Enhancing Intuitive Decision Making Through Implicit Learning

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ABSTRACT

A recent study published by the National Academies focuses on improving decision making (DM) abilities of small unit leaders, underscoring the significant weight that senior military leadership assigns to the art of training effective DM. DM training is often based on an analytical model which requires a methodical, step-by-step, time consuming approach to sequentially process data. While this model is appropriate for many military decisions, an interesting outcome from military operations in Iraq and Afghanistan has been the degree to which intuitive decision making (IDM), which uses a more holistic approach to processing information at a subconscious level, has been cited as playing a critical role in saving lives and enabling mission success.

IDM offers distinct advantages during ambiguous military missions. For example: a leader may be forced to make a time-critical decision for which he can neither afford to wait for detailed, quantitative data, nor analyze new information without risking the tactical initiative. Nevertheless, the processes underlying analytical DM have traditionally been viewed as more amenable to training than those which underlie IDM. Yet, a growing body of results, ranging from biological to cognitive, suggests that IDM uses some of the same underlying neurocognitive structures that are affected by implicit learning, non-conscious learning that occurs through repeated interactions with an environment.

In this paper we propose that IDM may be enhanced through a novel regimen that enables acquiring domain knowledge implicitly. We motivate the theory that targeted, implicit training automatically strengthens, at the neural, cognitive, and behavioral levels, the same capabilities that are needed for effective IDM. We also provide a framework for testing and implementing this theory. The results from this work will advance the body of research in understanding IDM processes and inform and direct successful training strategies to develop IDM training for military leaders.

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INTRODUCTION

Thanks to the awareness and quick actions of a 99th Regional Readiness Command (RRC) Soldier, however, no one was seriously injured by the [IED] attack--and he did this all while communicating with his wife on a cell phone... (Coleman, 2007)

Decisions within a military mission are often made under time-constrained, complex, dynamic conditions in response to incomplete or uncertain information. Examples of these decisions include detecting IED emplacements while in a rapidly moving vehicle or detecting atypical civilian behaviors indicative of covert enemy attacks. These challenges are compounded by the increasing push of decision making responsibilities to younger and more junior Warfighters combined with overall planned reductions in force size. Traditional training for decision making has focused on the development of analytic decision making skills (Newell & Simon, 1972) which require extensive training and practice to develop and which are poorly suited to today's decision making environment. Anecdotal evidence (e.g. cited above) and emerging science (Ross et al., 2004; Evans, 2008) suggest that there is another type of decision making which is better suited for dynamic and uncertain conditions, that can be harnessed to support Warfighter training: intuitive decision making (IDM).

Analytical decision making is mediated by processes that are time consuming, sequential, and methodical – the so called System 2 (Evans, 2008). Conversely, intuition is a speeded, effortless cue to the existence of meaningful information detected through one or more sensory modalities (Cohn, 2010) – the so called System 1. Importantly, IDM can support analytical decision making by generating prospective outcomes as the external problem space changes and can thus assist Warfighters in managing dynamic and uncertain environments (Evans, 2008). Intuition permits information extracted by automatic sensory processes, which operate on the time scale of hundreds of milliseconds, to be organized by pre-existing (top-down) knowledge. This unconscious organization of incoming information may elicit a feeling or impression of a solution (Cohn, 2010), which precedes insight or a sudden awareness of the solution (Figure 1).

