A. INTRODUCTION:

HUMAN AND ARTIFICIAL MINDS

Computer science, cognitive psychology, and neuroscience have a history of shared questions and inter-related advances. In his famous 1950 paper introducing the Turing Test, a paper published in Mind – A Quarterly Review of Psychology and Philosophy, Alan Turing (1) explicitly formulated the computer in terms of mimicking how humans do computations. Indeed, he introduced the word “computer” because that was the job title of humans who did numerical calculations by hand. In that paper, Turing also gave us the current meaning of the word “programming,” writing: “If one wants to make a machine mimic the behaviour of the human computer in some complex operation one has to ask him how it is done, and then translate the answer into the form of an instruction table. Constructing instruction tables is usually described as “programming.”

Evolving knowledge of the brain and its operations have also informed advances in computer science. Indeed, the history of neural networks – and the original use of the term – is roughly coextensive with that of modern computing machines. An early mathematical model of a single neuron was suggested by neuroscientists McCulloch and Pitts (2). John von Neumann and Alan Turing both explored network models inspired by McCulloch and Pitts’ earlier work (3). Marvin Minsky (4), a leading theorist of artificial intelligence in the 1970s, summed up the intertwined goals of cognitive psychology, human neuroscience and artificial intelligence this way: “I draw no boundary between a theory of human thinking and a scheme for making an intelligent machine; no purpose would be served by separating these today since neither domain has theories good enough to explain – or to produce – enough mental capacity.” Although we know much more today than we did in 1974 about human cognition and its neural underpinnings, and although computer science and its ability to build smart systems has advanced at a breakneck pace, Minsky’s conclusion is still apt, especially with respect to understanding and producing systems that learn.

Learning – adaptive, intelligent change in response to experience – is a core property of human cognition. The brain is a complex system that changes in response to the activations evoked by sensory input; the brain also helps create the experiences from which we learn by directing the actions of the body (5). Systems that learn have been the long-sought goal of artificial intelligence. In the 1980s, a team of cognitive psychologists, computer scientists, and early computational neuroscientists (Rumelhart, McClelland & The PDP Team, 6) extended McCulloch and Pitts’ network, figuring out how to automatically train multilayer networks of neuron-like input–output pairs. However, at the start of the 21st century, computer science, neuroscience, and cognitive psychology seemed to be moving apart in their approaches to learning – still borrowing from each other and with individual scientists sometimes jumping from one field to the other – but with big knowledge advances occurring in discipline-specific directions (3).

THE TIPPING POINT

In a remarkably short period of time, this has changed. Advances in technology and computing power have enabled machine learning, neuroscience, and the study of human learning to move from “toy,” that is, small-scale, approaches, to the study of learning from raw sensory input and to do so at the massive scale that constitutes daily life. There is general agreement (3, 7-10) that the advances in all three fields place us at the tipping point for powerful and consequential new insights into mechanisms of (and algorithms for) learning. These advances have the potential to revolutionize teaching and education, to yield behavioral interventions that precisely target change in specific neural processes, and (through powerful new machine learning approaches) to impact all of science as well as everyday life and society as a whole.

There is also an emerging consensus that the big breakthroughs will emerge through re-unifying the sciences of human learning, human neuroscience, and machine learning. ‘Thought-papers’ are increasingly making explicit calls to researchers in machine learning to use human and
neural inspiration to build machines that learn like people (3, 7-10), and for researchers in human
cognition and neuroscience to leverage machine learning algorithms as hypotheses about cognitive
and neural mechanisms. Finally, the potential value of joining behavioral, neural, and machine
approaches to understanding learning is being realized – and generating much interest – by the
dramatic advances in machine learning arriving from research teams such as Google’s Deepmind,
teams recruited from cognitive psychology, human and primate neuroscience, computational
neuroscience, as well as computer science.

These calls for joining efforts in a unified theory of learning have been picked up by funding
agencies. For example, the National Science Foundation recently called for proposals to build
Collaborative Networks on Learning. This funding initiative seeks to fund new research teams in
human learning, neuroscience, and machine learning. In the CFP, NSF wrote: “Learning is
complex, and many investigators from multiple disciplinary perspectives conduct research on this
topic. Advances in the integration and accumulation of this knowledge notwithstanding, key
knowledge remains fragmented across and within disciplines. Progress is hampered by the jingle of
studying different phenomena under the same name, and the jangle of studying the same
phenomena under different names. A deep and comprehensive understanding of learning requires
integration across multiple perspectives and levels of analysis… from the frontiers of science and
engineering…to innovation [that addresses] societal needs through research and education.”

THE NEXT FRONTIER
Schank (11), a seminal figure in the early days of artificial intelligence wrote (in the journal Cognitive
Psychology): “We hope to be able to build a program that can learn, as a child does….. instead of
being spoon-fed the tremendous information necessary.” At a top machine learning conference
(KDD) this summer, Professor Jitendra Malik, the Arthur J. Chick Professor of Electrical
Engineering and Computer Science at the University of California at Berkeley and a leading expert
in machine learning and computer vision, was asked by a student how to prepare for the next big
advances in machine learning. He was quite clear in his response: “Go study developmental
psychology seriously and then bring that knowledge in to build new and better algorithms.” He
recommended a paper by PI Smith as the place to start (12).

Using children as inspiration for machine learning makes good sense: by the benchmarks of
speed of learning, amount and diversity of knowledge, robustness, generalization and innovation,
human children (in their everyday worlds albeit perhaps not in schools) are the best learning
devices on the face of the earth. This proposal seeks a unified understanding of learning from a
human developmental perspective that is expressed in exploitable algorithms. To the best of our
knowledge, we will be the first formed cross-disciplinary team to actively pursue through our
research programs (as opposed to merely writing thought papers about the value of) a
computational understanding – that is grounded in brain systems – of learning from a human
developmental perspective.

INDIANA’S SPECIAL OPPORTUNITY
It is not true in general that engineering solutions closely follow biological solutions (consider
airplanes). It is even less true that engineers attempt to build solutions that follow biological
developmental pathways. And although engineering often provides new tools for measurements in
biology, it is not generally true that theories and algorithms developed in the context of engineering
problems have much to say about biological processes. What this emerging field of a science of
learning is trying to do – forming a new convergence of machine and human learning – is novel,
hard, and consequential. Indiana, with its recognized leadership in developmental science, has a
special role to play. Given financial investment at this tipping point, Indiana University can be at the
leading edge of this new field.
The team members are ready:

- We have been meeting for a year discussing the specific aims, our rationale and paths to achieving them.
- We have been part of continuing collaborations relevant to this new field and have started new ones directly relevant to this proposal.
- We have already talked to program officers at NSF and ONR and are being encouraged in our efforts.
- We have already solved many of the cultural barriers that exist across disciplines (different names for the same phenomena, different goals) that may stymie other groups.
- We operate within the interdisciplinary culture of the Cognitive Science Program, one of the top-rated programs of its kind in the world and one that has a well-established culture of fostering collaborative research that pushes through the bounds of narrow disciplinary perspectives.
- We already collaborate in interdisciplinary training with six members of the team also faculty with the Training Program in Integrative Developmental Science, an NIH T32 funded program now in its 22nd year (with 5 predoctoral and 3 postdoctoral lines).
- As our individual curriculum vitae and external grant records show, we are a group of faculty with outstanding records of significant contributions to science, already leaders or emerging leaders in the contributing fields.

B. SPECIFIC AIMS

Our goal is a new unified field of science that encompasses human and machine learning that incorporates behavioral, neuroscientific, and computational insights across all three fields. The idea is NOT that human and machine learning are or should be the same. Rather, the idea is that there are formally specifiable principles that characterize learning in general, and that an integrated approach will get us to those principles, resulting in useable new insights for both human learning and for machines. This means that the proposed research is fundamentally different than typical modeling or computational approaches. To succeed, we cannot just develop new algorithms that beat current state of the art approaches in machine learning, nor simply detail new circuits in the brain, nor just show that some training regimen is particularly effective with children. Nor will it be enough to show that we can build a model that learns in some domain like children do or that mimics some aspect of neural processing. For this new unified field to reach its promise, we also have to do the hard analytic work of understanding how and why these algorithms, circuits, and regimens have the effects that they do. This is the major innovation of the formation of this new research area.

RESEARCH AIMS

The proposed research focuses on **visual learning** – faces, objects, letters, numbers and algebraic equations as illustrated in the figure below. These images in the figure are taken from the ongoing individual and collaborative research of team members – head-camera images from 1 month old to 2 year old infants from the research of Yu, Smith and Crandall (25-27), children’s hand written letters and numbers from the work of James, Landy, and Smith (28-30), and algebra equations from the work Landy and Goldstone (30).
Visual learning is central to all aspects of human intelligence and a core interest within the research programs of the contributing faculty. Although there are still many unsolved problems, more than 50 years of neuroscience research provides a well-documented understanding of the basic structure of the human visual system. Machine vision is a rapidly progressing field and arguably the most advanced domain in machine learning and, in deep learning nets, the core idea approximates the bottom-up cortical pathways that serve human visual object recognition. The current state of knowledge provides the foundation on which to pursue potentially transformative questions of how young children so readily learn what they do and how we might build non-biological machines that can do as well.

The research aims derive from three ideas.

1. **Reuse.**

Modularity, reuse and hierarchy are central principles of the human visual system and of the multi-layered (deep) networks used in machine vision (13). Reuse may be defined as the use of the same module (e.g., a layer in neural network) for solving very different problems (e.g., recognizing faces and algebraic equations). However, another relevant sense of reuse is the "repurposing" of a component for a task for which it was not originally intended. This is a compelling fact about human learning. Specialized brain regions that served specific functions such as face recognition were traditionally assumed to have evolved to fit those tasks. However, culture has changed more rapidly than human brains have evolved. As a result, many modern tasks -- reading, mathematics -- are performed by brains that evolved for other purposes (14). In brief, the brain solves new cognitive tasks by reusing brain regions that could not have evolved for those purposes and does so by forming new patterns of connectivity out of these components, and by adapting the internal structure of those components through experience. Developmental and educational psychologists do not talk about reuse. But they do talk about the “cascade” and “readiness” -- the far reach of past learning into future learning. For example, early block play predicts later mathematics learning (15), as does precision of visual discrimination of textured patterns (16). We seek, through the study of reuse, to understand how past learning in one domain leaves hidden competencies and hidden deficits that do not show their effect until later learning in some more difficult task. For example, by hypothesis, infants’ early learning about visual objects tune and train components essential to learning about visual symbols. Under **Specific Aim 1**, we will pursue the computational and learning consequences of reuse by (1) testing the hypothesized predictive relations between perceptual skills across domains in young children, (2) conducting training experiments with children that measure the behavioral and neural consequences of training in one domain (e.g., objects) on later learning in another (e.g., letter recognition); and (3) conducting parallel experiments on deep-learning networks. Again, we seek not just to achieve learning by the algorithms but to analyze the internal workings of machine learners to understand the principles of reuse. The computational value of reuse for learning systems is that it enables learners over a series of different tasks to become progressively better learners of anything. The downside is that if early learning is not optimal, later learning may falter, a downside highly relevant to understanding the potent forces of poverty (and unequal early learning environments) on school achievement.

