factors. These factors may include a wide range of complex variables that are extremely difficult to assess and compare. For example, a senior leader may have to choose between acquiring two different weapon systems. Each system will have proponents within the legislative and executive branches. There are budgetary implications (what happens if you anger someone on the Appropriations Committee?), bureaucratic factors (for example, the recommendations of his/her own staff) and personal relationships to consider. These “political” factors cannot be measured explicitly, but they are extremely important for senior leaders. Decision tools may not be able to weigh these factors, yet these considerations are often as important, if not more important, than performance characteristics associated with the system in question.

Jim Lambert

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

Systems engineering as a profession has several aspects, including:

(i) The disciplined application of optimization, simulation, requirements-analysis, systems-integration, and other methodologies to address unprecedented technology challenges of large scale and scope;

(ii) The identification and modeling of all components of a system, considering for each component its purpose, structure, and function, and considering the interactions and interdependencies of all components;

(iii) The multifaceted approach to systems modeling, wherein multiple complementary perspectives and decompositions of a system are the very definition of intelligence in design.

To study cognitive aspects of decision making in a context of systems engineering can assist that stakeholders (owners, users, operators, customers, affected others, … associated to a particular systems engineering effort) are engaging and benefiting from one another by sharing scientific data and objective evidence in effective negotiation.

2. What are the main research gaps within you field/area of interest?

The research gaps for cognitive aspects of decision making in the field of systems engineering include:

An inability to recognize and address emergent system behaviors, which can lead to new or unanticipated uses of the system and/or unforeseen risks.

An inability to balance quantified and nonquantified factors in a repeatable process.

A challenge for large-scale systems to respond to and recover from rare or extreme events.

The need and inability to monitor incipient risks and/or intelligence data over time in risk incident databases.

Inadequate or missing principles with which to address risk and uncertainty in budgeting and cost estimation and accounting for large-scale enterprises and systems.

Inattention to the needs and opportunities for the diversification of investments in large-scale system, particularly for protection from rare and extreme events.

Missing a formalization of assumption-based decision making as a complement to evidence-based decision making for unprecedented technical challenges.

The curse of dimensionality of resource allocation to sources of risk distributed in geographic space and time, and across multiple stakeholders.

3. Which numerical methods and models are used to support/describe risk-based decision making?

The numerical methods and models used most often to support decision making in systems engineering applications include:

The decision matrix, which enumerates the decision space and the outcomes space;

Decision trees, for sequential decisions including planning for operation, and strategic and tactical decisions;

Event trees, to address what is the probability distribution of the consequences of a particular initiating event;

Fault trees, to address how could a particular events occur as a function of basic events occurring, and with what probabilities;

Markov models, to address what are all the states of a system, and what are the probabilities in time of transitions among these states;

Linear and nonlinear programming, to model decision variables, state variables, constraints, and objective functions in large-scale optimization;

Multiobjective (multicriteria) tradeoff analysis, in which utility functions are often constructed implicitly or explicitly to understand the negotiating positions of one or more stakeholders or decision makers;

Cost-benefit and cost-effectiveness analyses which aim to reduce multiple objectives to fewer or a single monetary objective;

Methods of propagating uncertainty in mathematical models including Monte Carlo simulation, fuzzy arithmetic and fuzzy logic, probability bounds analysis, error analysis, first-order second-moment (FOSM) methods, and others.

4. How spatial and temporal scales in decision making are addressed?

Decision making with a spatial dimension is increasingly addressed by geographic information systems. However the size and dimensionality of these problems will continue to challenge the visualization capabilities of GIS. An example is resource allocation for wide-scale disasters.

Temporal scales in decision making are addressed by Markov decision processes, which formulate or derive an optimal policy for a dynamic system. As with spatial scales, the dimensionality of such approaches challenges human comprehension and machine capabilities.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Experimental studies are needed to better understand:

> How decision makers might synthesize (or fail to synthesize) qualitative and quantitative factors that are relevant to a decision problem, particularly for risks of extreme events.

The needs and opportunities of diversification of infrastructure investments against emergent risks of extreme events.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

My research addresses:
Synthesis of quantitative and qualitative evidence for decision making;
Sequential decision making for risk of extreme events, including planner for operation and preparedness for natural and man-made hazards;
Canonical design of risk, safety, and security programs in industry, government, and the military;
Diversification of infrastructure investments against emergent risks of extreme events;
Resource allocation to distributed safety and security technologies;
Scenario-based planning of infrastructure investments, particularly for large-scale systems;
Applications to international development, climate change, multimodal transportation planning, system safety and security, future energy systems.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

Three challenges in integrating rigorous decision support tools in tactical and/or strategic decision-making are:

1. While many agree how to calculate with probabilities in a decision model, it may be impossible to find any two individuals to agree precisely on the meaning of the probabilities.
2. Utility/value functions change rapidly with time and with the acquisition of new evidence and experience.

Risk analysis theory and methodologies still differ considerably across its applied disciplines including human health, environmental and ecological impacts, financial and economic systems, project management, engineering/technology, and others.

Benoit Morel

Introduction:

In my field of cybersecurity, one of the major challenges is automatic detection of malicious activity. Anomaly-based intrusion detection has become a meeting point between artificial intelligence and decision making.

Bayesian decision making is the preferred approach. It provides the most promising framework to address the many challenges involved.

In host based intrusion detection, the information which has to be analyzed comes under the form of system calls or control flow, i.e. events that affect the state of a processor. From the analysis of such information, the challenge is to elicit evidence of malicious activity.

The difference between malicious and legitimate is itself problematic. A computer can have a very large set of possible behaviors. Many of them are clearly legitimate, some of them are clearly very suspicious, but many of them can be both. Making a determination solely on the basis of the frequency of those behaviors or patterns leads to the well known problem of false positive (treating every suspicious event as a potential malicious one) or false negative (by putting the threshold for malicious event too low). Furthermore the distinction between malicious and legitimate has to be made in a hostile environment, i.e. in a context where the attacker will try to fool the detector. It has been shown that in many circumstances "mimicry attacks" can fool detectors relying only on statistical acquired sense of what is legitimate or not.

An additional complication is the "context dependence". What in some cases can be construed as legitimate, does not in others. Some additional rules or restrictions are applied to situation where computers are used for mission critical functions, with security implications. A database build on simplistic statistical learning would fail to capture that. Building a database which reflects these more subtle aspects of security is still work in progress, at best…

As we speak, anomaly- based automatic intrusion detection has a lot of room for improvement. But it has quite a history and has inspired a number of good ideas from which the field of cognitive decision making could learn.

The general tendency: using Bayesian classification paradigm:

Bayesian classification has now an impressive history and huge impact in health policy for example. Bayesian networks are applied to many situations with success. When it comes to cybersecurity, the problem is to identify malicious events which are purposefully or naturally difficult to detect. The false positives have so far been the nemesis of anomaly-based detection.

Schemes based on Bayesian classification such as EM- algorithms have been suggested in the context of intrusion detection[5]. EM (for Expectation maximization) is a Maximum likelihood algorithm which is used to relate observables to distributions of the events which generate them. It is an optimization algorithm whose efficiency and versatility in real time situations of relevance for cybersecurity is suspect.

Malicious activities in cybersecurity can take an increasingly large set of forms. From the exploitation of software vulnerabilities (such as buffer overflows) they can also proceed from code injection (SQL or Cross site scripting) or other exploitation of weaknesses in the implementation of web-applications.

Still there is sense that automatic intrusion detection is best approached in the spirit of probabilistic thinking and that there is no better approach than a Bayesian based approach.
The proposed approaches may still be made to do the job. For that they will have to overcome the so far excessive overhead associated with classifying schemes such as the EM algorithm.

The information fed to the analyzer may also be refined. There is a debate on whether the information provided by the system calls adds or substitutes to the information provided by control flow or forms of computer behaviors recorded[6].

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[5] R. Puttini et al, A Bayesian Classification Model for Real-Time Intrusion Detection, Bayesian Methods and Maximum Entropy Methods in Science and Engineering , 22nd Workshop (2003)
[6] Sharif, M. et al, Understanding Precision in Host Based Intrusion Detection, in RAID (2007), Kruegel et al Ed.

The problem of this information is closely connected with the problem of the data base that is used by the analyzer. Making the determination that an activity is malicious or not the result of an optimization may be flawed, as it is not clear that what one optimizes is a good proxy to make that determination.

To be more concrete, what information could the analyzer have of cross site scripting, i.e. that the same origin policy has been violated through code injection? What kind of database can possibly be used for that?

Another suggestion is to assign a degree of suspicion (anomaly score value[7]) to events. This kind of approach does not suffer necessarily from the overhead of a real time optimization procedure. It relies on the quality of the database.

What is malicious for some computers is not necessarily so for another involved in a completely different mission. Data bases to a certain extent should be different for different computers. Data bases represent the "intelligent" part of the computer. It is where the cognitive aspect of the decision making resides. The databases should act as support for judgment for the analyzer. They should change and reflect some form of "experience".

Implementation of a Bayesian framework:

Let the Boolean variable ζ refer to whether one deals with a malicious event or not. By definition: $\zeta = 1$ means that the event is malicious. Otherwise $\zeta = 0$. The variable of interest is: $P(\zeta = 1)$, the probability that one event is malicious. All the paraphernalia of data, measurements and detection, can be represented by another Boolean variable X. By definition $X = 1$ means that there is evidence for something malicious, i.e. something abnormal.