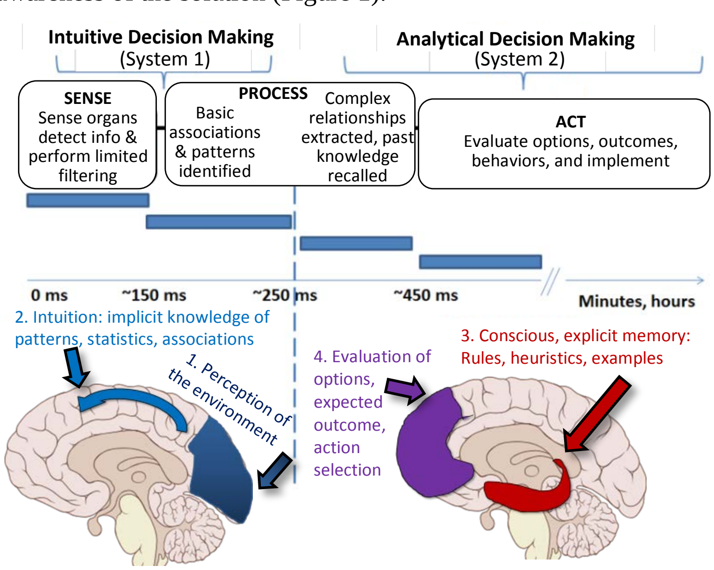

Figure 1: *Top.* Two decision systems work to transform information into action. System 1, the IDM system, acts rapidly and below conscious awareness to extract basic patterns and relationships from information present in the environment. System 2, the analytical decision making system, uses the same environmental information but also applies more complex cognitive processes. Intuition can either directly lead to action or can facilitate analytical decision making system. (Temporal sequencing after Luu et al, 2014; Luu et al, 2010; Philiastides & Sajda, 2007). *Bottom.* Following activation of one or more sensory organs, brain regions like the amygdala, basal ganglia, parietal and occipital lobes contribute to IDM *(left 1, 2)*. Brain regions like the hippocampus and the prefrontal cortex contribute to analytical decision making *(right 3, 4)*.

According to Bowers et al. (1990), intuition can assist the decision maker with discovering plausible solutions from which to choose when encountering novel information. Until recently, intuition was assumed to require the same types of training and experience as required by analytical decision making (Ericsson et al., 1993), to enable trainees to structure new data in a way that enables fast understanding and quick guidance to correct solutions (Kahneman & Klein, 2009). Recent studies, ranging from the neural to the cognitive and behavioral (Lieberman, 2000; Duffy & Kirkley, 2004; Jung-Beeman et al., 2004; Luu et al., 2010) suggest that this assumption should be modified. Combined, these studies suggest that IDM processes share some of the same underlying neurocognitive structures and processes as a type of learning known as implicit learning (IL; Dreyfus & Dreyfus, 1980; Ericsson et al., 1993) (Figure 1, bottom left). IL appears to accelerate a novice's ability to learn deep structures and rules embedded within information if delivered in an appropriate manner. This means that IL may provide a shortcut to enhance effective IDM in novice Warfighters.

Current decision making training and decision support systems are rooted in analytical, linear processes. Yet, as the military continues to engage with ambiguous, complex and rapidly changing operational environments, these systems may be insufficient to prepare the Warfighter for these dynamic decision-making spaces. Analytical decision making is poorly matched to time-sensitive, dynamic and uncertain situations. Contrastingly, IDM is a cornerstone of this type of rapid decision making. This paper provides a theoretical basis and outlines a technical approach for enhancing IDM via IL. Establishing this new paradigm for training intuition requires a four-fold effort: (1) characterizing the link between IL and IDM; (2) developing and validating a paradigm for using IL to enhance IDM; (3) using this characterization to develop a computational model that links IL with IDM; and (4) creating a training methodology and technology that capitalizes on these models to enable effective IDM in non-experts.

CHARACTERIZING THE LINK BETWEEN IMPLICIT LEARNING & INTUITIVE DECISION MAKING

Implicit Learning

Implicit learning (IL) is traditionally defined as a memory process through which environmental statistical regularities are extracted and used to support predictions and improved performance in familiar environments. This type of memory is outside of conscious awareness (i.e., learners cannot verbally report what has been learned) and is known to depend on distinct brain systems from those that support conscious, explicit memory (Reber, 2013). The measurement of IL requires task environments that possess an underlying statistical structure that is in fact related to outcomes or states, even if only probabilistically. In other words, there must be regularities present, which if utilized, will facilitate or improve performance. Because IL occurs outside of awareness of the existence of the regularities, subjective reports about learning cannot be used to assess the state of IL. Instead, IL is generally assessed by examining conditions where the underlying regularities have been altered once the IL is posited to have occurred. Removing these regularities impairs performance and demonstrates the existence and the degree to which IL has already occurred.

Intuitive Decision Making

Intuitive Decision Making (IDM) has been characterized in multiple ways. From the perspective of the two types of decision systems (System 1 and System 2), "intuition" can be understood as the interaction between prior knowledge structures and incoming information (Evans, 2008). Stated differently, intuition can be conceptualized as the unconscious process that permits information extracted by automatic sensory processes to be organized by top-down knowledge structures. This unconscious organization of incoming information may elicit a feeling or impression of a solution (Perrig, 2000), which precedes insight or a sudden awareness of the solution. According to Bowers et al. (1990), intuition can guide the judgment process by assisting with the discovery of plausible solutions from which to choose. This definition partially captures the distinction between intuition and insight; however, it does not distinguish between the processes involved with intuition and outcomes of such processes (Dane et al., 2008).