2. **Self-generated training sets.**

Before formal schooling, in their natural everyday worlds, children are not fed training data by some external force that selects what to show them and when. Instead, young children learn by doing. And what they do directly determines what they see and the data set for learning. This might be viewed as a “feel-good” notion about active engagement and children’s interests. But we are looking for more than this; we want to algorithmically understand the principles of self generated training sets, and why and how they may produce robust inventive learning. One case we consider
in this proposal is how children learn basic object categories; their progress is markedly different from state-of-the art machine vision. Young children learn their first 100 or so object categories quite slowly— with many repetitions and examples; this part is much like current state of the art machine vision (17). But after those 100 objects categories, they can learn a whole category from experience with a single instance (17,18). For example, a single experience with a John Deere tractor leads to adult-like use of the word “tractor” from that day forward. We believe this prowess stems in part from the structure in training sets for visual object recognition that children present to themselves. Current state-of-the-art machine vision uses training sets that are primarily photographs of objects that are selected by the computer scientists doing the training. They typically present as many different training instances of the object categories to be trained as possible and then test generalization to new instances (new photographs). These training sets are not at all like the training sets for everyday learning by children, as children actively select their own visual experiences— by where they look, how long they look, by their body movements, by picking objects up, by building towers of blocks or by scribbling. Under Specific Aim 2, we will conduct a series of parallel human training and machine learning studies designed to reveal and exploit the structure in self-generated data sets. The human learning studies also include pre- and post-training imaging to understand how the dynamics of functional patterns of connectivity across multimodal brain regions support robust learning and generalization.

We will specifically examine the role of information selection by the learner (and its timing with respect to current state of the learning), the dynamic structure of self-generated visual information, and the use of multimodal information. Through this aim, we will delve deeper into the creation of neural systems and apply this knowledge to the construction of biologically motivated machine learners. Doing this will require us to move beyond the current feed-forward deep networks used in machine vision to new approaches that incorporate time and re-entrant signals.

3. Percepts and concepts.
Thinking and reasoning are not the same as perceptual discrimination and categorization. Seeing that the algebraic equations 5x+y and 5(x+y) are different does not mean that one understands the meaning difference. However, significant evidence suggests that advanced mathematicians rely heavily on trained perception and action routines, and moreover write equations in ways that spatially highlight meaning (19,20). This suggests a potentially direct link between perceptual learning and higher-level concepts. The nature of this link between perception and cognition is one of profound interest both in human learning (behavioral and neural) and in machine learning (21,22). In this project we will move into the territory of symbolic deep networks and models that combine deep learning and variational inference (23,24). We will attempt to understand the relation between neural networks and logical representations, bridging the gap between a system that can learn to recognize and a system that can learn the function that generates the regularities in the data set, and in so doing the power to invent and to reason. Under Specific Aim 3, we will concentrate on two problems: (1) how children go from heuristics about how number names map to multi-digit numbers to understanding the principles of base 10 notation; and (2) how the perceptual and conceptual properties of algebraic equations interact to support high level mathematics reasoning.

EXCELLENCE AIMS
Our goal is to build a community that collaborates across cognitive psychology, human neuroscience, and artificial intelligence and that makes sustained high impact contributions beyond the life of this grant and the specific projects proposed here. To build this new exciting and consequential field, we cannot simply collaborate but need to become a community that is skilled in thinking and integrating the fields and comfortable enough to challenge, to admit when we do not know, and to be brave in designing new kinds of experiments that span people and machines. However, no single scientist can be expert across all kinds of analysis and time scales relevant to
this project. Accordingly, developmental scientists must acquire both the conceptual and practical skills that enable them to work in science teams in which members may bring expertise from different disciplines with different cultures. Accordingly, in addition to the research itself, we have three **excellence aims**:

(1) **To become community with a shared vision of integrative and high-integrity science.** To this end, we attack the research aims as a true collaborative team, in integrated projects. That is, the proposed research is **not a stabled set of ongoing projects but a new (and daring) effort.**

(2) **To increase the size of the community at Indiana.** To achieve a critical mass and world-class impact, we need to hire additional individuals on the analytic-theory side of machine learning as its links with human cognition and with human neuroscience. There are outstanding individuals currently in PhD programs and post-doctoral positions. We also need to recruit and to be open to other faculty already here at Indiana.

(3) **To train the next generation in these field and in doing make a name for Indiana as one that is truly building a transformative new field of learning.**

### C. RESEARCH DESIGN AND METHODS

**Aim 1 - REUSE**

**Collaborative Team:** Behavioral studies: Yu, Smith, Landy, Goldstone, James; Neuroimaging studies and analytics: James, Pestilli, White, new hire; Machine Learning: Crandall, Yu, new hires; Theoretical Analyses: Jones, Goldstone, Sporns, Natarajan, new hire.

**Rationale.** The figure (adapted from 31) is a cartoon of the hierarchy of cell types that comprise the human visual cortex. Lower cells selectively respond to simple lines at specific retinal locations. Higher levels respond to distinct categories—a tree, a face, the letter H. The feed forward activation means that the response patterns of the higher layers compute over the patterns of lower layers. Recognizing a tree or a face or an H all depend on the precision, tuning, and activation patterns of lower layers. This is how past learning may create hidden competencies or deficits that determine later learning. The second figure (from 32) illustrates how disruptions at lower layers disrupt higher layers. Disruptions in the response patterns in lower layers could have minor or severe consequences, and, since the system is nonlinear, these may be surprising. Further, the consequence may not be observable in the ‘next level’ after the disruption, but may only be observable far downstream. Another consequence of early layer deficits or competencies are lateral effects: adjacent cell assemblies can affect one another at the same level.

State of the art machine vision algorithms and deep learning networks have a similar hierarchical structure as the layers as the human visual cortex. Indeed, they are called “deep” precisely because of their relatively many layers of hierarchically organized neuron-like units (3, 7, 8). Thus, these deep-learning networks provide us with a way of studying and understanding the principles of reuse and hidden competencies and deficits.

But how can we find—in human learners or in machine learners—**hidden** competencies and deficits? What are the sign posts that some later learning is reusing—and being constrained by—
some earlier learned component? We will use two routes. The first is behavioral. What does it mean to be able to recognize a dog or the letter H? In many human and machine recognition studies, the standard is recognizing high quality instances under normal viewing conditions. But we are looking for potentially subtle indications that processes involved in recognition of an early-learned class of objects may have strengths or weaknesses that have downstream effects on later learning. Accordingly, we will challenge recognition systems, measuring recognition in both optimal and in very challenging suboptimal conditions. The second route is by looking inside the learner – using neuro-imaging measures with humans and analyzing the activation patterns within layers for the machine learners.

The specific research question motivating this project is how past learning, even long ago, influences learning in a different matter. We focus on 4- to 6-year-old children learning about letters, words, numbers, and multi-digit numbers. For children who are having difficulty in this new learning, can we find traces of hidden deficits in simple visual discriminations, in face discrimination, or in the recognition of common objects (two domains in which the dense periods of visual experience are, respectively, early infancy and toddlerhood)? Can we find evidence of these differences that mark the role of reuse through neuroimaging? Can we build these same patterns of better and less good learners in machine learners and identify their hidden competencies and deficits? And if we can, can we analytically determine the weak layer(s) of learning and is there a way – after the fact – to fix it? For example, one recent theoretical analysis (33) of feed-forward deep learning nets suggests that the weakest layer determines performance but also learns most rapidly. The fact that the weakest layer learns faster than other layers could be advantageous. But because human children use the same visual system to solve many different problems, later learning that finds an optimal solution to one task (e.g., letters) might not find the optimal solution to the many other tasks (e.g., multi-digit numbers) that need to be also learned. Our approach is absolutely novel with deep relevance for understanding reuse, for understanding why preschool learning matters, for developing effective education and remediation programs, and for understanding how machine learners may optimize learning in multiple overlapping tasks.

**Child study details.** We will conduct two studies with 4 to 6 year old children, one measuring competencies across domains (simple visual stimuli, faces, objects, numbers, letters); the other is a training study. Both have neuroimaging components. In total, 200 children (representative samples including 20% of children with family incomes that meet the standard for free-lunch at school) will participate in the behavioral only studies and 100 total children will participate in the neuroimaging component in addition to the behavioral component. In the Measuring Competencies study, Children will be presented with tasks measuring their ability to detect, discriminate, and recognize simple stimuli (lines), faces, common objects, letters, and numbers under optimal and suboptimal viewing conditions. We will use a well-understood search task paradigm with which we have experience (54) in which children are presented with visual arrays in which one object is different from the rest and their task is to find that different object. We use eye-gaze (via eyetracking systems) as the principal dependent variable. The arrays will be manipulated to challenge the visual system including degree of clutter, contrast, and blur. The children in the smaller sample study will also provide evidence of cortical processing of the same stimuli under these demands and conditions. As we manipulate the categories and visual challenge, we will observe activation patterns in different brain regions enabling us to observe how neural systems respond to these challenges and to locate regions (layers) implicated in the observed individual differences in children’s responding. In the Training Study, we will train children (in an 8 week training procedure following the methods of James (28) and including pre- and post-test imaging). to improve line, face and object detection under suboptimal conditions. Will this improve the performance with letter and numbers, visual forms about which children this age are just beginning to learn?

**Machine learning studies.** We will mimic child study 1 by training feed-forward networks in face and object recognition and then clamp learning in early layers (after different amounts of training) to
understand how differential learning in these areas limits or supports more rapid learning of letters and numbers. We will purposely disrupt processing in individual layers to determine the outcome. In an innovation with respect to measures of machine learning, we will test the networks under suboptimal as well as optimal visual conditions and link performance to that of children. We will analyze the trajectories of learning and how layer-specific learning changes as a function of weaknesses and strengths in prior learning (33, 34). We will mimic child study 2 by then giving these networks extensive training in suboptimal conditions (an unprecedented training procedure in this field) and then retesting their performance and re-analyzing – layer by layer – their learning.