The probability of error (= misdetermination) associated with a particular detection system is[8][9]:

$$P(E) = P(X = 1, \zeta = 0) + P(X = 0, \zeta = 1) \qquad (1)$$

The famous Bayes theorem states that:

$$P(X = 1, \zeta = 0) = P(X = 1 \mid \zeta = 0)P(\zeta = 0) = P(\zeta = 0 \mid X = 1)P(X = 1) \quad (2)$$

In EQ2 there are three probabilities which can be referred to as "false positive":

$P(X = 1, \zeta = 0)$ is the probability that the detector signals an while in fact it is not the case..

$P(X = 1 \mid \zeta = 0)$ is the conditional probability that even if there is no attack, the system of detection will go on alert.

$P(\zeta = 0 \mid X = 1)$ is the conditional probability that when an alert is given, it is a false alert.

From EQ 2, it is clear that they are three different numbers.

In the same way there are three probabilities which can called false negative, which appear in the expression:

$$P(X = 0, \zeta = 1) = P(X = 0 \mid \zeta = 1)P(\zeta = 1) = P(\zeta = 1 \mid X = 0)P(X = 0) \quad (3)$$

The conditional probabilities $P(X = 1 \mid \zeta = 0) = 1 - P(X = 0 \mid \zeta = 0)$ and $P(X = 0 \mid \zeta = 1) = 1 - P(X = 1 \mid \zeta = 1)$ are figures of merit of the detection system. They represent the "cognitive dimension of the detection system. This suggests that using X as a Boolean variable may be enlightening. It is also suboptimal. X should be a vector in a space of several dimensions. The conditional probabilities have to take their value in a multidimensional space, whose dimension depends on the specific of the problem.

Making the determination of an attack "dynamical":

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[7] Cova M. et al, Swaddler: An Approach to Anomaly-based Detection of State Violations in Web Applications,

[8] T.S. Cover, IEEE Transactions on Systems, Man, and Cybernetics, January 1974, pp. 116-117

[9] This applies to the problem of classification, when the probability that the "thing" under investigation has equal probability to be one or the other. This should not be applied to the case where frequency can mess up the interpretation. It is important to bring the probability to a level where this criteria can be used…

In the same way that human determination of guilt is the results of several iterations and of a continuous investigation or monitoring of activity, Bayesian decision making could be a protracted process based on analysis of a process. The variable of interest is $P(\zeta = 1)$. It measures the degree of suspicion of the system. That variable can be made a function of time. Through the observation that each time the observable X takes a value it can be construed as changing the value of $P(\zeta = 1)$ as:

$$\tilde{P}(\zeta = 1) = (1 - X)P(\zeta = 1 \mid X = 0) + X\,P(\zeta = 1 \mid X = 1) \qquad (4)$$

. EQ.4 implies that each time a measurement is made, the value of $\vartheta = P(\zeta = 1)$ is updated into $\tilde{\vartheta}$ as:

$$\begin{aligned}\frac{\tilde{\vartheta}}{\vartheta} &= \frac{(1-X)P(X=0 \mid \zeta=1)}{\vartheta P(X=0 \mid \zeta=1) + (1-\vartheta)P(X=0 \mid \zeta=0)} + \\ &+ \frac{X\,P(X=1 \mid \zeta=1)}{\vartheta P(X=1 \mid \zeta=1) + (1-\vartheta)P(X=1 \mid \zeta=0)}\end{aligned} \qquad (5)$$

EQ.5 relates ϑ and $\tilde{\vartheta}$ through the probabilities that constitute the figures of merit of the detectors. A necessary and sufficient condition for the evidence of an attack (X=1) to increase the value of $\vartheta = P(\zeta = 1)$ or that X=0 reduces its value is:

$$P(X = 0 \mid \zeta = 1) + P(X = 1 \mid \zeta = 0) < 1 \qquad (6)$$

It is only when EQ.6 that a measurement adds useful information. It is easy to show that if actually $\zeta = 1$ and EQ.6 is satisfied, eventually $P(\zeta = 1) \to 1$, and if $\zeta = 0$, eventually $P(\zeta = 1) \to 0$. The speed of the convergence depends on the value of the figures of merit of the detector i.e.: $P(X = 1 \mid \zeta = 0)$ and $P(X = 0 \mid \zeta = 1)$.

Discussion: Becoming multivariate and the curse of dimensionality:

Instead of one the detection system could (and should) make several measurements in parallel Instead of EQ.4, the evolution of the evidence is controlled by the result of several measurements. We assume that the result of the experiments was: $X_i = x_i$, where $x_i = 0 \text{ or } 1$.Eq.4 is then replaced by:

$$.\ \tilde{P}(\zeta = 1) = P(\zeta = 1 \mid X_i = x_i, i = 1,\ldots n) \qquad (7)$$

If there were no correlations between the different measurements, in EQ.7,

$$P(\zeta = 1 \mid X_i = x_i, i = 1,\ldots n) = \prod_{i=1}^{n} P(\zeta = 1 \mid X_i = x_i) \qquad (8)$$

But one should expect that there would correlations between the different measurements. The “cognitive” challenge is partially to build appropriate matrices $P(X_i = x_i, i = 1,\ldots n \mid \zeta = 1)$ from which $P(\zeta = 1 \mid X_i = x_i, i = 1,\ldots n)$ can be derived.

How does cognition come in?

In the scheme proposed, the intelligence of the system is captured in $P(X_i = x_i, i = 1,\ldots n \mid \zeta = 1)$. This supposes first a choice of “measurements” $X_i,\ i = 1,\ldots n$. Then it supposes establishing a system of adaptive algorithms to estimate $P(X_i = x_i, i = 1,\ldots n \mid \zeta = 1)$. Learning means among other things that $P(X_i = x_i, i = 1,\ldots n \mid \zeta = 1)$ changes with time. Context dependence implies among other things that there are correlations among the measurements. It also suggests that the set $X_i,\ i = 1,\ldots n$ may be a bit more heterogeneous than being restricted to “measurements”.

In summary, the complexity and challenge of Bayesian based cognitive dynamic decision making can be reformulated as being able to find a wide enough but still parsimonious set of variables $X_i,\ i = 1,\ldots n$, such that present detection techniques permit to estimate $P\left(X_i = x_i, i = 1,...n \mid \zeta = 1\right)$ continuously and thereby use EQ.7 to have systems making autonomously fundamental decisions over time about the nature of events in complex situations with a high degree of reliability.

It is not obvious that such determination requires the use of an optimized algorithm. In that sense the scheme proposed in this paper differs from the main stream of Bayesian tradition[10].

Summary: “responses” to the seven questions:

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)
To account for the context dependence of many decision, an element of cognition is necessary. It is not very easy to codify, but in the scheme proposed, it enters in the data base.

2. What are the main research gaps within you field/area of interest?
In the context of cybersecurity, the tendency has been to try and import a form of Bayesian decision making inspired from classifiers. Little has been done to customize the approach to the needs of the field. One major challenge is building an adequate database.

3. Which numerical methods and models are used to support/describe risk-based decision making?
I tried to be as explicit as possible as to the methods to be used. In addition the methods tend to be optimization based approached such as EM algorithm.

4. How spatial and temporal scales in decision making are addressed?
The temporal issues are fundamental as they play an important role in the ultimate determination.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.
Experimental studies are based on tests in the wild. So far they have been limited by the inability to control the false positive rate.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.
The generalization to other situations is straightforward. It applies to situations where the decision process is protracted and can be made dynamical. There are many situations like that.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.
Decision problems may be NP-complete. When this sis the case, the development of non-deterministic heuristics become necessary.

[10] Karny M. (Ed.): Optimized Bayesian Dynamic Advising, Springer (2006)

Amlan Mukherjee

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

Successful management of complex projects requires effective decision making. The two main reasons *motivating* the study of construction decision-making is:

- As experienced construction managers are retiring, they are leaving a void in the industry that incoming novices cannot easily fill. An understanding of expert construction decision-making will allow us to shape construction management curriculum and methods of practice in a way that will allow us to retain the knowledge of experienced construction managers even after they have retired.
- Construction decision-making research tends to focus on optimizing resource interactions constraining construction projects (Martinez and Ioannou 1999), even though human decision-making has critical impacts on resource interactions. Studying the cognitive aspects of decision-making will provide a comprehensive understanding of the construction management domain by including a focus on resource interactions, and human-resource interactions.

A well accepted, if rarely investigated, relationship between expertise in construction decision-making and experience justifies the investigation and further understanding of the cognitive aspects.

Expertise in construction management is dependent on the ability to make critical decisions, and select appropriate management strategies to complete the project on schedule and under budget. Experience is a critical component of expertise for construction managers. Handling unique real life project scenarios allows them to assimilate patterns of information and inductively construct and organize knowledge about the construction management domain that cannot be easily formalized or perceived analytically. In critical situations they tend to isolate, recognize and match the pattern of the problem at hand with familiar patterns that they have encountered before. Novices on the other hand tend to concentrate on the surface features of the problem at hand (Chi 1988). Experiential learning allows expert construction managers to develop an intuition that sets them apart from novice construction managers.

Studies of experts and novices shows that experts notice features and meaningful patterns of information, which cannot be reduced to isolated facts and propositions but are instead ’conditionalized’ to specific circumstances (Bransford et al. 1999). The process of conditionalizing allows experts to develop the “expertise” that guide their decision making processes. Experts also have the ability to retrieve information on a selective basis befitting the context of the problem at hand. The shift from novice to expert is a shift from one system of beliefs about the world, one set of concepts and one set of problem solving capabilities to another (Carey and Wiser 1983). We believe that such a shift is in essence a shift in the underlying cognitive differences of novices and experts. By studying the cognitive differences in the problem solving and decision-making approaches of novice and expert construction managers, we can start understanding expert knowledge organization.