We define IDM phenomenologically as feeling like speeded, effortless thinking. IDM uses the intuitive feeling of the solution to determine the decision, and for a decision to qualify as intuitive, an individual should not be aware of applying an explicit decision rule (though this may be difficult to determine in post hoc interviews). In contrast, we can easily define the alternative, analytical decision making, as a case where the decision making process is based on a reportable series of cognitive steps taken consciously.

Linking IL and IDM

The parallels between IL and IDM are rooted in the fact that a decision making process relies on bringing prior knowledge (facts, rules, heuristics, probabilities) to bear on the decision context. When that information is based on IL, there will be no conscious experience of memory retrieval. Instead, the information retrieval process reflects a "gut instinct" or even a sudden, unexpected insight. This process then forms the basis of the intuitively made decision. Recent research provides support for this link at the neural, cognitive, and behavioral levels (Lieberman, 2000; Jung-Beeman et al., 2004; Luu et al., 2010).

PARADIGMS FOR ENABLING IMPLICIT LEARNING

Methods within the basic science of memory systems provide paradigms in which IL can be separated from explicit learning. Many of these paradigms include a critical decision making step that demonstrates the close connection between IL and IDM. These paradigms frequently identify manipulations that selectively disrupt explicit processing, such as by adding a cognitive load (e.g., a secondary effortful task such as rehearsing an 8-digit number) or speeding up responses. These same manipulations are often used in decision making research as reflecting an intuitive, reflexive, automatic process (in other words, processed by System 1). Techniques for creating and assessing IL provide valuable insight into creating IDM during training because this approach focuses on conditions in which the acquisition of knowledge happens outside of conscious awareness but can still be applied to a decision judgment.

Artificial Grammar Learning

The first paradigm to clearly show that IL can be acquired in a controlled laboratory context was the Artificial Grammar Learning (AGL) paradigm (Reber, 1967; 1989). In this task, which coined the term IL, participants are shown strings of apparently random letters (e.g., "TQSLV") that unknown to them, are constructed using a hidden finite-state automata that provides statistical structure. After an incidental interaction with a set of rule-following strings (e.g., copy from immediate memory), participants are surprised with a test in which new strings are shown and they are required to make "grammaticality" judgments. Participants must decide if they feel that these new strings follow the same rules as the originally studied strings. Making this judgment at a rate of better-than-chance indicates that they have learned the statistical structure of the study items even though they did not intend to learn it. Of note, an important practical element of the task is that participants virtually always complain that the test is impossible because they were not informed that they were supposed to be learning the rules explicitly. Therefore it is necessary to carefully construct task instructions with encouragement to guess or go with a "gut instinct" to even get participants to respond. Once they are making their judgments, which they generally feel are random, it is observed that they are able to tell rule-following strings at better-than-chance rates, indicating that IL has occurred.

With the ability to isolate IL, the AGL paradigm allowed for assessment of the neural basis of knowledge represented in the brain outside of awareness. Studies with patients with neurological memory impairment indicated that the brain system associated with conscious memory, the medial temporal lobe (MTL) memory system, did not support this kind of learning (Knowlton, Ramus & Squire, 1992). Subsequently, neuroimaging studies identified posterior cortical regions in parietal cortex (Skosnik et al., 2002) and implicated the basal ganglia (Lieberman et al., 2004) as being important components of this kind of learning. The basal ganglia is a subcortical structure that is connected by reciprocal loops to most cortical processing areas of the brain. This structure is associated with motor function and reward processing; it also appears to play an important role in many implicit learning tasks.

Implicit Category and Hidden Rule Learning

Another set of experimental paradigms in which IL can be connected to IDM are those based on implicit category learning (ICL). In these tasks, participants are exposed to a set of stimuli that are covertly derived from an underlying statistical structure. Subsequently, they are able to make category judgments about novel stimuli even though they are unaware of what the rules governing the category are. One type of paradigm is based on passive exposure to visual patterns (Keele & Posner, 1968) and appears to result in visual cortex reorganization as the basis of learning (Reber, 2009; Aizenstein et al., 2000; Gureckis, James, & Nosofsky, 2011; Reber, Stark, & Squire, 1998). As in the AGL task, a key component of the paradigm is the need to encourage participants to guess or go with a hunch in selecting responses.