**Significance.** Our approach is innovative its parallel experiments with children and deep-learning networks. Our approach is innovative in going beyond performance by using neuroimaging in children and analyses of the internal workings of the networks to understand the internal processes. Our use of challenging visual tests will allows us to discover hidden competencies and deficits – in children and in machine learners. But perhaps more importantly, Study 1 highlights the importance of understanding the underlying mechanisms of learning, such as reuse, in the lives of children. We know that early inequalities in children’s environments have early effects – in brain and behavior – prior to school that may determine children’s abilities to succeed in school. But we do not understand the mechanisms nor the developmental pathways. Study 1 is a first but important step built on a theoretical understanding of reuse in hierarchical learning systems, and in so doing it goes beyond the usual approaches of teaching to the test, and randomized trials to see what works without understanding why. Truly effective training requires a principled understanding of exactly what is limiting learning and then knowing how – precisely – to go in and fix it.

**Aim 2 – SELF-GENERATED TRAINING SETS**

**Collaborative Team:** Behavioral studies: Yu, Smith, Landy, Goldstone, James; Analysis of the statistical structure and dynamics in self-generated sets: Jones, Sporns, Smith, Yu, Ryoo; Neuroimaging studies and analytics: James, Pestilli, White, new hire; Machine Learning: Ryoo, Crandall, Yu, White, new hires; Theoretical Analyses: Jones, Goldstone, Sporns, Natarajan, new hires.

Learning changes the human brain and those changes alter how human learners engage with the world. This creates a brain-body-environment complex dynamic system in which learners actively select and create the learning information, that information unfolds in time, and the learning experience is inherently multimodal – involving more than vision. None of this is like the so-called state of the art machine vision that trains feed-forward bottom up networks by showing them still photographs selected by the trainer and presented in random order. For example, Yu, James, Smith and Crandall’s pioneering work putting head cameras and head-mounted eye trackers on toddlers as they played with objects has shown toddlers create dynamic views in which a single object at a time dominates (e.g.,25-28; 35-36). These one-dominating object views are visually larger than other objects in play because toddlers move their eyes and heads close to objects of interest, because they use their hands (and short arms) to bring objects close for viewing. In this work, we have also shown that the objects views that toddlers show themselves become increasingly structured in ways likely to support more view-invariant object recognition and more abstract shape perception; specifically they increasingly hold the object and rotate it major axis in depth (27, 35-39). Machine vision models (e.g. 40-41) have shown that these rotations play a role in building visual representations (at the top of the hierarchy of layers) that extract abstract 3-dimensional shape; studies of toddlers show, in turn, that these self-generated rotations predict rate of object name vocabulary development (38) and later learning about the mathematics of geometry (42). Goldstone, Landy, Smith and James (29, 43-45) have also studied the self-generation of visual information created when the learner writes letters and numbers or moves the components of an algebraic equation around to solve the problem. All these behaviors both are products of what the learner has already learned and determiners of the input for the next training moment. There
are many theoretical reasons (46-48) to suggest that these are computationally powerful properties and may be essential to creating human-like learning. Here we seek to do what Professor Malik proposed to those machine-learning students at KDD: seriously understand these developmental phenomena and then write new and more powerful machine learning algorithms.

We will focus on four (deeply inter-related) computational consequences of self-generated training sets: (1) **selection** of the visual information itself; (2) the **time scales** of mathematically smooth visual experiences; (3) **prediction and just-in-time** new information that depends on the learners current state; and (4) the role of **multi-modal** time-locked information. We will study learning in three contexts: (1) toddlers’ visual object recognition and its relation to manual activities with objects; (2) 4 year olds’ learning about letters and numbers, including multi-digit numbers; and (3) 12 to 14 year olds’ learning about algebra. We will conduct 4 kinds of studies:

(1) **Collecting and analyzing the training set as created by active learning.** We will collect and analyze the dynamic, learning dependent, and multimodal nature of real-world data sets from the learner’s point of view. We will use head-mounted eye trackers (we have considerable experience, even with toddlers, e.g., (35)) to collect both moment to moment scene changes as the learner engages with the material and to collect momentary eye-gaze and the precise sampling of available information, because what the learner looks at determines what the learner can learn. We will conduct the experiments in a shared smart room facility in Psychological and Brain Sciences that will enable collecting dense time data on all body movements (heads, hands, trunk). We will study two different visual learning tasks: (1) toddlers learning to visually recognize everyday objects (e.g., cup, spoon) via active play (12 to 24 months, n=100); 4 year olds (n=100) learning about less-everyday objects (e.g., garlic press, vise) through play as well as about letters and numbers by writing, copying, and creating letters and numbers out of sticks. We will also measure recognition and discrimination of these entities in optimal and suboptimal conditions. The goal is to characterize the structure in these self-generated training sets, the individual differences in that structure, and their relation to individual differences in object recognition performance. These data, important in their own right, are also critical to developing new algorithms that can exploit this structure.

(2) **Training experiments** will be conducted in which 4 year olds (n=300) are trained (8 weeks, again following the procedures of James, see (28,43)) via self-generated actions, by watching the dynamic visual events created by others’ actions, and through static pictures. Half the children will be trained on all three tasks, half on just one (e.g., just faces or just letters). This allows us to assess the role of optimizing learning across different categories of stimuli rather than one class. All children will be tested for recognition in all domains and detection under optimal and suboptimal conditions of visual information. A subset (n=100) of the children will also participate in pre- and post- neuroimaging experiments. These experiments build on the groundbreaking work of James (28, 43, 49, 50) who has shown the direct benefit of action and the motor system involvement in visual learning and in temporal processing. One critical area is the Supplementary Motor Areas (pre-SMA and SMA proper) in the frontal cortex. This is involved in several aspects of integrating information over time, including association at the sub-second and supra-second level, sensory information, and sensorimotor information (51). These regions both receive information from – and transmit information to – the visual system, creating a network that may underlie learning through temporal association of what has been done or seen and what is done or seen next. This region becomes involved when learners act – by writing, dragging, or moving objects – but not when watching. We will seek to document this effect, and the role of motor behavior and planning, in visual learning more generally. Critical to the analyses of the neuroimaging data in concert with the multidimensional properties, Pestilli, White and Sporns are developing a new computational framework to encode the multi-dimensional aspects of brain connectivity, concurrent and previous behavior, and visual input.

(3) **Modeling experiments and analysis.** Feedforward networks are useful as models for an initial understanding of neuronal signaling as one goes up the hierarchy, and they explain a fair bit about
vision and visual learning. But they are fundamentally unlike the brain in terms of their connectivity and dynamics and are limited to the computation of static functions. Rather than computing a static function on each of a series of image frames, vision takes a time-continuous input stream and interprets it through ongoing recurrent computations that include input from other modalities and at multiple time scales. We will train machine learners to match the training of self-generated data sets in component 1 and each of the training conditions of component 2. We will use learner generated video information to train networks, an area in which we are already collaborating and have expertise (25, 55, 56). Table 1 (derived from papers by 7,8, 46-48) provides a further map to our plan of attack in linking the behavioral evidence on learning to neural processes to algorithms.

<table>
<thead>
<tr>
<th>Computation</th>
<th>Potential algorithmic/ representational realization(s)</th>
<th>Potential neural implementation(s)</th>
<th>Putative brain location(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rapid perceptual classification</td>
<td>Receptive fields, pooling and local contrast normalization</td>
<td>Hierarchies of simple and complex cells</td>
<td>Visual system</td>
</tr>
<tr>
<td>Complex spatiotemporal pattern recognition</td>
<td>Bayesian belief</td>
<td>Feedforward and feedback pathways in cortical hierarchy</td>
<td>Sensory hierarchies</td>
</tr>
<tr>
<td>Learning efficient coding of inputs</td>
<td>Sparse coding Continuous or discrete attractor states in networks</td>
<td>Thresholding and local competition</td>
<td>Sensory and other systems</td>
</tr>
<tr>
<td>Decision making</td>
<td>Reinforcement learning of action- selection policies in PFC/BG system</td>
<td>Reward-modulated plasticity in recurrent cortical networks coupled with winner-take-all action selection in the basal ganglia</td>
<td>Prefrontal cortex</td>
</tr>
<tr>
<td>Decision making</td>
<td>Winner-take-all networks</td>
<td>Recurrent networks coupled via lateral inhibition</td>
<td>Prefrontal cortex and basal ganglia</td>
</tr>
<tr>
<td>Routing of information flow</td>
<td>Context-dependent tuning of activity in recurrent network dynamics</td>
<td>Recurrent networks implementing line attractors and selection vectors</td>
<td>Common across many cortical areas</td>
</tr>
<tr>
<td>Working memory</td>
<td>Continuous or discrete attractor states in networks</td>
<td>Persistent activity in recurrent networks</td>
<td>Prefrontal cortex</td>
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<td>Representation and transformation of variables</td>
<td>Population coding</td>
<td>Time-varying firing rates of neurons representing dot products with basis vectors, nonlinear</td>
<td>Motor cortex and higher cortical areas</td>
</tr>
</tbody>
</table>

**Significance.** Aim 2 pushes hard against the limits of current knowledge about the dynamic regularities in training sets, in the role of the learner in creating those training sets, and the kind of learning algorithms that can make use of that structure. But this is where we have to go if we want to understand visual learning, as involves top-down effects related to expectation and attention, as well as active exploration of a scene through a sequence of eye movements and through motor manipulations of the world. With the recurrent loop expanded to pass through the environment, these processes sample different parts of a scene sequentially, potentially selectively sampling the most relevant information for learning.
Aim 3 –PERCEPTS AND CONCEPTS

Collaborative Team: Behavioral studies: Smith, Landy, Goldstone, James; Analysis of learning: Jones, Smith, Yu; Machine Learning: Natarajan Crandall, White, new hires

Feed-forward neural networks are very good at finding categories of things but they are not good at figuring out why categories have the structure they do nor at reasoning from that knowledge. But humans are very good at this. For example, 7 year old children readily generalize multi-digit number names to written form – knowing that “five hundred and forty six” refers to “546” and not to “456”, even if they have never seen that number before. Feed forward deep learning nets are not good at this. But another powerful form of machine learning is variational or Bayesian modeling. Bayesian modeling based Bayesian statistics aims to capture the processes assumed to have generated the data leading to models that can explain and reason from the structure in the data (9, 10, 21). Such models are not at all brain like and do not learn in the usual sense, incrementally improving over time. Instead, they make inferences over probability distributions. However, there is a growing push (e.g., 57-61) and growing ideas about how to take the best of these two approaches to yield a more complete theory of learning. For example, one approach uses analysis by synthesis. A bottom-up classification model and a top-down generative model are concurrently learned so as to best represent the distribution of the inputs in a maximum-likelihood sense. The learning can be performed using the wake-sleep algorithm (61). In the wake phase, the recognition model “perceives” training images, and the generative model learns to better reconstruct these images from their internal representations. In the sleep phase, the generative model “dreams” of images, and the recognition model learns to better infer the internal representations from the images. By alternating wake and sleep phases, the two models co-adapt and jointly discover a good representation for the distribution of images used in training. Other ideas blend prediction, reinforcement, and top-down training (see Table 1). All these approaches embrace the idea that perceptual and conceptual learning are products of the same learning machinery. This idea fits the behavioral research. For example, Landy & Goldstone (45) have shown that good mathematical reasoners become proficient at mathematics not by trumping or overruling perception and action in favor of abstract reasoning, but rather by adapting these concrete processes to better fit mathematical needs. For example, good mathematical reasoners tend to have their visual attention naturally drawn to the multiplication of 3 by 4 in “5+3×4” which leads them to correctly calculate 17 rather than 32, which they would get if the did the 5+3 operation first.