2. What are the main research gaps within you field/area of interest?

Recent research in construction decision making has investigated strategic decision-making of construction managers who are given the opportunity to reason with the causal knowledge of key performance factors and indicators (Dissanayake and AbouRizk 2007). A subjective method for modeling construction performance was presented using cognitive maps to represent mental models or internal knowledge representation of construction managers. They used fuzzy cognitive maps to model the cause and effect relationship between concepts that present themselves in a construction project. The concepts are represented as nodes in a graph, and the links between the nodes represent the cause and effect relationship between concepts. While this research is important to our own, it leaves the following gaps in understanding human decision-making:

- The relationships between the concepts are not automatically inferred from the data - instead they are identified using subjective inputs from experts
- While the model is informed by subjective expert input, its goal is to understand delays and cost overruns in a construction project, rather than to understand the knowledge organization of experts.

The focus of the study is limited to resource interactions rather than on understanding the impact of human decisions on resource interactions in a complex dynamic task environment[11]. Soibelman and Kim (2002) focused on analyzing construction databases data mining methods to investigate delays in construction projects. They analyzed the US Army Corps of Engineers construction database. Even though, this research did not explicitly investigate human decision-making, it focused primarily on developing a framework for identifying how the project variables such as weather can be related to the

[11]A decision-making environment which changes as a function of the sequence of decisions, independently of them, or both, is referred to as a dynamic task environment (Edwards 1962).

occurrence of delays in the project. Their analysis method provides a good foundation for human decision-making data. It does not, however, include the influence of the contexts in which decisions are made by construction managers on project delays.

3. Which numerical methods and models are used to support/describe risk-based decision making?

Answer[12]

Existing methods of risk analysis cover a broad spectrum of methods ranging from estimating contingencies as a fixed percentage of the entire project cost, to using static probabilistic methods, discrete event simulations and using interactive dynamic simulations to explore future scenario spaces and classifying it by impact and probability. The study of uncertainty in construction has predominantly involved estimating cost overruns and schedule delays in projects and estimating input parameters in simulating construction operations and processes. *Risk analysis* in construction involves estimating the probabilities needed as input data for the evaluation of decision alternatives.

Traditionally contingency is budgeted into construction cost estimates as a fixed percentage of the total cost (Mak and Picken 2000), based on previous experience with similar projects. Among other deterministic approaches, contingencies are calculated based on the risk associated with individual activities. Such approaches are limited in quantifying the degree of confidence associated with the contingencies identified. Touran (2003) explored probabilistic methods of assessing and allocating contingencies to construction projects. His premise was that the events causing delays and budget impacts during construction projects occur randomly in time according to a Poisson process. While this approach offers a probabilistic alternative to analyzing contingencies dues to unexpected project change orders, it only accounts for events that are independent and do not take into account dependent events that occur due to cascading constraint violations during the project implementation.

Research in construction discrete event simulations has produced general purpose platforms such as Simphony (Hajjar and AbouRizk 2002) and STROBOSCOPE (Martinez and Ioannou 1999) that have been very useful in modeling construction processes and operations. They emphasize optimizing resource use and allocation. Such simulation systems have primarily focused on using statistical approaches to quantifying uncertainty associated with different model inputs and parameters to increase the accuracy of simulation output. A Bayesian method to update the input penetration rates of a tunnel boring machine was used in a Simphony simulation of a tunneling operation (Chung et al. 2004). Similarly, STROBOSCOPE allows statistical distributions to be incorporated in the model to reflect variations in simulation input parameters (Lee and Arditi 2006).

Some research efforts use belief networks to model relationships between construction processes and events to calculate the risks arising from the combined interactions between the identified variables (McCabe et al. 1998; Nasir et al. 2003). Along similar lines, Anderson et al. (2007) explore uncertainties arising from the underlying structure of the construction management domain. This work builds on the approach that uses temporal semantics (Mukherjee and Rojas 2003) to reason about construction activities and unexpected events resulting from constraint violations and extends it to using an unified temporal constraint network. The network provides a platform to query different project futures resulting from violations of individual or combined constraints. Uncertainty associated with each particular future is its probability of occurrence conditional to what has already transpired. The system is dynamic because the network is constantly updated to reflect recent decisions taken by managers.

4. How spatial and temporal scales in decision making are addressed?

The construction management domain can be studied as a complex system, which has multiple interacting components (schedule, cost, resource distribution and availability, etc.) with multiple feedback loops (Sterman 1992). This complexity is distributed over spatial and temporal scales. Temporally, a construction project is driven by a schedule that is defined by critical constraints. The constraints can be defined by resource requirements, activity sequencing requirements (certain activities must precede others by specific time intervals allowing materials like concrete to set) and by space constraints. For example, in the interest of making optimal use of a crane the schedule may prioritize immediate finish to start relationships between all erection activities. Space on a construction project affords storage of resources (e.g. steel beams and prefabricated components) that also influences schedule constraints. In addition, schedules are developed so that crews working on different activities do not intersect, and result in congestion and lowered productivity. Hence activity precedence

[12]The following sections are derived from Anderson et al. (2007).

constraints, resource limitations, and interactions of crews and resources in space combine together to define interdependencies that exhibit spatial and temporal complexity. Any decisions influence the dynamics of the entire system.

Situational simulations are used to specifically study the impacts of decision-making over temporal scales. They create simulated scenarios that are controlled and can be presented at different evolution rates (large impacts in very short time - large impacts slowly developing over long periods of time etc.). The collected data is used to analyze the relationships between the time at which the situation started to develop, the time at which the decision-maker perceives the situation, the time at which a decision is taken and finally the time at which the system responds to the decisions. Figure 1, presents a simple plot of the traces defining project performance (Schedule Performance Variance (SPV)) and crew management decisions taken to mitigate the impacts of unexpected events (Watkins et al. 2008). It is difficult to collect such time lag data from real construction projects because they are not controlled and difficult to monitor. Controlled simulated environments on the other hand are very useful in collecting such time lag data and analyzing alternative decisions that could be made to mitigate losses from crisis scenarios.

Agent based modeling (ABM) methods have been used to simulate dynamic spatial interactions between individual labor crews on a construction site to investigate the emergent impacts of congestion on construction labor productivity (Watkins et al. 2008). Future work will integrate the ABM with the situational simulation so that decision-makers can explore what-if scenarios in a simulated environment which illustrates the spatial and temporal dynamics of constraints and complex interactions defining the construction project.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Experimental studies should be aimed at studying the dynamics of human decision-making in construction management. Situational simulations (Rojas and Mukherjee 2006, Rojas and Mukherjee 2005, Rojas and Mukherjee 2003) provide an interactive simulation platform that can be used to explore "what-if" construction scenarios, estimate risks and contingencies, test alternative plans during construction, and facilitate the capture and analysis of decision-making data. They create temporally dynamic clinical exercises of construction project scenarios that expose users to rapidly unfolding events and the pressures of decision making. Such simulation environments can be used as experimental test beds to collect human decision-making. The challenge lies in analyzing large volumes of construction decision-making data to find the anatomy of a good decision.

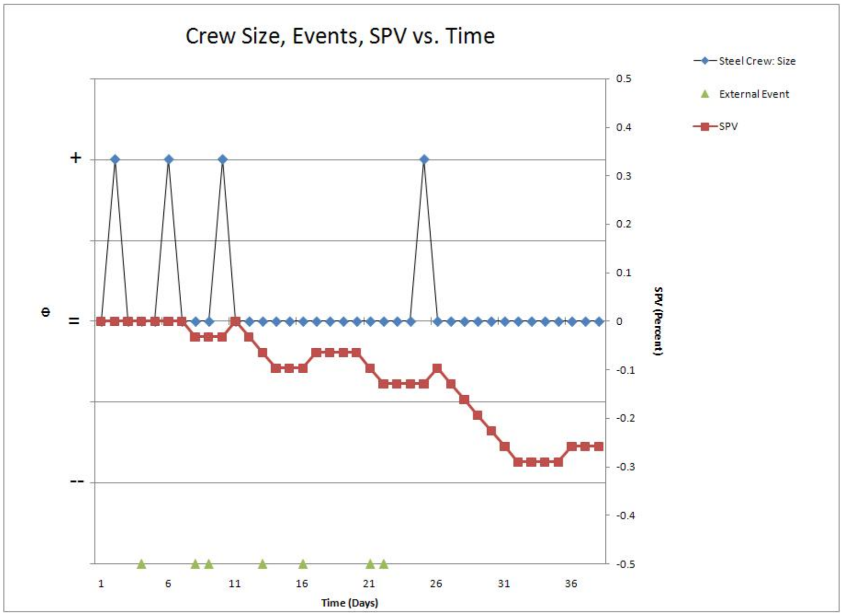

Figure 1. Crew size, schedule, and external events vs. time

The design of such environments must consider the following:

- A formal discipline of human interaction within the simulation environment to facilitate the collection of decision-

making data within controlled interactive simulated environments (Watkins et al. 2008)
- Categorize the simulation environment by dynamics, complexity, opaqueness and dynamic complexity characteristics of the controlled scenario (Gonzalez et al. 2005).
- Develop formal mathematical semantics to capture human decision-making data collected from the simulation environment.
- Employ data mining methods to analyze patterns in the decision-making data that reflects the knowledge organization of the human subjects

Cognitive models of decision-making developed from the data collected in simulated environments can be validated as follows:
- Observe decisions that are made in real life complex projects
- Investigate if the decisions made in the real life project scenarios reflect the patterns developed from the data collected in the simulation environment

If the patterns do not match, then compare the real life scenarios with the simulated scenarios, and using an iterative process, rebuild the simulated scenarios and/or reconsider data analysis models