An additional well-studied paradigm for ICL involves creating visual categories based on a hidden rule that is difficult to verbalize. Typically this requires integrating information across visual dimensions in ways that are not easily deduced explicitly and these tasks are referred to as information integration tasks (Maddox & Ashby, 2004). This type of learning occurs outside of awareness and requires participants to make a category membership judgment based on a hunch or a guess. The basal ganglia plays an important role in this type of learning as well (Nomura et al., 2007). This ICL paradigm has the further advantage of being well-suited to manipulating knowledge acquired during learning, which permits assessments of the operating characteristics of IL and explicit hypothesis testing (Maddox & Ing, 2005; Zeithamova & Maddox, 2006). In addition, interactions between the two systems can be examined (Nomura & Reber, 2012) which should provide an experimental model of the process by which an expert decides whether to rely on their intuition or a more explicit, deliberate analysis.

PRELIMINARY RESULTS: AN IMPLICIT LEARNING PARADIGM TO TRAIN INTUITIVE DECISIONS

Figure 2. (A) Sample stimuli presented during the learning phase of the TreasureQuest paradigm. (B) In a post-training test phase, these confusable images forced participants to use their intuition to identify the precise stimulus previously associated with reward.

A newly developed task for creating an experimental context in which decisions must be made intuitively using implicitly acquired information is TreasureQuest. In this task (see Figure 2A), participants are instructed that a treasure is hidden behind one of four silhouette images. In an initial learning phase, four distinct images are presented and participants have to guess the location of the reward. The images repeat across several trials; the typical approach to this kind of task is for participants to attempt to memorize the images that are rewarded.

At the start of the experiment, participants fill out a personality questionnaire and then are instructed to use a gut feeling to make their guesses in the learning phase to encourage an intuitive mindset. To give the participants a sense that their guessing is effective, rewards are given on 50% of trials (rather than the chance rate of 25%). Following training, a set of test trials are administered in which the participants now have to choose a previously rewarded silhouette among three other extremely similar stimuli (see Figure 2B). Recognition of the prior image is very low for these easily confusable stimuli; thus, participants must rely entirely on an intuitive sense of which object to choose in order to obtain the reward.

In a preliminary pilot study, 27 volunteers completed the learning phase that contained 52 sets of four different naturalistic objects. During the thirteen test trials, participants could only rely on their intuition and exhibited a reliably higher-than-chance accuracy rate (see Figure 3; t-test against chance level, p=0.0021). Thus, the training phase had boosted participants' confidence in their intuition and created an implicit association between the correct silhouette and the probability of reward. Although the magnitude of the effect was modest, the paradigm is promising in that even the very brief learning phase produced a statistically reliable increase in intuition. By using key aspects of an implicit learning paradigm design to reduce reliance on conscious, explicit strategies and the build-up of an implicit association incidentally over practice, we are able to create controlled conditions in which implicit knowledge is used to guide intuitive decisions based on a "hunch" or guessing. This type of paradigm will allow us in future work to characterize key operating characteristics and component processes involved in IDM so as to maximize training efficacy.

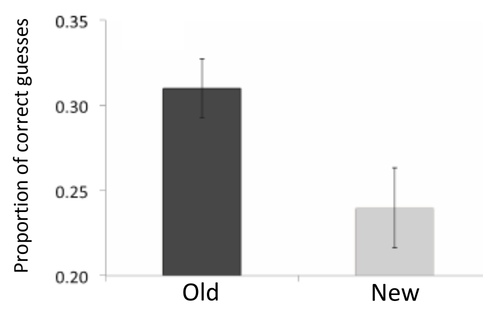

Figure 3. Participants' implicit knowledge of the previously rewarded silhouette is expressed as better-than-chance selection of the correct image.