We will conduct two long term training studies with first and second graders on reading and writing multi-digit numbers and one with seventh to ninth graders on algebra. Both will use training apps, and notably the algebra training app developed by Landy and Goldstone (19, 20) called Graspable Math (GM) (http://graspablemath.com), which allows users to interact in real-time with math notation using intuitive as well as trained perception-action processes. In the next year this tutoring system will be used with 100 6th grade students in Australia, all 7-8th grade algebra classes in Henrico County, Virginia, 4 math classes from 7-9th grades in Monroe County School Corporation, and more than 500 students who annually visit the Math Assistant Center (MAC) at IUPUI in Indianapolis. Here we will use this guided training to track changes in perceptual learning (recognizing forms, reading handwritten or crowded forms, and measuring both speed and accuracy) and also measuring conceptual knowledge – the principles of base 10 notation (that the 5 in 456 means 5 sets of 10 items) and explicit understanding of the rules of algebraic decomposition, including the generation of equations.

The training materials will be used to train symbolic deep-learners. In particular, based on the tasks given to students in classroom contexts, we will create large corpora of symbolic mathematical expressions with goal states. For the multi-digit number reading training, input-output pairs would include “82 -> eighty-two” and “four hundred seventy-six -> 476.” For the algebraic reasoning training, pairs would include “4x+2=6 -> x=2” and “Kayla has 3 dogs and each dog has 4 collars. How many collars are there? -> collars=3X4.” By employing machine learning techniques including variational methods, analysis by synthesis, Deep Boltzmann machines, Deep Belief
Networks, Stacked Auto-Encoders, as well as Advice Seeking systems (62-65), the goal of training would be for the networks to develop internal representations that capture important regularities in the input patterns – regularities that allow the networks to solve the trained problems as well as previously unseen transfer problems. By training machines like these to solve these problems, we gain insights into what are the actual regularities present in the training corpus, which can be used to guide human mathematics instruction, and we fundamentally augment our ability to automatize the discovery process in highly structured STEM domains.

**Significance of Aim 3.** Aim 3 attempts to close the big divide in machine learning and in theories of human cognition – between learning about the training materials to representing the regularities in the training set in terms of the principles or function that could generate those instances. The research will also provide new insights into the development of mathematical symbol systems and have direct impact on educational practices. The work will provide evidence at the heart of developmental theory – how early experiences pave the way for downstream effects and how development is much more than teaching to a test: early learning that is bottom-up and perceptual might be part of the process for the advanced conceptual learning that finds and reason from the underlying principles and functions.

### D. Timetable

<table>
<thead>
<tr>
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<td>Learning seminar</td>
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<td>Submit Research grant (Aim 2)</td>
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E. Significance and Impact
There are fields of contemporary research that seem on the edge of science fiction – machines that learn like children, algorithms in the brain, and rewiring and returning the brain with precision training – that are not yet realities. But we are close and the consequences for people – for education, for remediating the unequal environments that, by preschool, may prevent children from having a fair chance at life – are great. Building computational prowess that can help people solve hard and important problems such as cancers and climate change also require building systems that can learn – that can find regularities – from complex data sets. For all these reasons, we need a field that studies learning by going deep, beyond what a first grade teacher or grandmother knows (study, practice, work hard). Instead, we need to know how learning builds on itself, how all the learning and tasks we do drive change, the kind of learning mechanisms recruited by different properties of different training sets, and how learners go from knowing the training material to forming the abstract principles in a domain that enables us to be inventive, to think, to be scientists. This is what we are trying to do. The task will be hard, but the contributing fields are ready.

F. Future Funding/Sustainability
This area of research is sustainable in two ways. First the faculty salaries are justifiable by their contribution to teaching. Psychological and Brain Sciences has one of the largest undergraduate majors and enrollments in the College and the Informatics attracts and is expected to continue to attract many majors. The three proposed faculty will be regular tenure track faculty who will teach as well as do research. Indeed, it is arguable that this new emerging area will increase enrollments in both majors as this is a high impact and high profile area of concentration for which there are many jobs. We are also confident in the interest of funding agencies in this research domain. There have been increasing calls for proposals for just this area of research: the NSF “Learning” call as described earlier plus their Computational Cognition initiative which reads in part “The National Science Foundation (NSF) is interested in receiving proposals to existing programs, listed below, that explore computational models of human cognition, perception and communication and that integrate considerations and finding across disciplines. Proposals submitted to programs in SBE should include a rigorous computational context, and proposals submitted to programs in CISE should include a rigorous cognitive context. Also targeting this precise area is the - Explainable AI initiative the human-aware data driven modeling (D3M) and the Communicating with Computers initiative, all through DARPA. Also making a call for convergent work on learning across these fields is DOD initiative BAA-RQKH-2015-0001 Methods and technologies for personalized learning, modeling and assessment.

Because the visual symbol focus is highly relevant to STEM education, submissions to IES, NSF and NIH are also planned. These sources are particularly relevant to Aim 3. Relevant foundations include James S. McDonnell Foundation under the two current funding programs: Understanding Human Cognition and Studying Complex Systems, the Nuffield foundation (mathematics education) and the Whitehall foundation (neuroscience). We also plan to submit a graduate training grant to NSF’s Research Traineeship Program and have already discussed this plan with program officers. Our collective effort and long term history of external funding provides quite clear evidence that we can external funding. We expect to obtain multiple grants and to continue to so over the next decade.
G. New positions proposed: The speed of advances in machine learning, particularly in the form of deep learning networks has been astounding, occurring in less than 10 years. These new machine learning approaches both mimic aspects of human brains and they learn from real world and enormous data sets, data sets not unlike the 20,000 words that a child hears a day or the 12 hours a day of viewing scenes filled with objects. These statistical learning engines, like humans, learn from weak supervision. The integrative use of these networks in the context of understanding how brains and people learn is new. Accordingly, although Indiana has recently been hiring machine learners (Crandall, Ryoo, White, and Natarajan and cognitive psychologists like Jones and Yu with machine learning backgrounds), IU is understaffed in this emerging area needs to load up in this area if it is to be in the game in future science (and in training). This is a real gap for the university in general and it is certainly a significant for this proposal. Because the advances, approach, and potential are new, the game-changing machine learners nationally and internationally are more the most part very young (within 5 years of their PhDs). This is who we need to hire, and there are many exciting new PhDs emerging who are being trained in jointly in cognitive psychology and machine learning and in human neuroscience and machine learning at Stanford, Berkeley, MIT, NYU, Colorado, among other top schools. For this project we seek to hire these young individuals who will bring with them the new expertise and perspective to add to the excellence that already here. We specifically seek:

(1) A computational neuroscientist, ideally in vision, with a special interest in visual learning and in deep learning networks. Given the short lifespan for some neuroimaging technologies, a strong preference will be given to individuals demonstrating versatility in their science and strong formal and theoretical grounding.

(2) A machine learning researcher working at the front-end of current knowledge – that is, in symbolic deep nets or recurrent multi-layered networks. The ideal candidate for this position would have demonstrated research interests not limited to optimization of learning, but would also be motivated to compare machine and human learning mechanisms, and propose learning algorithms that learn in human-like ways.

(3) A theoretician of complex multi-layered networks adept at formal analysis of why and how these networks work as they do and, ideally, with an interest in how they relate to emerging principles within human neuroscience. The primary criterion for hiring in this position will be research excellence in artificial or natural neural networks. An additional important consideration will be the individual’s ability to contribute to training in and teaching of methods necessary for conducting research in learning in networks: linear algebra, advanced statistics, computer programming, robotics, and data science.

H. IU and External Collaborative Arrangements: NONE

I. Metrics and Deliverables: In assessment and evaluation, it is important to distinguish measures of the activities in the program from measure of the outcomes -- what one hopes to foster by the program activities, and of being explicit about what are and are not measurable goals. The figure below outlines the components to be evaluated: the research programmed partitioned into inputs (the investment from IU), the activities we will with that investment, and the outputs (that is, the specific deliverables from these activities). We then consider the outcomes these activities are designed to foster – measured with respect to the short-term, mid-term, and long-term goals. The measures –both surveys of participants and objective measures – for each component are listed at the bottom of the figure. To evaluate the Program, we evaluate the inputs into the program through objective measures. Outcomes measures assess what these activities were designed to foster – placement, sustained contributions to research and integrative research that helps define the new
field. For these, the planned measures are objective achievements as listed in the figure. The activities and objectively measured outcomes are listed in the figure below.

<table>
<thead>
<tr>
<th>The Research Program</th>
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<tr>
<td><strong>Inputs</strong></td>
<td><strong>Activities</strong></td>
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<tr>
<td>Hires</td>
<td>Research Collaborations</td>
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<td>Joint mentoring Conference Presentations</td>
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<td>Speakers</td>
<td>Collaborative presentations</td>
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<td><strong>Short-term</strong></td>
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<td>Increase faculty &amp; PhD students in the EAR</td>
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<tr>
<td>6. DE Rumelhart, JL McClelland, the PDPresearch group (Eds.), (19860 Parallel distributed processing: Explorations in the microstructure of cognition. Volume I: Foundations, MIT Press, Cambridge, MA.</td>
</tr>
</tbody>
</table>


Personnel

David Crandall 20% effort – Associate Professor, School of Informatics and Computing. Expertise: machine learning, computer vision, deep learning nets, structure from motion, analyzing and modeling large amounts of uncertain data, egocentric vision, human vision.

Robert Goldstone 20% effort – Professor, Psychological and Brain Sciences, Program in Cognitive Science. Expertise: Human cognition and perceptual learning, cognitive modeling, large set data collection – crowd-sourced, in educational settings, online, large data set analysis.

Karin James 20% effort—Associate Professor, Psychological and Brain Sciences, Program in Neuroscience. Expertise: neuroimaging, neurodevelopment, perceptual and motor learning, visual object recognition.

Michael Jones 20% effort – WK Estes Professor, Psychological and Brain Science, Program in Cognitive Science. Expertise: Computational models of memory and language, attention in reading and visual navigation, artificial intelligence, machine learning, data mining.

David Landy 20% effort – Assistant Professor, Psychological and Brain Sciences, Program in Cognitive Science. Expertise: Computational and theoretical approaches to formal reasoning, mathematical cognition and perception, numerical reasoning, distributed cognition.