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

Our research aims to develop formal cognitive models that describe the nature of human decision-making and the impacts of human interaction on the construction project management. The goal is to apply the understanding of how experts and novices differ in their knowledge organization, information processing, risk assessment and decision-making in construction management crisis scenarios, under varying reaction times, and delayed information availability, to the development of real time decision-making aids. Specifically, we design and use interactive situational simulations of the construction management domain to collect human decision-making data; and develop analytical quantitative approaches using methods founded in statistical data mining to develop situation models of expert decisions. We define situation models as transient internal organizations of information that decision-makers in dynamic complex environments use to comprehend a scenario and formulate effective decisions. It is an instantiation of their mental models using their awareness of the situation at hand. We choose to define and measure situation models instead of studying situation awareness or mental models directly because each of these are founded in psychological constructs such as memory and knowledge schemas that are difficult to formally measure. Instead, we intend to estimate internal cognitive organization driving decision-making by directly measuring the immediate information defining the situation and the organization of the decision made within the well defined context. Detailed analysis of the conceptual foundations of this research and the analytical methods used can be found in research by (Watkins and Mukherjee 2008) and (Watkins et al. 2008)

From an experimental stand point, our research focuses on the development of situational simulations that can be used to collect and analyze human subject decision making data. Anderson et al. (2007) describe the underlying structure of situational simulations, and the implementation of the Interactive Construction Decision-making Aid (ICDMA). The simulation is driven by temporal constraint networks that can represent and reason about construction management information to simulate realistic scenarios. ICDMA simulates using data from a real life construction project. A discipline to collect data using the ICDMA was developed, and the initial analysis of data collected using ICDMA can be found in (Watkins et al. 2008).

The broader impact of this research is in understanding the cognitive aspects of decision-making under uncertainty in dynamic task environments. The critical questions that are of general importance to the field of decision-making are:
- How do novices and experts differ in how they react with respect to the rate of change of events in the environment?
- How do novices and experts differ with respect to availability of feedback in the environment? What is the impact on their decision-making if feedback is delayed?

These questions are of general import to decision-making (Kersholt 1994) and results can be applied to the understanding of diverse dynamic task environments such as natural hazard management (Wood et al. 2009).

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

The three main challenges in integrating decision-support tools in real time strategic decision-making are:
- Crisis scenarios in real life are the best laboratories for understanding the anatomy of good decision-making and harvesting useful data that can be used to develop decision-making aids. However, given the nature of crisis scenarios - especially in high stakes environments - documentation and collection of dynamic real time data as the scenario develops

is usually of very low priority and very difficult to accomplish.

- Interactive simulation platforms are reasonable testbeds for studying decision-making - however, results from such studies are contingent to the validity of the models driving the simulations and its ability to appropriately emulate the domain in the highest level of reasonable detail. In addition, there is the problem of objectively capturing human-subject data and analyzing it to draw quantitative relationships between identified variables. Depending upon the nature of the domain and complexity involved, this can be a very difficult problem. For example, domains like construction management are temporally and spatially more limited than domains like natural hazard management, in which the spatial dimension is highly variable and can range from a few square miles to thousands of miles.
- Models driving decision-making aids are very difficult to accurately validate and establish as trustworthy within a typical life-cycle of a research project. A robust model needs inputs from a large and diverse sample of expert human subjects as input, and the model predictions need to be compared with an equally diverse sample of real life scenarios. Access to both of these can be a challenge. Even if the models can be validated by comparing them against real life performance, given the high stakes involved in most dynamic task environments, there would be limited willingness to implement and trust the system.

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Leonid Perlovsky

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

The mind still works much better than algorithms

2. What are the main research gaps within you field/area of interest?

Detection, tracking, fusion multiple platforms, integrating sensor data with intelligence

3. Which numerical methods and models are used to support/describe risk-based decision making?

We develop novel cognitive algorithms

4. How spatial and temporal scales in decision making are addressed?

They are included directly into models of objects and situations

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Brain imaging is used to uncover/validate cognitive mechanisms
Specific models are developed from data collection exercises and from operational data

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

Developed cognitive algorithms that improved performance by two orders of magnitude vs. previous state of the art

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

Establishing working relations with operational groups
Transitioning to operations
Funding

Barry G. Silverman

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

see Section 1 – Intro (1st para),

2. What are the main research gaps within you field/area of interest?

See last 2 para's of Sect. 1 – Intro
Also, see Sect. 1.1

3. Which numerical methods and models are used to support/describe risk-based decision making?

Not sure what "risk-based decision making is, but the modeling approach I use is primarily agent based, though since I use a model of models approach, my agents straddle many methods, whatever best suits the human behavior theory shred being implemented (difference equations, multi-attribute utility, game theory, rules/logic statements, procedural algorithms, stochastic sampling of non-deterministic parameters, etc, etc.). See the descriptions in Sect. 2.

4. How spatial and temporal scales in decision making are addressed?

This is primarily the topic of Sect. 3. The spatial problem is modeled differently depending on the area of operation. Section 3 shows it varies from international to state/sub-state, down to neighborhoods and village streets.

Temporality is generally handled by the simulator clock and varies from near real time (eg., when having conversations with the agents) to much faster-then-real-time (eg, a tick can be 1 week or 1 month in the state and cross-state sims).

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Sect 4 recaps 2 types of validity assessment studies (historic correspondence and SME assessment), though the effort to rely on best of breed theories is an attempt to increase the internal validity of each component or subsystem, while the idea of model of models is a quest for ontologic adequacy as well.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

See attached paper.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

I think these are the same as the answer to #2 above.

Is Systems Engineering the New Social Science? Or,
A Multi-Resolution Architecture for Analytic Studies of The Socio-Cultural and Cognitive Layers of a Society

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ABSTRACT

What are we in the Modeling & Simulation (M&S) community to do with the volumes of 'human terrain' data now being published by the military and others in databases of the demographics and needs/values/norms of populations of interest? This paper suggests that the M&S community would be remiss if it did not rise to this challenge and suggest next steps for the use of this human terrain data resource. These datasets are a key asset for those interested in synthesis of two major agent-based modeling paradigms – the cognitive and the social – as this paper argues. We pursue this argument with a case study integrating a cognitive agent environment (PMFserv) and a social agent environment (FactionSim) and applying them to various regions of interest (MidEast, SE Asia, Africa) to assess their validity and realism.

1 INTRODUCTION AND PURPOSE

Thought leaders in the military, and indeed funded programs, are focusing on the needs, values, preferences, and customs/norms of local peoples in order to better understand their allegiance and to determine how to influence them in 'hearts and minds' campaigns against local adversaries: e.g., see Chiarelli (2006), Petraeus (2005), Kilcullen (2004), among others. This is what McFate & Jackson (2005) call "human terrain" -- the human population and society in an environment of interest (area of military operations) characterized by sociocultural, anthropologic, and ethnographic data and other non-geophysical information about that human population and society. Of interest is to model how Diplomatic, Intelligence, Military and Economic (DIME) actions might effect the Political, Military, Economic, Social, Informational, and Infrastructure (PMESII) Systems of the region of interest.

In this talk we pose the question of what could the field of modeling and simulation (M&S) add to the topic of human terrain? Specifically, we are particularly interested in human terrain as a complex social system and hence we want to explore the question of what can agent-based simulation offer? That is, if we use the data of human terrain systems to help model the 'parts' and their micro-decision processes, can we observe macro-behaviors emerging that are useful for analysts to know about? Finally, if we want to model and simulate a social system from the bottom up, then it seems that we need to approach it with agent technology that covers both the social processes that influence people as well as cognitive processes that people use in reasoning and emoting over their fates. That is, we are curious about what can 'socio-cognitive' agents offer to the study of human terrain or social systems?

Sun (2004) and Zacharias et al. (2008) provide a useful survey of the respective fields of social agents and cognitive agents and show that there are very few environments that straddle both topics to provide socio-cognitive architectures. In this paper, we therefore illustrate one such architecture and provide some insights into how it works, what it is useful for, and whether its outputs provide any validity. While this is relatively mature, COTS software, we close with discussion of future research needs so such tools will better support human terrain analyses.

1.1 Design Inquiry

Of vital importance to this approach is (1) adopting best-of-breed theories from the social sciences (those that are descriptively valid); (2) keeping an openness to the wide array of systems methodologies and tools, whatever works best for implementing each theory (eg, adaptive agents, operations research, knowledge management systems, etc.); and (3) a design inquiry approach aimed at learning about a given social system. The point of such a synthesis is to better understand what unexpected effects emerge as a result of policy interventions in network-centric worlds where the social system is complex and poorly understood. This cannot be reliably done in the absence of social science, and not solely with social descriptions and black box models. The point is that systems design is the methodological glue that can and must shift the fundamental science in this field.

The saying "no strain, no pain, no gain" comes to mind. Social scientists need to attempt implementations of their theories in virtual (agent-based) worlds. Simply the 'effort to implement' will cause them to better define fuzzy qualitative models, improve their accuracy (not precision), stress test the limits of their theories, validate their models against data, and identify gaps between their reductive theories needing high priority attention. Systems engineers must facilitate this implementation and realize that they are modeling and simulating teleological, social (not mechanistic) systems. They should avoid blindly imposing their familiar mathematical and technological prescriptions, and instead learn to be desciptive modelers – ones who handle the breadth and depth of best-of-breed models, theories, knowledge, and data drawn from across social science sub-fields. There is no single formula on how to evolve the paradigm. So, both sides (SS and SE) must be prepared to follow an adaptive organizational design inquiry pathway – to measure how well they are doing, to explore the meta-methodology and paradigmatic level, and to deepen the conversations about tearing down disciplinary barriers and synthesizing new methodologies, approaches, and techniques.