COMPUTATIONAL MODELS THAT LINK IMPLICIT LEARNING & INTUITIVE DECISION MAKING

To make the characterization of intuition accessible to new training technologies, an "executable" representation of these data must be developed. Over the past several years, various machine learning classification techniques have been developed that help organize large, multi-scale sets of time series data. These multivariate decoding classifiers (Mitchell et al., 2004) have the ability to take into account the full spatial pattern of brain activity, cognitive measures and behavioral outcomes. Moreover, once trained on data from one group of individuals, these classifiers appear to be transferrable to other, never-before-encountered individuals with little reduction in accuracy (Shinkareva et al., 2008). New developments in these computational techniques have created the opportunity to bridge data about the neurocognitive basis of IL and IDM. Here, we provide a modeling framework to put the mechanisms of IL and IDM on firm computational ground that is informed by behavioral data, and grounded in cognitive neuroscience. The resulting computational model embeds a comprehensive theory of IL and IDM that will guide specific recommendations for rapid development of expert intuition.

Mixture-of-Experts Framework

A key challenge for understanding how we use intuition in problem solving is the simultaneous roles of multiple types of cognitive processing that depend on distinct memory systems within the brain. Implicit learning mechanisms are generally observed to operate independently and in parallel to explicit memory processes (Rugg et al., 1998). In complex problem solving, the fact that there are two parallel processing streams operating within the brain means that observation of solely the behavioral response is often ambiguous about the type of processing that drove the response. We can capture this phenomenon in a Mixture-of-Experts (MoE) framework in which we hypothesize separate "experts" that map onto explicit and implicit types of processing (Figure 4). In this framework, both processing streams feed information forward that can ultimately be used to drive the final decision process. By using this computational framework, we can account for both kinds of decision-making; further, we open up the possibility of using neuroimaging techniques to look inside at the brain for the neural signatures of the two types of processing to both test and refine the broader computational theory.

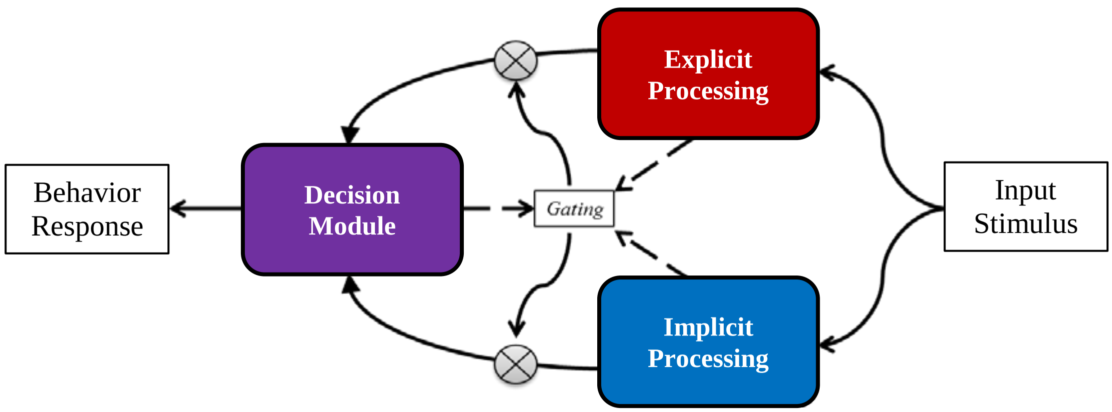

Figure 4: General Mixture of Experts Cognitive Framework. Information flows from the input stimulus to parallel streams for implicit and explicit processing. The result of each independent "expert" is then evaluated in a final Decision Module. Gating processing reflects the hypothesized competition and potential inhibition between types of processing.

Under this modeling approach, environmental information (input stimulus) is available to implicit and explicit processing streams that each operate independently in different areas of the brain. Information feeds forward to a decision module where a single behavioral response is selected as an action or decision. In addition, the model allows for a gating process to inhibit or enhance processing in one stream or the other. This framework captures situations where strategic factors cause decision making to be locked into one mode or another—such as when a person is exclusively focused on explicit processing and no influence of implicit processing or intuition is evident. In this case, implicit processing is dormant due to inhibitory gating from the explicit process. Yet, this situation can be remedied via training to provide top-down control over the gating process so that implicit information can be used, as is used in the paradigms described in the section above.

Expanding the Framework: Increasing the Accuracy of Implicit Processing Models

However, the overarching MoE framework leaves open important questions about the operation of each of these processing streams. Computationally, implicit processing can be represented as learning important features from the environment and grouping those features into categories that are functionally similar based on those features. This learning can be performed with either (1) prior knowledge of the categories or, in the more difficult case, (2) without prior knowledge of the categories. Current efforts focus on improving and evaluating new features to extend our models.