Sriraam Natarajan 20% effort - Associate Professor, School of Informatics and Computing. Expertise: Machine Learning, Artificial Intelligence, Relational Learning, Reinforcement learning, Graphical Models, Continuous Time Bayesian Networks.

Franco Pestilli 20% effort – Assistant Professor Psychological and Brain Sciences, Program in Neuroscience, Program in Cognitive Science. Expertise: Human neuroscience, vision, model based neuroanatomy, perceptual decision making and learning.

Michael Ryoo 20 % effort – Assistant Professor, Computer Science and Informatics. Expertise: Egocentric vision, computer vision, machine learning from video, stochastic representation, robotics.

Linda Smith 20% effort – Distinguished Professor Psychological and Brain Sciences, Program in Cognitive Science. Expertise: cognitive, perceptual, motor development in infants and children, cognitive modeling, large and temporally dense data collection and analysis, experimental design, developmental theory, egocentric vision, development of visual object recognition, word learning.
Olaf Sporns 20% effort – Distinguished Professor, Psychological and Brain Sciences, Program in Cognitive Science, Program in Neuroscience. Expertise: Computational neuroscience, connectomics, cognitive function in distributed networks, graph theory, perceptual and motor learning

Martha White 20% effort – Assistant Professor, Computer Science and Informatics. Expertise: Machine learning from large data sets, reinforcement learning, representational learning, artificial intelligence

Chen Yu 20% effort—Professor, Psychological and Brain Sciences, Program in Cognitive Science, School of Informatics and Computing. Expertise: Statistical learning, word learning, egocentric vision, large and temporal data sets, wearable sensors, data mining, perceptual, motor and word learning.
BIOGRAPHICAL SKETCH

Provide the following information for the Senior/key personnel and other significant contributors. Follow this format for each person. **DO NOT EXCEED FIVE PAGES.**

**NAME:** Smith, Linda B.

**eRA COMMONS USER NAME (credential, e.g., agency login):** smith4@indiana.edu

**POSITION TITLE:** Distinguished Professor Psychological and Brain Sciences

**EDUCATION/TRAINING (Begin with baccalaureate or other initial professional education, such as nursing, include postdoctoral training and residency training if applicable. Add/delete rows as necessary.)**

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<td>University of Pennsylvania</td>
<td>Ph.D.</td>
<td>09/77</td>
<td>Cognitive Psychology</td>
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A. **Personal Statement**

For over 30 years I have studied early perceptual, motor, and cognitive development with an emphasis on how these processes influence infants and toddlers learning of their first object names and object categories. **My research program has been continuously funded since my first grant in 1978 (funded by NSF) by NIH and/or NSF since.** I have published over 200 papers. Specifically relevant to this proposal is my program of research studying the role of attention, perception and action, and statistical learning in early word learning, my recent research on ego-centric vision in infants and toddlers, the study of the development of visual object recognition. I am PI of an Institutional Training Grant (NICHD, 5 predoctoral lines, 3 post-doctoral lines now in year 22).

B. **Positions and Selected Honors**


C. **Contribution to Science**

My earliest contributions focused on a unified account of developmental differences in perceptual categorization and perceived similarity of multidimensional stimuli. The work culminated in a mathematical
model of attention and discrimination that explained developmental changes as well as a larger pattern of phenomena in the adult literature understood under the framework of integral and separable dimensions. The theoretical framework has relevance to fundamental problems in category learning, in the development of executive control and in the perception of number.


My second contribution emerged from this earlier work on perceptual classification (and is deeply informed by that work) but focused on how very early word learners were biased to used some dimensions over others when generalizing newly learned words. The phenomenon—sometimes known as the shape bias—suggests that children learn the regularities the underlie classes of categories (artifacts versus substances, for example) and then use these regularities to generalize the name of one learned instance to the whole category. The research—still ongoing—showed how the shape bias depended on word learning, how it supported future word learning, how it was delayed in children with language delay, and how it varied with the linguistic properties of the specific language being learned. My current research is focused on how the development of the shape bias depends on prior advances in visual object recognition, advances, which in turn depend on the visual experiences generated by object manipulation.


A third contribution is in the domain of theory and developmental systems, of how development is multi-causal dependent on complex interactions across levels of analysis and over multiple time scales.


A fourth contribution concerns statistical learning, how very young word learners may learn word-referent pairings by aggregating over individually ambiguous learning experiences.


The fifth contribution is the use of multimodal and dense real time measures to capture first-person—egocentric—visual experiences of the 3-dimensional world as they move and actively explore their world and interact with social partners. This work, using head cameras, head-mounted eye-trackers, and motion sensors has revealed that infant and toddler visual experiences are fundamentally different in their content and in their dynamics, in ways that play a critical role is learning about objects, in social interactions, and in object name learning.


Complete list of published works since 2005 (selected publications since 1975) and PMCID numbers since 2008: [http://www.iub.edu/~cogdev/publications.html](http://www.iub.edu/~cogdev/publications.html)

D. Research Support
Current

R01HD 28675 (PI: SMITH) 08/01/1995 – 07/31/2017
NIH/NICHD The shape bias in children’s word learning.
The major goal of this grant, during the current funding period, is to understand the relation between early changes in shape perception, category learning and early noun learning in typically developing children and in late talkers.

R01 HD074601 (PI: Yu) 6/1/2013 – 5/31/2018
NICHD How the sensory motor dynamics of early parent-child interactions builds word learning
Role: co-PI (Smith, Bates co-PIs, PI Chen Yu)
This research seeks uses dual-head mounted eye-tracking in a longitudinal study of toddlers and parents as they engage with and as parents name objects with the goal of understanding the links between parental responsivity, real-time attentional coordination, and long term outcome in language development.

BCS 1523982 (PI Smith) 12/01/2015 – 11/30/2018
NSF Comp Cog:Collaborative Research on the Development of Visual Object Recognition
This research uses head cameras to capture a corpus of in the home infant perspective scenes to study the visual properties (and natural statistics) of scenes with respect to developmental changes in visual object recognition.

DRL 1621093 (PI:Smith) 09/01/2016 - 6/31/2020
NSF Collaborative Research: Using Cognitive Science Principles to Help Children Learn Place Value

Recently Completed

1R21HD068475-01A (PI: Smith) 01/08/2012 – 12/31/2013
NIH/EYE Embodied attention in toddlers.
This research examines the role of head stabilization and eye-head alignment in stabilized visual attention, and the role of spatially localized visual attention in the learning of 12 to 24 month olds.
Role: PI
David J. Crandall

School of Informatics and Computing
Indiana University
Bloomington, IN 47405
djcran@indiana.edu

Professional Preparation
– The Pennsylvania State University, Computer Engineering B.S., 2001
– The Pennsylvania State University, Computer Science and Engineering M.S., 2001
– Cornell University, Computer Science M.S., 2007
– Cornell University, Computer Science Ph.D., 2008

Appointments
2016 – Associate Professor, School of Informatics and Computing, Indiana University
Core faculty in Computer Science, Informatics, Cognitive Science, and Data Science
2010 – 2016 Assistant Professor, School of Informatics and Computing, Indiana University
2008 – 2010 Postdoctoral Associate, Department of Computer Science, Cornell University
2001 – 2003 Senior Research Scientist, Eastman Kodak Company

Five Related Products

Five Other Significant Products
– David Crandall, Andrew Owens, Noah Snavely, and Daniel Huttenlocher. SfM with MRFs: Discrete-continuous optimization for large-scale structure from motion. IEEE Transactions on


Synergistic Activities
- Area Chair, IEEE Conference on Computer Vision and Pattern Recognition, 2016; Area Chair, IEEE Winter Conference on Applications of Computer Vision, 2016; Co-Chair, International Workshop on Social Web for Environmental and Ecological Monitoring 2016 (at AAAI International Conference on Weblogs and Social Media); Data Challenge Chair, ACM Web Science Conference 2014; program committees of 38 other conferences and workshops.
- Associate Editor, Image and Vision Computing; Associate Editor, Digital Applications in Archaeology and Cultural Heritage; ad-hoc reviewer for 17 other journals.
- Supervised 20 undergraduate research projects including 8 NSF REUs, including a winner of an IU Provost’s Award for Outstanding Undergraduate Research.
- Advise 7 PhD students, serve on 21 Ph.D. student committees; supervised 33 additional M.S. and Ph.D. graduate independent study projects. Developed new courses in probabilistic graphical models and computer vision.
- Serve on committees for: Informatics Undergraduate Curriculum, Undergraduate Research, Diversity Celebration, LGBT Student Support Services outreach.

Collaborators and Co-Editors (28)
Denise Anthony (Dartmouth), Dhruv Batra (Virginia Tech), Johan Bollen (IU), Katy Borner (IU), Kay Connelly (IU), Ying Ding (IU), Alyosha Efros (Berkeley), Geoffrey Fox (IU), John Franchak (UC Riverside), Kristen Grauman (Texas), Salit Kark (University of Queensland), Apu Kapadia (IU), Noam Levin (Hebrew University of Jerusalem), Y unpopular Li (Google), Luca Marchesotti (Xerox), Andrew Owens (MIT), John Paden (Kansas), Maryam Rahnemoonfar (Texas A&M), Josef Sivic (INRIA), Linda Smith (IU), Noah Snavely (Cornell), Emmanuel Munguia Tapia (Samsung), Robert Templeman (NSWC Crane), Peter Todd (IU), Roman Yampolskiy (Louisville), Zhixian Yan (Samsung), Jun Yang (Samsung), Chen Yu (IU).

Graduate and Postdoctoral Advisors (4)
Lee Coraor (PSU), Rangachar Kasturi (USF), Dan Huttenlocher (Cornell), Jon Kleinberg (Cornell).

Thesis Advisor and Postgraduate-Scholar Sponsor (8)
Current grants and contracts

- (PI) NSF Information Integration and Informatics (III), “CAREER: Observing the world through the lenses of social media,” 2013–2018, $547,964 (with $48,000 REU supplements).
- (Co-I) NSF DIBBs, “CIF21 DIBBS: Middleware and High Performance Analytics Libraries for Scalable Data Science,” 2014–2019, $5 million, with Geoffrey Fox, Judy Qiu, Fusheng Wang (Emory), Shantenu Jha (Rutgers), Madhav Marathe (Virginia Tech).
- (PI) for Indiana University’s subcontract from ObjectVideo, for Intelligence Advanced Research Projects Activity (IARPA), on “Visual analysis for image geo-location,” 2012–2016, $359,009.
- (PI) IU Social Science Research Commons, “Big Data Approaches for Characterizing Urban Landscapes and Inequality,” 2016–2017, $15,000, with Tom Evans (IU Geography).