2 COGNITIVE AGENT MODELING

This section presents PMFserv, a Commercial Off The Shelf (COTS) human behavior emulator that drives agents in simulated gameworlds. It was developed over the past 8 years at the University of Pennsylvania. PMFserv agents are unscripted, but use their micro-decision making as described below to react to actions as they unfold and to plan out responses. For each agent, PMFserv operates its perception and runs its physiology and personality/value system to determine fatigue and hunger**,** injuries and related stressors, grievances, tension buildup, impact of rumors and speech acts, emotions, and various mobilization and collective and individual action decisions. The result is emergent macro-behaviors.

A performance moderator function (PMF) is a micro-model covering how human performance (e.g., perception, memory, or decision making) might vary as a function of a single factor (e.g., sleep, temperature, boredom, grievance, etc.). PMFserv synthesizes dozens of best-of-breed PMFs within a unifying mind-body framework and thereby offers a family of models where micro-decisions lead to emergence of macro-behavior within an individual. None of these PMFs are ‘home-grown’, but instead are culled from the literature on behavior science. One can turn on or off different PMFs to focus on those aspects of interest to the current users.

What follows is a listing of some of the major PMFs in the collection. This talk will overview these and their derivation and synthesis into a unified whole (PMFserv). Interested readers should consult Silverman et al. (2006a, 2007a) for details.

2.1 Major PMF Models Within Each PMFserv Subsystem:

Perceptual System (world markup services)
- Gibson Affordance Theory (world markup, perceptual types, activation dynamics)
- Perceptual cues and stimuli – (Brunswikian Social Judgment Theory)
- Janis-Mann Coping Style/Stress (5 stress-based levels for focus of attention)

Value System Module (Captures a person’s values, culture and personality)
- Goal-Standards-Preference (GSP) Trees
- Bayes Importance Estimators
- Multi-Attribute Utility Functions
- Affective Reasoning -- Cognitive Appraisal

Personality Profiling Tools (Well established instruments now encoded with GUI sliders)
- Hermann Political Leader Profile Instrument
- Modified Maslow-Follower Profile
- Hofstede Cultural Factors Instrument
- UN Globe Study Cultural Factors

Social Relationship Module
- InGroup Hierarchy Designator
- InGroup-OutGroup Alignment/Trust/Credibility
- Automated Motivational Congruence Assessment (correlation between GSP trees)
- Identity Repertoire Theory/Automated Group Membership Updating/Group Exit-Enter Barriers
- Eidelson 'Dangerous Ideas' Model (sacred values, grievances, injustices, distrust)
- Hirschman Model (Exit, Voice, Loyalty) – Produces Civil Rights Demand Curve (Phase Shifts)

Physiology/Stress Module (reservoir metaphor, calibrate to actual individuals, automatically updated)
- Nutrition, Digestive Processing, Muscle Energy and Wastage
- Fatigue Processes, Homestatic Need for Sleep, Adrenalin, Drugs
- Injuries – blunt/acute, lethal/non-lethal (chemical, biological, restraint, etc.)
- Three types of stress (effective fatigue, time pressure, event/emotion stress)
- Integrated Stress computation (infers 1 of 5 coping styles for perception and decisions)

Decision Processes/Choice Module
- Subjective Expected Utility & Best Response Curves
- 5 Stress-Based Coping Styles (3 of them are algorithms of Nobel Prizes)
- Campaign Plans & State Transition Nets
- Model of Others' Model of Me (Intentionality)

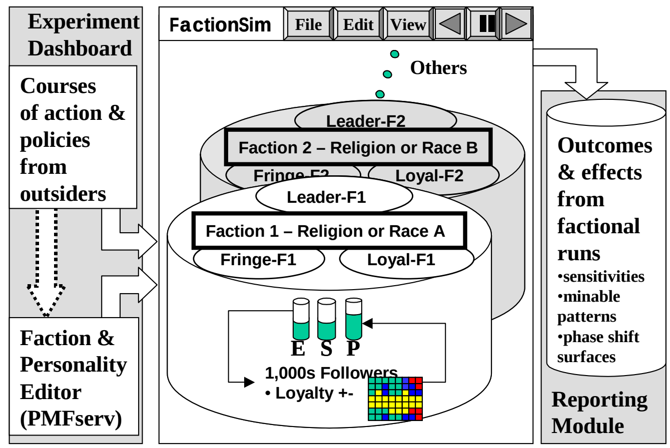
PMFserv has been deployed in a number of applications, gameworlds, and scenarios. A few of these are listed below. To facilitate rapidly composing new casts of characters we have an Integrated Development Environment (IDE) in which one knowledge engineers archetypical individuals (leaders, followers, suicide bomber, financier, etc.) and assembles them into casts of characters useful for editing scenarios. The talk will overview the IDE and explain the knowledge engineering methodology we follow to assure the highest internal validity of the profile of a given agent.

Many of these past applications have movie clips, Tech Reports, and validity assessment studies at www.seas.upenn.edu/~barryg/hbmr . Several historical correspondence tests show PMFserv mimics decisions of the real actors/population with about 80% correlation: e.g., see Silverman et al. (2006b, 2007b).

3 SOCIAL AGENTS, FACTIONS, AND THE FACTIONSIM TESTBED

The previous section overviewed the modules of a cognitive agent as well as some of its parts that give it a social orientation. In this section we turn to additional modules that turn the cognitive agent into a socio-cognitive one. Specifically, The layer we added atop PMFserv to satisfy this criterion is called FactionSim. This layer facilitates the codification of alternative theories of factional interaction and the evaluation of policy alternatives. FactionSim is a tool that allows conflict scenarios to be established in which the factional leader and follower agents all run autonomously; use their groups' assets, resources, and institutions; and freely employ their micro-decision making as the situation requires. Macro-behaviors emerge such as, but one example, followers either supporting their leader's decisions and/or rejecting their group's leadership and replacing him (sometimes violently) -- or -- withdrawing membership and mobilizing to a new group. Leader agents leaders often find it difficult to move to alignments and positions that are very far from the motivations of their memberships unless they can impose authoritarian restraints. This environment thus implements PMFserv within a game theoretic campaign framework.

Figure 1: Models and Components that must be synthesized for a FactionSim Testbed



To set up a FactionSim game one simply profiles the items overviewed in this section. These may be edited at the start, but they all evolve and adapt dynamically and autonomously as a game plays out. In addition there are other parameters that are automatically generated (e.g, the 22 emotions of each agent, relationship levels, models of each other, etc.). Profiling includes the following social theory parameters and models, for some of which this list includes a citation (a web interview is used by SMEs to fill in these parameters in about 12 hours time):

Major Groups/Factions of an AO:
- □ Philosophy, Sense of Superiority, Distrust, Perceived Injustices/Transgressions
- □ Leadership, Membership, Other Roles
- □ Relationship to other groups (ingroups, outgroups, alliances, atonements, etc.)
- □ Barriers to exit and entry (saliences)
- □ Group Level Resources such as Political, Economic and Security Strengths
- □ Institutional infrastructures owned by the group
- □ Access to institutional benefits for the group members (Level Available to Group)
- □ Fiscal, Monetary and Consumption Philosophy
- □ Disparity, Resource levels, Assets Owned/Controlled

Region's Resources:
Security Model (force size, structure, doctrine, training, etc.)
- Power-Vulnerability Computations (Johns, 2006)
- Skirmish Model/Urban Lanchester Model (probability of kill)

Economy Model (Dual Sector - LRF Model - Lewis, 1954)

- Formal Capital Economy (Solow Growth Model)
- Undeclared/Black Market (Harrod, 1960, and Dominik, 2000)

Political Model (loyalty, membership, voting, mobilization, etc.) (Hirshman, 1970)

- Follower Social Network (Axelrod, 1998; Epstein, 2002; Lustick et al., 2004)
- Info Propagation/Votes/Small World Theory (Milgram, 1967)

Institutions available to Each Group: (Public Works, Protections, Health/Education, Elections, etc.)

- □ Capital Investment, Capacity for Service, # of Jobs
- □ Effectiveness, Level of Service Output
- □ Costs of Operation, Depreciation/Damage / Decay
- □ Level of Corruption (indicates usage vs. misuse), Group Influence

Agents (Decision Making Individual Actors) that fill the roles (leaders, followers, ministers, etc):

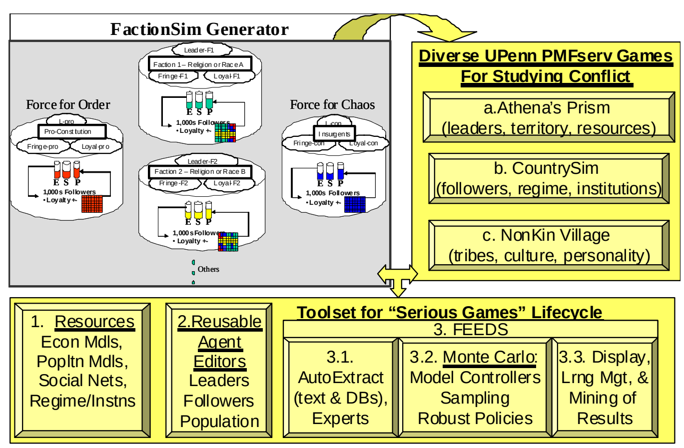
- □ Value System/ GSP Tree: Hierarchically organized values such as short term goals, long term preferences and likes, and standards of behavior including sacred values and cultural norms,
- □ Ethno-Linguistic-Religious-Economic/Professional Identities
- □ Level of Education, Level of Health, Physiologic/Stress Levels
- □ Level of Wealth, Savings Rate, Contribution Rate
- □ Extent of Authority over each Group, Degree of Membership in Each Group
- □ Personality and Cultural Factor sets (conformity, assertivity, humanitarianism, etc.)