A first step in expanding the MoE framework focuses on representing how humans learn new rules in an unsupervised manner. Recent research by Baker, Saxe, & Tenenbaum (2009; 2011) has modeled the computational basis of human social reasoning, a type of implicit processing, using inverse planning to uncover the underlying mechanisms. Inverse planning characterizes people's conception of other agents' context-dependent behavior in terms of probabilistic, causal models of agents' planning and reasoning processes, formalized using Markov decision processes (MDPs). Based on these findings, the MoE framework can be updated to include this formalization as shown in Figure 5. An agent in the world assesses the world state, the agent state, and its goals. Using an MDP, it decides on an action to take and then updates the agent and world states. For example, an agent representing a person deciding where to eat lunch (goal) may take into account how hungry they are (agent state), their food preference (agent state), where they are (world state), and where the restaurants are (world state) before deciding where to move next (action). From this model, an observer is able to determine some information about goals and agent state (e.g., what type of food they prefer and how hungry they are) from observable information.

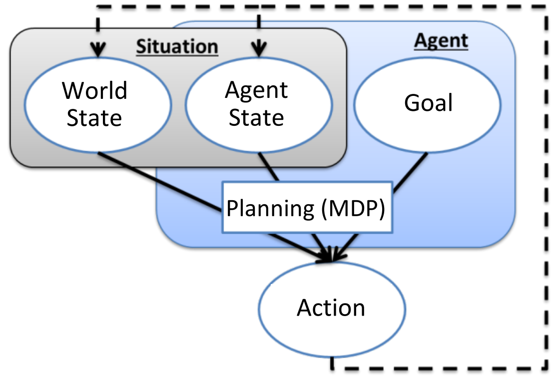

Figure 5: Planning agent action selection, used for inverse planning implicit processing.

This formalization can be improved by using a Bayesian inference model in place of an MDP model (Baker et al., 2011). However, a cost of the Bayesian approach is that information about the agent or agent world must be pre-coded into the model, which does not reflect how actual IL occurs. A more realistic scenario for IL may be that little or no pre-coded information exists, and that the *both* the categories and their relationships used in IDM are learned. This is an instance of non-parametric learning. Dirichlet process (DP) mixture models (Neal, 2000; Sanborn, Griffiths, & Navarro, 2006) provide potential to perform exactly this processing. The key innovation in Dirichlet process mixture models is that they place no limit on the number of components used in representing a probability density, allowing this number to be automatically determined by the structure of the observed data. In this way, DP mixture models can be used to flexibly learn categories of parameters of arbitrary models or theories.

Furthermore, DP mixture models can be extended to become hierarchical DP (HDP) mixture models (Teh et al., 2006). These models provide a simple recipe for representing the probability densities associated with multiple categories simultaneously. The mixture components thus constitute a “theory” of the domain that is common to all categories, picking out the relevant features and clusters of objects that are likely to compose categories. Recent research has shown how HDP mixture models can unify classical prototype and exemplar models of human categorization, adaptively transitioning from prototype-like to exemplar-like representations as more data are acquired, and explaining human categorization performance within both regimes (Griffiths et al., 2007).

Evaluating Computational Models of Implicit Learning & Intuitive Decision Making

Most theories of problem solving and decision making have focused largely on processing represented in the explicit processing stream that reflects conscious, deliberative analysis of input. The effects of implicit processing appear occasionally as a sudden intuition that, when accurate, reflects the operation of non-conscious processing or memory. Decades of memory systems research have established the existence of these multiple types of processing in the human brain and provided hypotheses about the neurocognitive basis of each type of memory. However, very little research has examined the important practical questions of how information across regions may be effectively combined to guide decision making. The Decision and Gating processes implied by the MoE framework (Figure 3) will need to be characterized and understood more thoroughly in order to develop an accurate theory for how implicit intuition can best influence explicit decision making. Using the computational tools outlined here (inverse planning, Bayesian inference), neuroimaging methods will be able to examine how these processes operate and how their operation can be influenced by different approaches to training. The first-order evaluation of the models will be their ability to capture a wide-range of laboratory findings where the roles of implicit and explicit processing can be precisely controlled. The ultimate evaluation of the models will be the ability to draw training recommendations from them that practically improves the rate and quality of training exercises, and development of expert intuition.