Past grants and contracts

- (PI) NVidia donation of Tesla two K40 boards (approximate value of $10,000).
- (PI) Google Travel Award, 2014, to attend Google I/O and Research at Google, $2,500.
- (Co-PI) IU Collaborative Research Grant, “A Novel Multimodal Methodology to Investigate Communicative Interactions Between Parents and Deaf Infants Before and After Cochlear Implantation,” 2013–2014, $67,000, with Derek Houston, Linda Smith, Chen Yu, David Pisoni, Tonya Bergeson-Dana.
- (Co-PI) IU Faculty Research Support Program, “Understanding active vision and sensorimotor dynamics in autistic and typically developing children,” 2011–2012, $75,000.00. PI: Chen Yu.
- (PI) Lilly Endowment, Inc. and Indiana University Data to Insight Center, “Mining photosharing websites to study ecological phenomena,” 2010 – 2011, $49,838.68.
BIOGRAPHICAL SKETCH

Provide the following information for the Senior/key personnel and other significant contributors. Follow this format for each person. DO NOT EXCEED FOUR PAGES.

NAME
Goldstone, Robert

POSITION TITLE
Chancellor’s Professor of Psychological and Brain Sciences

eRA COMMONS USER NAME (credential, e.g., agency login)

EDUCATION/TRAINING (Begin with baccalaureate or other initial professional education, such as nursing, include postdoctoral training and residency training if applicable.)

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<td>1986</td>
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<td>University of Illinois – Urbana Champaign</td>
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<td>University of Michigan – Ann Arbor</td>
<td>Ph.D.</td>
<td>1991</td>
<td>Psychology</td>
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NOTE: The Biographical Sketch may not exceed four pages. Follow the formats and instructions below.

A. Personal Statement

My laboratory’s research is on how long-term learning, for example protracted perceptual learning, affects the information that people extract from a particular learning situation. For example, infants create perceptual units from their experiences, and then use these formed units to construct their experiences that follow (Needham, Goldstone, & Wiesen, 2014). Another example of our research bridging multiple scales is a recurring thread that we humans gradually change our perceptual and attention systems to become better high-level reasoners in math and science. We are interested in bridging putatively “low level” perceptual and attention processes with higher-level cognition (Goldstone, Landy, & Brunel, 2011). Consistent with the research thrust in applied education research, we have pursued three areas of application of our theorizing about learning processes. First, we have designed tutoring systems in mathematics based on our “Rigged up Perception and Action Systems” framework (Goldstone, Landy, & Son, 2010). Second, we have proposed general principles like concreteness fading for improving educational outcomes (Fyfe, Mcneil, Son, & Goldstone, 2014). Third, we have studied general factors related to similarity, ordering, presentation format, and instructions that can speed students’ learning of concepts in science (Braithwaite & Goldstone, 2013; Carvalho & Goldstone, 2104)

B. Positions and Honors

Positions and Employment
Assistant Professor, Indiana University, 1991-1996
Associate Professor, Indiana University, 1996-1998
Full Professor, Indiana University, 1999-2016
Director of the Indiana University Cognitive Science Program, 2006-2010

Other Experience and Professional Memberships
Member of the Board on Behavioral, Cognitive, and Sensory Sciences, National Research Council, National Academy of Sciences. 2014
Member of National Research Council Committee for “How People Learn II: The Science and Practice of Learning,” 2015-2016.
American Psychological Association’s editor search committee for Psychological Review, 2013-2014
Founding Chair of the Glushko Prize for Outstanding Doctoral Dissertations in Cognitive Science, 2010-2013
Rumelhart Prize Selection Committee, 2007-2011 (Chair: 2009-2011)
Associate Editor of Cognitive Psychology, 2007-2016
Executive Editor of Cognitive Science, 2001-2005; Board of Reviewers, 2006-2016
Senior Editor of Topics in Cognitive Science, 2007-2016
Scientific advisor for the Network for Sensory Research (Mohan Matthen, PI), 2011-2016
Member of Department of Education, Institute of Education Sciences, Postdoctoral Research Training Proposals grant review panel, 2010
Member of Department of Education, Institute of Education Sciences, Basic Cognitive Processes, permanent grant review panel (review panel meetings twice per year), 2009-2011
Member of Advisory Board of GlassLabs Games, SRI, 2013-2014.
Member of Advisory Board for Fostering Interdisciplinary Research on Education, NSF grant, Purdue University, 2010-2012
Member of Advisory Board on the PhET Middle School DRK12 project, Department of Education, University of Colorado, 2010-2014
Advisory board member for UCSD’s NSF Science of Learning Center on “Temporal Dynamics of Learning,” 2006-2010
Advisory board member for the Pittsburgh NSF Science of Learner Center, 2007-2014 (Chair: 2009-2014)
Advisory Board for the Institute for Intelligent Systems, University of Memphis, 2015-2016
Advisory Board for the Generalized Intelligent Framework for Tutoring (GIFT), University of Memphis and Army Research Laboratory, 2014-2016
Review panel, National Science Foundation, Directorate of Education and Human Resources; Division of Research, Evaluation, and Communication; Research On Learning and Education (ROLE) 2002, Winter and Summer (chair)
Associate Editor for Psychonomic Bulletin and Review, 1998-2000

Honors
Marquis Award for Most Outstanding Dissertation in Psychology, University of Michigan, 1991
American Psychological Association (APA) Division of Experimental Psychology 1995 Young Investigator Award in Experimental Psychology: Learning, Memory, and Cognition.
American Psychological Association (APA) Division of Experimental Psychology 1995 Young Investigator Award in Experimental Psychology: General.
James McKeen Cattell Sabbatical Award, 1997-1998
American Psychological Association (APA) Distinguished Scientific Award for Early Career Contribution to Psychology in the area of Cognition and Human Learning, 2000
National Academy of Sciences Troland research award for “novel experimental analyses and elegant modeling that show how perceptual learning dynamically adjusts dimensions and boundaries of categories and concepts in human thought”, 2004
Elected Fellow of the Society of Experimental Psychologists, 2004
Elected Fellow of the Cognitive Science Society, 2006
Elected Fellow of the Association for Psychological Science, 2007

C. Selected Peer-reviewed Publications (selected from 267 publications)


D. Research Support

"Teaching the visual structure of algebra through dynamic interactions with notation" (R305A1100060), Department of Education, Institute of Education Sciences, (PI: David Landy, University of Richmond; Indiana University sub-contract PI: Robert Goldstone), $1,092,484 ($683,492 to Indiana University), May 2011-April 2015.


BIOGRAPHICAL SKETCH

Provide the following information for the Senior/key personnel and other significant contributors in the order listed on Form Page 2. Follow this format for each person. DO NOT EXCEED FOUR PAGES.

NAME
James, Karin Harman

POSITION TITLE
Associate Professor of Psychology

eRA COMMONS USER NAME (credential, e.g., agency login)
khjames

EDUCATION/TRAINING (Begin with baccalaureate or other initial professional education, such as nursing, include postdoctoral training and residency training if applicable.)

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<td>University of Western Ontario</td>
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<td>05/01</td>
<td>Experimental Psychology</td>
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<tr>
<td>Vanderbilt University</td>
<td>Postdoctoral</td>
<td>08/04</td>
<td>Experimental Psychology</td>
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A. Personal Statement.
A significant proportion of my research program centers upon how learning through manual interaction with the world creates and changes cognitive development. Since 2008, I have been specifically investigating how handwriting experience changes both behavior and brain systems of pre-literate children. As such, I have significant experience investigating both reading and handwriting processes in young children and in adult populations. I also have expertise regarding recruitment, experimental protocol, design, data analyses, and data interpretation of scientific studies on developing populations. My research program uses cross-sectional, micro-genetic and longitudinal designs to research questions in children aged 18 months to 18 years. My research has been funded by both the NIH and NSF as well as internal grants. My federally funded work is collaborative, both internally and externally, providing me with experience with working within a research team. Given my experience, my contribution to the current proposal is significant and I will be the primary investigator on these research studies. The following publications are a sampling of this work (role: senior author).

* American Psychological Association Spotlight paper, May, 2016
e. Vinci-Booher, S. James, T. & James, K.H. (in press). Functional connectivity among visual and motor regions is enhanced with handwriting, but not typing, experience in the pre-literate child. Trends in Neuroscience and Education.
For a list of all publications, see: [http://www.ncbi.nlm.nih.gov/sites/myncbi/1LY4bkKzV-05d/bibliography/48069806/public/?sort=date&direction=ascending](http://www.ncbi.nlm.nih.gov/sites/myncbi/1LY4bkKzV-05d/bibliography/48069806/public/?sort=date&direction=ascending)

B. Positions and Honors

**Positions and Employment**

2004-2007  Research Scientist, Indiana University, Psychological and Brain Sciences  
2007-2013  Assistant Professor, Indiana University, Psychological and Brain Sciences  
2013-present  Associate Professor, Indiana University, Psychological and Brain Sciences

**Other Experience and Professional Memberships**

1998-2000  Canadian Society for Brain, Behaviour and Cognitive Science  
1998-2000  Association for Research in Vision and Ophthalmology  
2000-  Vision Sciences Society  
2004-  Cognitive Neurosciences Society  
2007-  Society for Research in Child Development  
2008-  Cognitive Development Society


C. Contributions to Science

1. How handwriting experience affects literacy skills. Illiteracy is a major problem in the United States, with only 60% of children reaching basic literacy skills by 4th grade. Even though the highest predictor of literacy in fourth grade is letter knowledge in preschool, few attempts have been made to systematically investigate how to increase letter knowledge skills in preschool. In 2010 I found that by training preschool children to print letters by hand, when asked to subsequently perceive letters, networks were activated in the brain that are used for reading in the literate adult. These networks were not active after children typed letters or learned letters through other forms of practice such as tracing or visual only study. These findings were replicated and extended to show that only self-generated handwriting (not watching others) activated this network after training. Through this research program, I was also the first investigator world-wide to acquire functional MRI data from 4 year-old children. This research has resulted in numerous invited talks, invited book chapters, media (Wall Street Journal, New York Times etc), and general interest from school boards and educators country-wide. My role in this research is as the principle investigator. I design and execute the experiments, analyze the data, interpret and disseminate the findings. The results of this work have the potential to change the way we teach children about letters, and can have a significant impact on pre-literacy skills and on educational curriculum.