Note that in addition to leaders and followers of groups, FactionSim models institutional agents (ministers are PMFserv agents). They autonomously dispense services and resources via institutional infrastructures. Typical institutions include the economy (markets, jobs, banking), educational system, the health system, the judicial system, the police and security forces, the utilities/infrastructure (e.g., energy sector, the transportation system, and communication systems), as well as various institutions of a modern polity including an electoral commission that conducts elections and collects votes. These institutions and the institutional economy module are new additions this past year to the FactionSim and they are being extended for the purpose of building virtual countries and AOs. FactionSim (as does PMFserv) also supports plug-in of more detailed models of these dimensions, though there does not seem to be a literature on this topic of corruptible institutions or of bottom-up economic models, especially in the developmental economics field. Still, the goal of this framework is to identify and synthesize best-of-breed third-party models so that a better capability evolves.

4 EXPERIMENTATION AND EXPLORING SIMULATED SPACE

It is worth pausing briefly to review some of the tools that have been and/or are being constructed by the systems science & engineering students and postdocs (and some programming staff). These are tools that enable one to explore social system design questions in ways not otherwise possible. To facilitate this overview, Figure 3 provides a useful illustration. The upper left shows the PMFserv-FactionSim capability described earlier. The bottom of the chart shows a series of added tools that enhance the ability to generate application worlds/games. These include efforts to support openness and plugin of 3rd party models (economic, political, etc.), add a library of reusable agent profiles, and build out a suite of tools to automate the rapid instantiation and studying of new scenarios – the FactionSim End to End Data System (FEEDS). We will describe some of these tools shortly along with each of the three categories of social systems constructed to date and shown on the right side of Figure 3.

Figure 2 – Overview of How the PMFserv-FactionSim Capability Serves as a Generator of "Design Inquirer" Tools for Social System Training and Analysis



- **International Diplomacy** -- Athena's Prism is a distributed architecture, multi-player RPG that has been delivered as a fully functioning computer game (user-defined territories, each with 12 resource categories and 150 actions) to an agency of the US Government in mid 2005, and which has been used to help analysts generate ideas for influencing potential international crisis situations. The game forces players to play the roles of world leaders and is in the genre of the Diplomacy boardgame except you can rapidly author new scenarios for any set of countries around the globe. When analysts want to study multiple possible outcomes, PMFserv is used to profile the relevant world leaders and it then simulates their action choices in the gameboard. This has been used for study of the sensitivity of various world crises to alternative ways to influence them. The interested reader is referred to Silverman, Rees, et al. (2005) for details.

- **State and Sub-state Actors** -- CountrySim is our tool that elicits qualitative state and sub-state models from the heads of country and area experts. It quantizes these experts' models using the full set of FactionSim capabilities -- hierarchies of PMFserv agents play rival leaders and followers within a faction (and it allows many factions). Also, agents can play the institutional ministries that allocate services to the factions (or not). A population automata of up to about 60,000 "light" agents is also attached to support information dissemination and vote collection. Under DARPA funding we are applying this approach throughout 2008 to the modeling and simulation of 10 countries of Asia (eg, China, Russia, India, N. Korea, Sri Lanka, Bangladesh, etc.). Fourteen of the best country experts in the USA have been hired to use the web-enabled frontend to express their country model (all factions, institutions, leaders, follower archetypes), typically in about 12 hours time. The model controller and Monte Carlo dashboard permit studies to be run, while the back end of FEEDS supports measuring and inspecting the impact of policy interventions. The agents in the CountrySim are conversational and once one notices certain behaviors occurring, they can be interrogated to explain how they feel about the current state of the world, about their own condition, about the groups in the region and their leaders' actions, and why they took various actions and how they felt about doing so.

- **RegionSims and the NonKin Family of Tools** -- NonKin is the name of our generator intended to bring FactionSim into focus for human terrain in tactical regions (as Athena does internationally and as CountrySim does for states). Specifically, NonKin is a scenario generator meant for use to implement villages, towns, and city neighborhoods, including connectivity of these areas to higher level institutions and assets. Factions and institutions/organizations and roles are defined with the help of FactionSim, while agents are driven by the PMFserv engine. NonKin is a SimCity genre of game engine. It is a role playing game generator that permits users to participate in the region and interact with its participants. The agents, institutions, factions, militias, and so on carry out daily life and various economic, political, familial, and security activities. The more one learns about the population, factions, institutions, infrastructure (the ASCOPE items), the more faithfully the agent world recreates what is driving the actors in the real world. The intent is for this to ultimately be available for analysis as well as training.

5 CONCLUDING REMARKS

In summing up, our community would be remiss if it did not try to respond to thought leaders in the military who are struggling with how to promote deeper thought, rehearsal environments, and analytic capability about cultural issues and local population needs/wants. They have funded programs that collect HT data and conduct link analysis and social network studies. At the same time, they are unsure of what kinds of human behavior modeling to engage in beyond that, though simultaneously there is a need for DIME-PMESII type studies.

In this paper, I have argued that the HT datasets are an invaluable resource that will permit us in the human behavior M&S field to more realistically profile factions, and their leaders and followers. This in turn could help us to instantiate tools for those interested in analyzing alternative competing hypotheses for DIME-PMESII studies.

A parallel development has been the scientific struggles of those interested in unifying multi-resolution frameworks that permit modeling "deep" but few cognitively-detailed agents able to interact with and influence 10,000s of "light" socio-political agents. This is necessary if we are to have "socio-cognitive" agents useful for the types of analysis and training/rehearsal M&S worlds envisioned here. One such socio-cognitive agent toolset (FactionSim built atop PMFserv) has been described in this paper.

Such toolsets will only be useful to the extent they offer valid recreations of the actual leaders, followers, and populations of interest. In terms of validity of the current socio-cognitive agent synthesis, this research has tried to explore its robustness and cross-sample fitness. FactionSim agents passed validity assessment tests in two conflict scenarios attempted to date — (1) a group of 21 named Iraqi leader agents in 5 factions passed a Turing Test after extensive subject matter expert evaluation and (2) a separatism movement recreation involving a SE Asian leader (Bhuddist) and Muslim followers passed separate correspondence tests (correlations of over 79% to real world counterparts). Validity is a difficult thing to claim, and one can always devise new tests. A strong test, however, is the out-of-sample tests that these agents also passed. Thus the SE Asian leader and followers were trained on different data than they were tested against. Further, the complete structure of the model of the leaders was originally derived in earlier studies of the ancient Crusades (Silverman et al. 2005) and this was transferred to the SE Asian and Iraqi domains. The only thing updated was the values of the weights for the value trees and various other group relations and membership parameters – derived from open sources. So the structure of the leader model also survived and passed two out-of-sample tests relative to the Crusades dataset. While these may not be the ultimate tests, they are sufficient for our purposes and in order to consider the descriptive agents to be components useful for analytic experiments.

'Correctness' is more about the generative mechanisms inside the agents than whether any given predictions are accurate. If the generative mechanisms are roughly 'correct', one can have trust that experiments on agents will yield useful insights about the alternative policies that influence them. That is why one attempts to add cognitive capabilities inside of social agents. A caution to those attempting simulations with Human Terrain data – start with best of breed models (higher internal validity), then conduct adequacy tests, validity assessments, and replication of results across samples. Even after all that, social system simulations will rarely yield precise forecasts and predictions. Rather, their utility lies in exploring the possibility space and in understanding mechanism and causalities so that one can see how alternative DIME actions might lead to the same or unexpected PMESII effects.

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BARRY G. SILVERMAN is Professor of Electrical and Systems Engineering at the University of Pennsylvania where he is also Director of the Ackoff Collaboratory for Advancement of the Systems Approach (ACASA). He holds the BSE ('75), MSE ('77) and PhD (also '77) all from the University of Pennsylvania, is a Fellow of IEEE, AAAS, and the Washington Acad. of Science, and sits on the board of several organizations and journals in the intelligent systems fields. The focus of his research has largely been on aesthetic and cognitive engineering of embedded game-theoretic agents that can help humans improve their learning, performance, and systems thinking in task-environments. Over the years, his lab has produced or is in the process of creating an agent-based model of mind-body duality; patient training games and human physiology simulations; a terrorist campaign and crowd simulator; numerous autonomous and emergent agent tools; several distributed, computer-mediated, human-to-human collaborative systems; 3 role playing games (RPGs); and the AESOP interactive fiction game generator. As a result of all this work, Barry is also the author of over 120 articles, 12 books/proceedings, over 100 technical reports, 7 copyrighted software systems, a boardgame, and several research and teaching excellence awards.

ROBERT ROSS

1. **Why do we need to study cognitive aspects of decision making? (discuss application needs within your organization, in your field, or as you perceive within the military)**

My interest here is not as a researcher but rather from the policy formulation and execution perspective and from the perspective of a former "operator" who is trying to get current policy makers to use knowledge which is already available. Why is government so often so bad at making decisions that have credibility with the public? Why do people behave as they do during emergencies? What makes the difference between life and death in situations where there is ample opportunity to survive but many die nonetheless? Decision-making occurs all along the time continuum in disaster situations, starting long before an actual event as decisions are made about possible pre-event mitigations, pre-event contingency planning and other kinds of emergency response preparedness, and as actions are taken by government and members of the public both during an unfolding event and thereafter.