TYING IT TOGETHER: IL METHODOLOGIES & TECHNOLOGIES FOR ENHANCING IDM

One of the challenges of studying IDM is that the decision process can be studied but questions about the acquisition and character of the knowledge used in the decision process cannot be easily answered. A particular challenge in the study of expertise is the inability of experts to verbally describe information that had been acquired implicitly, which is represented outside of awareness. By applying IL theory and paradigms to these questions, we can derive principles and guidelines for IDM based on a focus on the learning process where the critical information needed for decision making is acquired. Our preliminary results suggest that in highly constrained decision-making settings, it is possible to train IDM in novices through IL techniques and to build dynamic models of this process.

The larger challenge is to demonstrate that it is possible to generalize these successes to the more unpredictable, dynamic and complex decision-making settings in which Warfighters will find themselves. This requires building a more complete methodology for training IDM and creating technologies to leverage this methodology. Past research on IL and IDM provides an initial set of "requirements" for these methodologies and technologies, which include:

- The statistical structure of the decision environment needs to be learned, using larger numbers of examples
- Training should be based on positive examples that show the statistical relationships to be learned
- Feedback based training likely needs the feedback to be received within 2s of the decision for updating of implicit knowledge to occur (later occurring, reflective techniques likely encourage explicit learning)

Implicit Learning Methodologies: Contrasting Cases

Previous studies demonstrated that experts differ from novices in their mental representations of knowledge, and that this plays a significant role in how they solve problems. In addition, experts are able to automatically recognize deep-level structures of novel, previously unencountered problems by activating knowledge structures in their memory that help them understand the nature of these novel problems and guide them to correct solutions. The predictive capability and speed with which a holistic solution is attained using recognition priming is seen as the hallmark of intuition-based decision making (Hodgkinson et al., 2008). From this perspective, intuition-based decision making occurs when bottom-up information (that comes in through various sensory systems) is interpreted and organized in a top-down fashion by pre-existing knowledge structures in the brain such that it elicits a feeling or impression of a solution that precedes insight or a sudden awareness of the solution (Luu et al., 2010; Perrig, 2000). Contrastingly, novices concentrate on the surface features only and are unable to automatically recognize the problem and find a correct solution to it. Instead, they utilize a slower, conscious, rule-based approach to problem solving, which is insufficient under circumstances in which time is scarce and stakes are high (Dreyfus & Dreyfus, 2005).

In order to rapidly improve novice's IDM performance, we must train them to organize new knowledge similarly to the way experts do. At a basic level, our research has already shown that implicit learning leads to more effective IDM when information to be learned is structured around learning simple statistical patterns (Figure 2). At a deeper level, it has been shown (Duffy & Kirkley, 2004) that this 'active learning' approach can enhance a novice's ability to learn deep structures and rules embedded within information if sufficient numbers of examples, and feedback, are provided. A relatively new approach to framing active learning is to use a combination of a problem-based and case-based learning methodology called - Contrasting Cases (Schwartz, 2008). In this method, two cases (i.e., problems or exercises) contrast along a meaningful dimension and while working through the two cases, the trainees derive the principle that underlies the contrast. While the types of tasks to which Warfighters will be exposed are complex, results from studies using more simplistic tasks (Rittle-Johnson, & Star, 2007; Schwartz et al., 2011) suggest that a Contrasting Cases approach enables novices to more quickly develop the deep structures necessary for making effective, intuitive decisions.

Implicit Learning Technologies: Scenario Based Training

Implicit learning is experiential and interactive. Because the appropriate number of experiences or interactions necessary for enabling effective IDM is currently unknown, it might very well prove too costly and time consuming to provide these examples "by hand." Consequently, we look to modeling and simulation based tools to provide the "experiential" component. These tools have the benefit of being able to generate thousands of contrasting cases in a short amount of time, ensuring that trainees will have a large space from which to sample and build their knowledge representations. The intuition models developed as part of this effort will enable the "interactive" component of implicit learning by informing the design of the training to facilitate IDM and enabling the training technologies to learn an individual student's strengths and weaknesses, and to tailor their training output accordingly.

Figure 6: The Virtual Observation Platform is a modeling and simulation based immersive team trainer designed to support implicit/experiential learning. Trainees will observe a virtually displayed location (e.g., a small town) from a combat outpost, located between 300–1000 meters away; they will be required to identify the patterns of activity within the region to establish a baseline, identify anomalies, and ultimately predict deleterious events before they occur (i.e., "left of bang").