2. The effects of active learning on subsequent cognitive processing. With a few notable exceptions (Gibson, Piaget), the effects that our bodily actions have on how we perceive the world was not a common motivation for understanding cognition until the recent popularity of the theory of embodied cognition. Prior to the spread of the embodied movement, my research was motivated by the question of how our manual interactions with objects shaped object recognition. I showed through various methodologies (human-computer interaction, virtual reality environments, psychophysical thresholding, and functional neuroimaging) that if we manipulate objects through self-generated action, we are better able to recognize those objects upon subsequent visual perception than if we passively watch the same object movement. Thus, self-generated action is key for enhancing learning. Further, I investigated the mechanisms that underlie these effects in adults and children, using fMRI. I continue to research this theme in adults and throughout development – the idea is pervasive thread that winds throughout my research projects. In adult populations, we have now shown the ubiquity of the benefits of active learning: It happens through computer-controlled action, manual action, can affect visual, auditory and multisensory processing. I have served as the primary investigator on all of these studies, and have trained 3 graduate students through this work. Four of approximately 12 publications on this topic are listed below.


3. The development of vision for action in the toddler. Developmental psychologists have seldom considered the effects of how infants and toddlers hold, turn, and manipulate objects on how they understand object structure for visual processing. Through a five-year, NIH R01 grant, on which I was P.I., we studied the effects that toddlers' actions had on visual competencies. We found that toddlers were able to perform visually guided actions, before they could make perceptual judgments, indicating the relative maturity of the action system that drives visual perception. We further found that toddlers' self-generated manipulation of objects developed from an immature, somewhat random pattern, to a well organized, adult pattern between 18 and 24 months of age. These manipulations were biased towards perceiving particular views of objects and were correlated with higher object recognition abilities, independent of age. This research contributes to the general idea that actions on objects change visual processing and that self-generated actions create the information upon which we develop mature object representations.


4. The embodiment of language processing. Traditionally, language has been thought to recruit a specific temporal-frontal processing network in the brain that is described as being amodal, or independent of sensorimotor systems. However this changed when researchers showed that action words were processed in motor systems that were effector-specific. I was interested to see whether or not this motor activation was experience dependent, that is, did it exist early in development prior to an extensive action repertoire, and would it change with training. First we documented that 5 year-old children also recruited the motor system
when hearing verbs, similar to the adult brain. Next, we showed that this activation was only created when children learned verbs through their own self-generated actions, not by watching a model. We have extended these findings to show that even novel sounds that are not from the known language can recruit these same sensorimotor systems, but only if the child learns them through self-generated actions. These projects demonstrate that associative learning – co-occurrence of action and perception in time - change brain processing – not only on a cellular level, but on a macro- level as well, and have pervasive effects on neural systems.


C. Research Support

Current and Pending Research Support

External:
National Science Foundation (NSF), 064707-00002B (2014-2018)
The role of gesture in word learning: Collaborative Research.
Co-PIs: James, K.H., & Goldin-Meadow, S. (University of Chicago)
Goals: To investigate the relationship between transitive action and representational gesture processing in the neural systems of young children. Responsibilities include all functional neuroimaging design, implementation, data analyses, interpretation and dissemination of findings.
National Institutes of Health P50 Center grant #HD071764 (2012-2017)
“Defining and Treating Specific Written Language Learning Disabilities”
Goals: A multidisciplinary, long term project centered upon the definition and intervention of reading and writing disabilities. My specific role is as external advisor on functional neuroimaging portions of the project, mostly surrounding pediatric neuroimaging.
NIH Training Grant “Integrative study of developmental process”
Role: Co-PI (P.I. Linda Smith)
Goals: A multi-investigator, multi-disciplinary project, in its 15th year, that strives to define developmental process across numerous domains. The focus is on training developmental scientists in theory, research methods and professional development. My role is as organizer/instructor of weekly seminar and a supervisory role for students and post-doctoral fellows interested in functional neuroimaging in pediatric populations.
Clinical and Translational Science Institute Core Facility Grant
Modern diffusion-weighted MRI protocol and analyses for early profiling and detection of reading disabilities in preschool children.
Role: Co P.I (with Franco Pestilli)
Goals: to track the development of both functional and structural brain changes as children learn to read form ages 4-7. Role: Design, implementation, data analyses and dissemination of results.

Internal:
Faculty Research Support Program
Interactions of sensory and motor processes in the brain
Goals: to understand the interaction among action and visual processing using a well-known psychophysical adaptation paradigm.
Role: Collaborator. P.I. Dr. Hannah Block

**Indiana University Imaging Research Facility Pilot Program**

- The development of neural systems used for handwriting

Goals: This project tracks neural change in preschool children as they learn to write by hand.
Role: Principle investigator

- Neuroimaging studies of the effects of writing on early mathematical understanding

Goals: To understand how different writing styles of 3-digit numbers affects neural processing of letters and numbers.
Role: Principle investigator

- Effects of active learning on word meaning

Goals: To investigate neural processing of words based on several types of semantic categorizations.
Role: Principle investigator
Sriraam Natarajan, Ph.D.

Professional Preparation

• B.E in Computer Science, University of Madras 2001. Honors: First class with distinction
• M.S in Computer Science, Oregon State University, 2004: "Multi-Criteria Average Reward Reinforcement Learning” (Advisor: Prasad Tadepalli)
• Ph.D. in Computer Science, Oregon State University, 2007: "Effective Decision-Theoretic Assistance Through Relational Hierarchical Models” (Advisor: Prasad Tadepalli)

Appointments

• Associate Professor, School of Computing and Informatics, Indiana University, Bloomington, IN [July 2016- Present].
• Assistant Professor, School of Computing and Informatics, Indiana University, Bloomington, IN [August 2013- June 2016].
• Visiting Assistant Professor, School of Computing and Informatics, Indiana University, Bloomington, IN [June 2013-July 2013].
• Assistant Professor, Wake Forest University School of Medicine, Winston-Salem, NC: Translational Science Institute [Dec 2010-May 2013].
• Assistant Professor, Wake Forest-Virginia Tech School of BioMedical Engineering and Sciences, Winston Salem, NC [Dec 2010-May 2013].
• Adjunct Assistant Professor, Department of Compute Science, Wake Forest University, Winston Salem, NC [June 2011-].
• Visiting Assistant Professor, Department of Compute Science, University of North Carolina, Charlotte, NC [June 2011-May 2013].
• Post-Doctoral Research Associate, University of Wisconsin-Madison, Wisconsin: Department of Biostatistics and Medical Informatics [Jan 2008-Nov 2010].

Related Publications

Other Significant Publications


5. Sriraam Natarajan, Prasad Tadepalli and Alan Fern, A Relational Hierarchical Model of Decision-Theoretic Assistance Knowledge and Information Systems (KAIS) 2011.

Representative Synergistic Activities

- Editorial Board Member, Journal of AI Research (JAIR), Data Mining and Knowledge Discovery (DMKD)
- Electronic Publishing Editor Journal of AI Research (JAIR)
- Co-chair, AAAI Student Activities Program 2016, 2017
- Co-chair, AAAI Student Abstracts 2014, 2015
- Senior Program Committee Member, IJCAI '15, '16, '13, ECML '16 AISTATS '15
- Program Committee Member, ICML '16, '15, '13,'12,'11, '10, '09, '08 IJCAI 11,'09, AAAI '17, '15, '14,'13,'12,'11,'10, '08, ECML '14,'13,'12, UAI '13 ILP '13

Active Grants

- NIH R01 Machine Learning for Identifying Adverse Drug Events 07/01/15-06/20/20 $335,000 (my share) Role: Co-PI. PI: David Page
- DARPA Communicating with Computers 08/1/15 - 07/31/20 $419,002 (my share) Role: Co-PI. PI: Dan Roth Co-PI: Martha Palmer, Jana Doppa, Julia Hockenmaier.
- ARO Young Investigator Human-in-the-loop Statistical Relational Learners 9/1/13- 08/31/16 $150,000 Role: PI
- DARPA DEFT 11/1/12 - 05/31/17 $300,000 (my share) Role: Co-PI. PI: Jude Shavlik Co-PI: Chris Re.
• Turvo Inc, research gift: Learning for logistics problems 4/1/15-03/31/18
  $225,000. Role: PI

• XEROX PARC Faculty Award: Learning from an Expert in Noisy, Structured domains: Adapting to Healthcare Problems 1/15/15
  $90,000 Role: PI - 12/31/17

• AFOSR SBIR: Enhanced Text Analytics Using Lifted Probabilistic Inference Algorithms 10/1/13
  $280,000 Role: Co-PI - 10/30/16

• NIH Adverse Drug Events 10/1/11 - 10/1/14
  $95,000 Role: Sub-contract from University of Wisconsin. PI: David Page

Completed Grants

• DARPA Machine Reading 4/1/11 - 12/31/12
  $128,500 Role: Subcontract from SRI International. PI: David Israel.

• NIH Subsystem Modeling Using Dependency Networks 9/1/2012 - 8/31/2013
  $10,000 Role: Co-I. PI: Edward Ip

• WFU Science Research Fund 10/1/11 - 4/30/12
  $8,000 Role: PI

Pending Grants

• DARPA Human is more than a labeler: Curating Probabilistic Logic Models with Human Advice 10/01/16-09/30/20
  $530,714 Role: PI.

• IARPA Guiding Probabilistic Learning in Relational Domains with Crowd-Sourced STs 09/01/16-06/20/20
  $800,000 Role: PI.

• ARO Human-Machine Collaboration in Relational Sequential Decision-Making Problems 01/01/17-09/30/17
  $60,000 Role: PI.

Collaborators and Other Affiliations

• Collaborators: R. Balaraman (IIT Madras, India), H.H. Bui (SRI International), R. de Salvo Braz (SRI International), A. Fern (Oregon State), K. Hauser (Duke University), K. Kersting (Technical University Dortmund, Germany), D. Page (UWisc-Madison), R. Parr (Duke University), D. Poole (University of British Columbia), J. Shavlik (UWisc-Madison)

• Graduate Advisor: P. Tadepalli (Oregon State)
BRIEF BIOGRAPHY

After receiving an undergraduate degree in biochemistry, Olaf Sporns earned a PhD in Neuroscience at Rockefeller University and then conducted postdoctoral work at The Neurosciences Institute in New York and San Diego. Currently he is the Robert H. Shaffer Chair, a Distinguished Professor, and a Provost Professor in the Department of Psychological and Brain Sciences at Indiana University in Bloomington. He is co-director of the Indiana University Network Science Institute and holds adjunct appointments in the School of Informatics and Computing and the School of Medicine. His main research area is theoretical and computational neuroscience, with a focus on complex brain networks. In addition to over 200 peer-reviewed publications he is the author of two books, “Networks of the Brain” and “Discovering the Human Connectome”. He currently serves as the Founding Editor of “Network Neuroscience”, a journal published by MIT Press. Sporns was awarded a John Simon Guggenheim Memorial Fellowship in 2011 and was elected Fellow of the American Association for the Advancement of Science in 2013.