Aspects of this have been studied and there are a number of good case studies already available. One such is the New York Academy of Medicine's study report titled "**Redefining Readiness: Terrorism Planning Through the Eyes of the Public**", available at **http://www.redefiningreadiness.net/** . A broader survey on work in this area, written for a popular audience, is" The Unthinkable: Who Survives When Disaster Strikes - and Why" by Amanda Ripley of Time Magazine. http://www.amazon.com/gp/product/0307352897/ref=s9sdps_c2_14_img1-rfc_g1-frt_g1-3215_g1-3102_g2?pf_rd_m=ATVPDKIKX0DER&pf_rd_s=center-2&pf_rd_r=1Y42R57FJDB5SE0A6STB&pf_rd_t=101&pf_rd_p=436516001&pf_rd_i=507846

Both of these comment on the tendency of those in positions of responsibility and authority to fundamentally distrust the public and consequently to withhold information which would better prepare the public to react to and survive many emergency situations.

2. **What are the main research gaps within you field/area of interest?**

This may not be a welcome idea in this group but I think that 90%, and perhaps more, of the problems in these areas could be effectively addressed if what is already know were effectively applied. Perhaps a question that could be asked is "Why is so much of what is already known being so studiously ignored?" What are the forces in play? Is it ignorance? Is it a cognition problem? Or are there external factors which prevent people who know what should be done from actually doing it? I would bet on all three.

3. **Which numerical methods and models are used to support/describe risk-based decision making?**

I prefer the term "risk-informed decision-making" to "risk-based decision-making" for the simple reason that too many factors other than risk (or at least "risk" as it would be defined by relatively dispassionate risk analysts rather than by politicians or others with a personal stake in the outcome) enter into decision-making. Any reasonably comprehensive list of numerical methods and models would be far too long to include here. Further, it is not at all clear that numerical methods and models play much of a role in a lot of risk-***driven*** decision-making. Risk, after all, is not a physical reality with mass or temperature that can be objectively determined using an established standard. Risk is a perception and two different decision-makers can look at the same set of facts and come to very different evaluations about the level of risk inherent in those facts. And both perceptions can be right. Both can also be wrong.

4. **How spatial and temporal scales in decision making are addressed?**

There is great variability in these areas. At one extreme, the Coast Guard pushes contingency planning down to local/operational levels (but within the context of a structured national process which provides necessary oversight, standardization and integration/aggregation) and also tries to pre-think likely scenarios, not just to develop potentially useful on-the-shelf answers but even more so to develop the ability to think rapidly when necessary. The Coast Guard also develops structured decision-support tools for a wide variety of tactical situations. Thus, the CG's approach addresses the spatial issue with an approach that is both locally attuned and nationally coherent/consistent, and it addresses the temporal issue with an approach that is both strategic (i.e., advance planning, pre-thinking and advance preparation of structured decision-support tools) and tactical/operational (i.e., an organizational ability to plan on the fly and to improvise in the face of situations which never match the hypothetical planning scenarios). Of course, none of this developed by accident.

At the other extreme, there are numerous examples of the exact antithesis of the CG's approach. Pick one. Unfortunately, there are many who seem to think that Hope is a Method, that wishful thinking is a war plan, that gut instinct is preferable to fact-based analysis, etc.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

I have no suggestions here.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

I am not doing research per se in these areas. Rather, I am trying to identify relevant research and literature and bring them to the attention of those involved in higher-order strategic thinking, policy formulation, etc. with the goal of operationalizing pertinent information and insights through vehicles such as better decision-making processes, contingency planning and emergency response preparedness approaches that are better attuned to the public, operational programs that more effectively take the public into account, etc.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

- the political imperative to do be seen aggressively doing something, even if we don't know what should be done – AKA as the "Ready! Fire! Aim!" syndrome
- policies driven by ideological beliefs or personal preferences rather than logic or evidence (e.g., ALL regulation is bad – therefore we should do away with regulations; the federal government should turn over all emergency response responsibility to the Red Cross and faith-based organizations; etc.) – AKA as the "Don't bother me with facts. My mind is made up." syndrome
- hyper-partisanship which results in every issue being seized upon as an opportunity to advance your party or yourself at the expense of your adversary (e.g., the gross distortion and bigoted demagoguery of the Dubai Ports World situation)

Beth Veinott

1. Why do we need to study cognitive aspects of decision making? (discuss application needs within your organization, in your field, or as you perceive within the military)

Classic choice theory focuses on how people make forced choices, and assumes that people have complete information, that the environment is well-defined and predictable. However, real world decision making is very different even among experts. In the context of decision making in military settings, our research focuses on what we refer to as macrocognition. Macrocognition are cognitive functions and processes that people use regularly in operational settings, but are not typically studied in academic cognitive research and decision making. Macrocognitive functions and processes include: sensemaking, planning, managing uncertainty, managing risk, maintaining common ground and problem detection. It is important to study these cognitive processes because they are the ones that are required and need to be supported in operational settings.

Second, we need to study cognition in decision making in order to develop tools and processes to support decision makers in the field. For example, MDMP is a decision analytic approach to decision making that requires decision makers to fully analyze the situation and several courses of action before making a decision. This approach works well when there is time for a full analysis and when the environment is well-defined and predictable. However, current and future operations will require decision makers to be armed with the knowledge of how to make decisions faster in situations with multiple players and high stress. The operational environment is changing, issues emerge, and goals may conflict (e.g., stop insurgents, protect civilians), so models that support this flexible and intuitive decision making are needed.

2. What are the main research gaps within your field/area of interest?

Developing models of decision making that take into account the complexity of the situation, it's dynamic and the emerging nature of information and goals over time, and the uncertainty.

Developing models of what people actually do – how they actually plan, how they make sense of the situation, how the manage uncertainty, and how and when they detect problems are still needed.

3. Which numerical methods and models are used to support/describe risk-based decision making?

One of the most popular models of risk is prospect theory (Kahneman and Tversky, 1979) which uses a perceptual psychological model of risk assessment as a contrast to expected utility. It posits that people are more risk seeking when it comes to losses (e.g., why people don't buy flood or earthquake insurance) and more risk averse when it comes to gains (e.g.,prefer $100 for sure than a 50% chance at $200).

Another model of risk is a weighted function in which people take into account the magnitude of the loss and the probability of that loss. Research demonstrates that people tend to be more sensitive to the magnitude of risk than the probability of loss for small probabilities.

At Klein, we focus on conceptual models of risk of which the two above are examples of "calculate and decide."

4. How spatial and temporal scales in decision making are addressed?

There is a large line of research on temporal scales of the following kind – would you rather have 15 dollars today or 30 dollars in a year? Typically, people engage in temporal discounting in the form of $15 today is worth much more than $30 in one month.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

People often criticize models by claiming that the modeler is doing a lot of parameter fitting in estimating the model. However, people often do the same in experimentation. In this case, they are in essence searching the parameter space of the human by running multiple versions of the same experiment in order to find the most interesting results that can be published.

In order to design effective experimental studies for model validation, one needs an appropriate model. By that, I mean the model needs to make predictions so that the hypotheses it generates can be falsified.

6. Discuss your own research related to the workshop theme and the broader context of decision making research in general.

While most academic research focuses on micro-cognitive functions (e.g., how values are combined, how information is weighted), we focus on studying experts in making decisions in real world contexts (e.g., fire fighters, commanders, military planners, and surgeons). About 30 years ago, Daniel Kahneman and Amos Tversky demonstrated that classic theories of choice based on probabilistic models might be effective normative models of choice, they were poor descriptive models. They matched neither the process that people engaged in, nor the choices that they made (e.g., people do not always maximize expected utility).

At Klein, we looked at a very specific context for decision making, expert decision making, and have found that the descriptive models of choice need to be revised again. This has resulted in Gary Klein developing the Recognition Primed Decision Model (RPD) (Klein, 1998) based on research on experts in a variety of operational settings.

The RPD model of decision making is based on two processes that experts engage in when making a decision. First, they quickly size up a situation and recognize which course of action makes sense (if context is familiar). Next, they tend to generate a single course of action and evaluate it by mental simulation.

In fact, in twenty years of research with experts we have found that they rarely generate multiple options in a give situation and evaluate them completely before choosing an initial course of action. In fact experts choose one course of action initially. One example of our approach is our Recognition Planning Model (RPM) which is based on the RPD model that was developed by studying experts making real time decisions in the field (Klein, 1998). RPM is flexible, supports fast replanning, and works well in the field. It focuses on capitalizing on experience and expertise in the planning process, while MDMP focuses on using decision analytic tools which in some cases can interfere with the process. Expert decision makers in the field, typically recognize the situation, and develop an initial COA quickly. They do not develop several COAs (as required in MDMP). The evidence that developing several COAs will result in the identifying the best COA is also weak. While RPM capitalizes on time pressure, time pressure tends to degrade performance in MDMP. Finally, it helps identify insufficient plans earlier in the process, thereby reduce the work of fixing the plans later.

At the conference, I will be talking about flexible decision making and planning that are needed when one's goals are ill defined and the environment is changing as in many current military operations.

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

1) The main problem that we see over and over in our work is that a tool is designed independent of a good understanding the user's situation or other tools. While the designers and builders have the best intention, the rule seems to be "build it, and people will use it." However, there are many COTS and GOTS that never make it off the shelf because they are not adopted or used. This happens because the tool may solve/support a challenge the user does not have so.

2) Related to the first challenge, decision support tools need to integrate into the process that people engage in and augment it, not interfere with it. This can be construed as knowing what aspect of the decision to

support. This is as much an issue of design of these aids (not knowing how people are actually making the decision) as it is about tool adoption. Build it and they will use it is not enough.

3) Decision support tools need to be flexible – because people need to be flexible and supporting this type of "flexecution" is difficult. This is related to the ideas that many decision are made very quickly and intuitively and designing tools to support these processes is challenging. Decisions making among experts is often fast, intuitive, and pretty good. Therefore a tool that slows this process down, has decision makers focus on different information, will adversely affect expert decision making.