The overarching training methodology will employ Scenario Based Training (SBT) which emphasizes embedding training approaches within an evolving and dynamic scenario (Oser et al., 1999), precisely the types of conditions that are suited to IDM. The scenario design, development, and implementation, as well as performance analysis are linked through SBT's validated three-phase approach: planning, execution, and assessment. The planning phase focuses on identifying learning objectives, competencies, and the required conditions and cues. These objectives are used to craft scenarios which embed cues to provide specific opportunities for trainees to practice or fine-tune required skills. In our case, objectives would be the rules that the students are to learn implicitly, embedded within context-appropriate scenarios. In the execution phase, trainees are exposed to the training scenario as well as specific instructional methods and techniques. During this phase, decision-making performance and other types of data (e.g., eye-tracking) are collected, which can be used to fine-tune the models of an individual's intuitive processes. Assessment marks the final phase, during which data are analyzed to provide feedback and after action review (AAR). Traditionally, scenarios, objectives and instructional facets are updated following the assessment phase, to refine the training that is being delivered. However, in our case, because we have a model of an individual's intuitive processes we can update that model using real-time assessments to adapt the training in real time during execution of the current scenario. We believe that this modified SBT process is ideally suited for quickly providing a range of training experiences, with feedback, tailored to an individual's needs. Figure 6 provides an example of a type of modeling and simulation-based training system that will be used to train IDM through IL.

Implicit Learning Technologies: Summary and Future Directions

Today's battlespace has moved away from an environment that solely emphasizes physical prowess, towards one that increasingly also demands cognitive prowess. In tandem with this shift, our force structure is decreasing in size. As a result fewer Warfighters must perceive, decide and act upon vastly larger amounts of information than ever before, over shorter time frames. Technology solutions that focus on decision aiding can mitigate some of this workload, but new approaches are also required to enable Warfighters to more quickly perceive, decide and act upon these large pools of information. Traditionally, it has been assumed that learning to make effective decisions requires years of training and experience. Yet, anecdotal evidence from the battlefield suggests that novices are able to make accurate intuitive decisions, suggesting that it may be possible to accelerate the development of one's intuitive decision capabilities.

In this paper, we hypothesize that IDM could be enhanced in novices through IL. We base this hypothesis on recent findings that show IL and IDM share many of the same neural, cognitive, and behavioral processes. We provide preliminary results which suggest that implicit learning can enhance IDM within a lab environment, provide a computational framework for modeling intuition, and introduce a training method and technology that could support large scale IL for enhancing IDM.

Significant work remains in order to better apply IL techniques to enhancing IDM including:

- More formally characterizing the nature of IDM and IL at the neural, cognitive, and behavioral levels: Traditionally, IDM has been studied at the behavioral level only (Hodgkinson et al., 2008). Recent developments in the cognitive neurosciences suggest that it is possible to characterize intuition across multiple levels of representation, thereby gaining deeper insight into how intuition works – and how it can be enhanced. For example, Luu et al. (2010) demonstrated for the first time – using a simple decision making paradigm – that it is possible to directly correlate decision making behaviors with neural markers derived from activity in these two systems to determine when intuition occurred and when it did not.

- Developing a comprehensive model of intuition: The most effective learning occurs when instruction is tailored to an individual trainee's needs. This allows the trainee to focus on addressing their weaknesses in a manner that is best suited to them. Building models of an individual's IDM processes will provide training technologies with the means for anticipating where these weaknesses may lie and for developing mitigations to address them. An important element of enabling this tailored training will be the ability of these models to blend neural, cognitive and behavioral data into a single comprehensive model.
- Training technologies and methodologies to enable effective IDM in non-expert Warfighters: The classical understanding of intuition is that it requires a high level of experience. By some estimates, achieving such expertise may require up to ten years of intense exposure to any number of a wide range of practical "training" exercises or many years of domain experience. At the core of our approach is the notion that this lengthy process can be significantly shortened through IL, and delivered through tools that can rapidly allow trainees to develop rules for structuring information. These training technologies must be built on both a more formal characterization of intuition and IL and more robust models of an individual's IDM processes.

It is our expectation that after addressing these outstanding challenges, we will have the capability to effectively and rapidly train novices to make intuitive decisions at a level similar to experts'. This capability, in turn, will allow fewer warfighters to appropriately and rapidly manage large amounts of information in order to successfully complete their missions in an increasingly cognitively-focused combat environment.

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