X.T. Wang

1. Why do we need to study cognitive aspects of decision-making?
(discuss application needs within your organization, in your field, or as you perceive within the military)

Studies of cognitive aspects in decision making have their historical roots in World War II when the military investigated the cases of aircraft crash caused by non-mechanical failures. The recognition of human errors causing safety failures and deficiencies in man-machine interaction has led to the development in human factors psychology and ergonomics to improve human operations and technological systems (e.g., Wickens & Hallands, 2000). Not until recently, more research attention has been shifted to social-cognitive decision making from the traditional focus on physical behaviors of human agents and operational characteristics of technical systems. Several lines of research in human factors emphasize critical roles of congestive aspects in human performance and connect behavioral decision making studies with real world problems. Wickens (2002) and his colleagues were among the first to introduce cognitive multiple resource theory in accounting for differences in dual task interference. Similarly, the studies of situation awareness in the field of human factors psychology concern with perception of the environment critical to decision-makers in complex, dynamic areas from aviation, air traffic control, power plant operations, military command and control. Defined largely as the perception of environmental elements within time and space, the comprehension of their meaning, and the projection of their status in the near future, situational awareness is a primary basis for subsequent decision making and performance in any operation system (Endsley, 1995). Recent work on shared cognition can be seen as another effort towards a better understanding of cognitive determinants of human decision making in social and organizational environments. Within situation awareness is the concept of shared cognition or shared mental models which assess how shared information, memory, knowledge, schema or belief among team members about a task context affect shared preference and group decision making (e.g., Richards, 2000).

3. Which numerical methods and models are used to support/describe risk-based decision making?

The mid-20th contrary saw the birth of several influential and now classic theories using numerical methods and mathematical formulations to define problems in information search and use under uncertainty. Information theory developmed by Claude Shannon (1948) considers the transmission of information as a statistical phenomenon and gave communications engineers a way to determine the capacity of a communication channel in terms of the common currency of bits and had its finger prints in the later development of computer science, artificial intelligence and human factors psychology. Signal detection theory is another major attempt to incorporate cognitive aspects into situations where a decision has to be made based on detection of a signal from noise. The theory goes beyond psychophysics by discriminating between the sensitivity of the decision agents and their (potential) response biases (e.g., Green & Swets, 1966).

More relevant to the current discussion is the advent the expected utility theory of decision making under risk (von Neumann & Morgenstern 1944). This normative theory provides a parsimonious set of rational axioms and operates under the principle of utility maximization. The success in accounting and explaining a large portion of variance in decision behaviors under risk has given the theory an authority status and made it a corner stone in economic theories.

However, A major problem of the normative theories of decision making is the lack of consideration of limited mental and environmental resources. Psychologist and Nobel Prize winning economist Herbert Simon’s (1956, 1990) proposed the notion of bounded rationality which emphasizes the two interlocked driving forces of decision making: the limitations of the mind, and the structure of the environments in which the mind operates. As a result, people do not optimize and maximize based on complete information and expected utilities of all possible options but instead apply a satisficing (satisfactory and surfacing) principle for information search and use.

Empirical studies of judgment and decision making have revealed various violations of utility principles and judgment and decision biases from rationality axioms (see Kahneman, Slovic, & Tversky, 1982; Slovic, Lichtenstein & Fischhoff, 1988; Tversky & Kahneman, 1986). These findings have challenged the normatively defined domain-general decision rationality and inspired a large number of studies to explore psychological mechanisms and heuristics of human judgment and decision making. From these converging studies, a new approach, the cognitive heuristic approach, to human judgment and decision making emerged. Much of the work in line with this approach has contrasted normatively defined rational performance with the use of cognitive heuristics (see Einhorn & Hogarth, 1981; Kahneman, Slovic, & Tversky, 1982). These cognitive heuristics are viewed as information-processing shortcuts which, although normally efficient, can lead to systematic decision biases or errors. Inherent in the heuristic approach is the idea that in coping with uncertainty, human decision makers tend to use some judgmental heuristics as general strategies for simplifying complex decision tasks. From this information-processing simplification viewpoint, emphasis in heuristic analysis of human-decision biases has traditionally been on the limited capacity of cognitive processes rather the other component of bounded rationality, environmental task structure and constraints.

Recently, from different theoretical perspectives, an increasing number of investigators have drawn research attention to various mechanisms beyond pure computational limitations upon the information-processing capacities and complexity (e.g., Cosmides, 1989; Cosmides & Tooby, 1992; Gigerenzer, Todd & the ABC group, 1999, Lopes, 1987). Some of these studies have provided evidence that the appearance or disappearance of human reasoning errors and decision biases depends on perceived social and ecological context. These studies have opened recent discussions concerning the nature of rationality and raised questions about how heuristics are selected and used in different task contexts based on different cues and reference points.

2. What are the main research gaps within you field/area of interest?

Recent developments in the evolutionary psychology, economics, management science, and behavioral ecology reveal that normative utility theories of decision making at risk contract five problems: (1) a focus on only logical consistency but not social consistency, (2) a focus on only individual utility but not collective utility, (3) a lack of consideration of how people search, use, and integrate cues of risks under cognitive, social and ecological constraints, (4) a lack of consideration of the effects of task requirements and personal goals, and (5) the use of a single number (expected value) to measure subjective utility at the cost of losing information about risk distribution.

At the heart of expected utility (EU) theory, and many contemporary models of decision-making, has been the idea that decision makers aim to maximize their EU. However, one common limitation of these normative models of decision-making is their lack of consideration of the variance in expected outcomes. The use of a single expected value (utility) for each choice option is done at the cost of valuable information about payoff distributions in each of the choice options. It is ironic that on the one hand economics is defined as a study of goal-directed behaviors, but, on the other hand, economic models of decision utility omit any reference point (e.g., the status quo, goal or bottom-line). The importance of outcome distribution and expected variance in payoffs for decision-making lies in the fact that under risk, one must consider not only those options which have the highest mean expected value, but also the positive and negative variations from the mean expected value across decision reference points (goals and minimum requirements).

7. List three main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

Main challenges in integrating rigorous decision support tools in real time and deliberative tactical and/or strategic decision making.

Most decision support tools are based on complicated statistical models and are information hungry. The underlying processes of these decision aids are often opaque to the users and are driven by utility calculations, probability principles (e.g., Bayesian networks), or expert options. These decision aids held users captive of overload data and instructions leaving little room for future research are computational intractability and data overfitting, both reduce the robustness of complicated statistical modeling. Many real-world problems are computationally intractable, which means that no machine or mind can find optimal strategy. In addition, decision making is characterized by risk and uncertainty associated with future outcomes. Overfitting thus occurs when prediction of future is heavily based on hindsight resulting in a high accuracy in predicting known data but low accuracy in predicting new data. A major reason for an overfit is the inability to ignore or trim out "noise" (irrelevant information) existed in the past data from the information that is relevant for the future (see Gigerenzer, 2008).

A solution for the above problems or challenges is to utilize an adaptive toolbox that consists of heuristics that take advantages of evolved capacities and environmental regularities (Gigerenzer 2008). This adaptive tool box approach is contest to traditional approach of general-purpose jack of all brands. As argued by Gigerenzer (2008) these heuristics are not used as second best nor due to our cognitive limitation. Instead, they exploit evolved capacities that come for free, and thus customized to solve diverse problems. For practical purposes, the goal is to use the results of the above analysis to identify and design heuristics and task environments that teach and improve decision making in real time. These heuristics are built from principles of cognition rather than axioms of rationality. These heuristics apply specific stopping rules for information search and processing. These heuristics avoid the problem of data overfitting and information intractability.

5. Discuss experimental studies that can be designed to help in model validation as well as in gaining new knowledge in the field.

Experimental studies designed to help in model validation as well as in gaining new knowledge in the broader context of decision making research in general

My research program focuses on social and ecological rationality of decision making and how decision makers utilize valid cues in coupled with their task-determined goals and minimum requirements to make heuristic-based choices.

We examined how people make use of risk distributions (e.g., the variance in expected payoff, the variance in reproductive fitness) to maximize the probability of reaching a goal and to minimize the likelihood of falling below a minimum requirement. The research on risk sensitive foraging shows that animals either seek or avoid variance according to their energy budget. Our research on human decision making found that while the goal setting remains the same, the minimum requirement for the survival of group members increases from a large group to a small group, and to a kin group. The setting of the minimum requirement differentiates the subjective utilities of the choice options of the same expected value (see Wang, 1996, 2002).

The Mean-Variance Heuristic

We proposed and tested a Tri-Reference Point (TRP) model that takes into consideration three reference points minimum requirement (MR), status quo (SQ) and goal (G) which demarcate the outcome space into four functional regions: failure, loss, gain, and success (Wang, 2008, Wang & Johnson, in prep). The four regions entail different value functions for the decision maker. Risk preference of the decision maker is thus determined by these value functions and can be directed according to the mean-variance heuristic: be risk-averse when the mean-expected values of choice options are above G or MR but risk-seeking when the mean-expected values are below the reference point G or MR.

The MR-Heuristics

We (Wang, 2008b, Wang & Ziebarth, in press) also exploited how in situations when uncertainty is high, familiarity is low, and information is incomplete, simple and robust heuristics based one's MRs or simple frequency counts perform against more complex and normative heuristics that consider both cue values and cue weights (such as, Franklin's rule). In the contexts of presidential choice, evaluation of social security reform proposals, and automobile selection, simple and MR-based heuristics outperformed the normative and continuous evaluation score-based heuristics in predicting both individual choice and overall preference of a group.

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