CONTACT

Olaf Sporns, PhD
Department of Psychological and Brain Sciences  
1101 East 10th Street  
Indiana University  
Bloomington, IN 47405  
Office: PSY 360  
Lab: PSY A308  
Homepage: http://www.indiana.edu/~cortex  
osporns@indiana.edu (email)  
Twitter: @spornslab

RESEARCH INTERESTS

Connectomics  Analysis of neuroanatomical connection patterns, relation of brain structure to functional connectivity, complexity of neural dynamics, human neuroimaging and clinical disorders, network evolution and growth, network damage and repair.

Computational Neuroscience  Dynamic models of brain networks, neural synchrony and binding, information-theoretical measures of functional interactions, models of cognitive systems, neuroinformatics.

Cognition  Cognitive function in distributed networks, dynamics of functional connectivity in brain imaging, embodied cognition, consciousness.

EDUCATION

1983-1986  Undergraduate studies in Biochemistry at Eberhard-Karls-Universität Tübingen, Germany.
1984-1986  Research Assistant at the Max-Planck-Institute for Developmental Biology, Tübingen.  
Research on the role of cholinesterases in brain development in the laboratory of Dr. Paul G. Layer.
1986  B.S. Biochemistry, Eberhard-Karls-Universität Tübingen, Germany.
1986  Research Assistant, Shanghai Institute of Cell Biology, Chinese Academy of Sciences.
1986-1990  Graduate studies at Rockefeller University, New York, NY.  
Research carried out in the Laboratory of Molecular and Developmental Biology and at The Neurosciences Institute.
1990 Ph.D. Neuroscience, Rockefeller University, New York.
Dissertation: “Synthetic neural modeling: computer simulations of perceptual and motor systems”.
Research Advisor: Prof. Gerald M. Edelman.

HONORS AND AWARDS

2001 Pew Scholars in Biomedical Sciences, Nominee for Indiana University.
2002 Outstanding Paper Award, International Conference on Development and Learning ICDL 02, MIT.
2002 Outstanding Junior Faculty Award, Indiana University Bloomington.
2004 Trustees Teaching Award, Indiana University Bloomington.
2008 Distinguished Faculty Award, College of Arts and Sciences, Indiana University Bloomington.
2011 Neuroimage “Editor’s Choice Award”, Methods and Modeling Section, shared with M. Rubinov
2011 Provost Professorship, Indiana University
2011 John Simon Guggenheim Memorial Fellowship
2013 Fellow of the American Association for the Advancement of Science (elected)
2014 Distinguished Professor, Indiana University
2014 Robert H. Shaffer Endowed Chair
2015 Trustees Teaching Award, Indiana University Bloomington
2015 Thomson Reuters “Highly Cited Researcher” in Neuroscience/Behavior
2015 Thomson Reuters: Listed as one of “The World’s Most Influential Scientific Minds” in Neuroscience/Behavior
2016 Distinguished Cognitive Scientist Award, UC Merced
2016 Grossman Award, Society of Neurological Surgeons

MAJOR GRANTS (FUNDED)

Completed

2002-2005 “Neuro-Robotic Models of Learning and Addiction”, NIH-NIDA R21 DA1564, PI
2011-2013 “Communities and Criticality in Brain Networks across Development and ADHD”, James S. McDonnell Foundation, Co-investigator (PI: Steve Petersen)
2010-2015 “Mapping the Human Connectome: Structure, Function, and Heritability”, NIH Blueprint Project, Co-Investigator (Pls: David Van Essen, Kamil Ugurbil)

Current

2012-2016 “Connectivity and Information Flow in a Complex Brain”, National Science Foundation, Co-Investigator (Pl: Ralph Greenspan)
2015-2018 “CRCNS: Linking Connectomics and Large-Scale Dynamics of the Human Brain”, National Institutes of Health, NCCIH, PI.
Books


Papers (from most recent)


David H. Landy

Professional Preparation
Alma College  Physics, Mathematics & CS  Alma, MI  B.S/B.A.1999
Indiana University  Cognitive Science/CS (joint degree)  Bloomington, IN  M.S. 2007
UIUC  Cognitive Science (Postdoctoral)  Urbana-Champaign, IL  2009

Appointments
2013-Present  Current Assistant Professor, Cognitive Science Department, Indiana University
2009-2013  Assistant Professor, Psychology/Cognitive Science Department, University of Richmond, Richmond, VA
2007-2009  Assistant Professor, Cognitive Science Department, Indiana University, Bloomington, IN

Products
Products Most Closely Related


Other Significant Products


**Synergistic activities**

**Professional Service:** Associate editor of *Cognitive Science Journal* (2015-present); Program Committee Member, *Cognitive Science* (2010-2015); Ad hoc reviewing for *Cognition, Journal of Experimental Psychology: Learning, Memory, & Cognition; Cognitive Psychology; Quarterly Journal of Experimental Psychology; Developmental Psychology; Cognitive Systems Research; Topics in Cognitive Science*

**Public Outreach:** Developer of two middle-school algebra design tools, *Algebra Touch* (Berry Software) and *Graspable Math* (Graspable, Inc), available for iOS and Chrome browsers, and used by over 400,000 learners.

**Teaching:** Developed courses in Cognitive Psychology, Cognitive Science, and the role of Cognition in Education, focusing on the teaching of mathematical and numerical reasoning.

**Collaborators & other affiliations**

**Collaborators and Co-Editors:**
Robert Goldstone (Indiana University), Erin Ottmar (Worcester Polytechnic Institute), Timothy Salthouse (University of Virginia), Colin Allen (Indiana University), Michael Anderson (Franklin & Marshall College), David Brookes (Florida International University), Lionel Brunel (Universite Paul-Valery Montpelier III), Arthur Charlesworth (University of Richmond) Zach Davis (University of Richmond), L. Elizabeth Crawford (University of Richmond), Aleah Goldin (N/A), Brian Guay (Duke University), Taylyn Hulse (University of Richmond), Jessica Lesky (Indiana University), Jaclyn Pierce (University of Richmond), Brad Rogers, (Indiana University), Noah Silbert (University of Cincinnati), Ryan Smout (N/A), Erik Weitnauer (Indiana University) Carlos Zednick (University of Osnabruck) Total = 23

**Graduate and Post-Doctoral Advisors:**
Michael Gasser (Indiana University), Robert L. Goldstone (Indiana University) Total = 2

**Thesis Advisor/Sponsor (Past 5 years):**
Brad Rogers (Indiana University Graduate Advisor), Caroline Williams (University of Wisconsin, Madison, External Doctoral Advisor), Erin Ottmar (University of Richmond, Post-doctoral sponsor), Erik Weitnauer (Indiana University, Post-doctoral sponsor), Tyler Marghetis (Indiana University, Post-doctoral sponsor). Total = 4
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<td>Project/Proposal Title: <strong>The Efficacy of From Here to There!: A Dynamic Technology for Improving Algebraic Understanding</strong></td>
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<td>Source of Support: Worcester Polytechnic Institute, Subaward from IES Goal 3</td>
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<tr>
<td>Total Award Amount:</td>
<td>Total Award Period Covered: 07/01/2017 to 06/15/2020</td>
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<td>Location of Project: Worcester, MA and Bloomington, IN</td>
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<td>Person-Months Per Year Committed to the Project:</td>
<td>Cal: 2</td>
<td>Acad: 1</td>
<td>Sumr: 1</td>
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<td>[ ] Current</td>
<td>[x] Pending</td>
<td>[ ] Submission Planned in Near Future</td>
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<td>Project/Proposal Title: <strong>Supporting Algebraic Literacy Through Distributed Dynamic</strong></td>
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<tr>
<td>Source of Support: IES CASL, Goal 2</td>
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<td>Total Award Amount: $1.4M</td>
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<tr>
<td>Person-Months Per Year Committed to the Project: Cal: 2</td>
<td>Acad: 0</td>
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</tbody>
</table>
Biographical Sketch: Michael N. Jones, Ph.D.

1. Professional Preparation

<table>
<thead>
<tr>
<th>Institution</th>
<th>Field of Study</th>
<th>Degree/Years</th>
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<tbody>
<tr>
<td>Nipissing University</td>
<td>Psychology</td>
<td>BA, 1995-1999</td>
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<tr>
<td>Queen’s University</td>
<td>Psychology</td>
<td>MA, PhD, 1999-2005</td>
</tr>
<tr>
<td>University of Colorado, Boulder</td>
<td>Cognitive Science</td>
<td>Postdoc, 2005-2006</td>
</tr>
</tbody>
</table>

2. Appointments

2015-Pres: William and Katherine Estes Endowed Chair of Cognitive Modeling
2013-Pres: Associate Professor of Psychology and Cognitive Science; Indiana University
            Adjunct Associate Professor of Informatics and Computing; Indiana University
2006-2013: Assistant Professor of Psychology and Cognitive Science; Indiana University
2005-2006: NSERC Postdoctoral Research Fellow at the Institute of Cognitive Science,
            University of Colorado at Boulder (Advisors: Tom Landauer and Walter Kintsch)

3. Research Foci

Computational models of memory and language; Big data science approaches to cognitive science; Knowledge-based intelligent systems; Computational synthesis of neuroimaging data; Statistical methodology for analyzing large-scale data.

4. Selected Honors and Related Experience

National Science Foundation CAREER Award
Psychonomic Society Outstanding Early Career Award
Federation of Associations in Behavioral and Brain Sciences Early Career Investigator Award
Google Faculty Research Award
Indiana University Outstanding Junior Faculty Award
NSERC Julie Payette Research Scholarship

5. Selected Leadership Positions

Editor-in-Chief, Behavior Research Methods (2014-2018)
Associate Editor, Journal of Experimental Psychology: General (2012-2014)
President, Society for Computers in Psychology (2011-2014)
Secretary-Treasure, Society for Computers in Psychology (2008-2011)
Chair, Psychonomic Society Digital Content Editor Search Committee (2014)
Editor, Big Data in Cognitive Science. Psychology Press (Taylor & Francis)

6. Selected Publications (selected from 70 peer-reviewed publications)

* I am bold, graduate students/postdocs working under my supervision are italicized.


7. Synergistic Activities

Service: Secretary-Treasurer (4 years) and President (3 years) of Society for Computers in Psychology (SCiP); Currently Experts and Industry Liaison for SCiP; Currently Editor-in-Chief of *Behavior Research Methods*, the leading methods and modeling journal in the field of psychology; Previously Associate Editor for *Journal of Experimental Psychology: General*, top journal in field of experimental psychology; NSF panelist on Computational Cognition/Cyber-Human Systems/Robust Intelligence programs; Member of NSF College of Reviewers; Chair of Psychonomic Society Digital Content Editor Search Committee; Have organized over a dozen high-profile symposia at international conferences.

Instruction: Have organized several Big Data workshops and symposia at major conferences, and have given tutorials to public and industry (including Google, Motorola, PayPal, Intel) on integrating cognitive models with machine intelligence to tackle practical tasks in industry. I am Editor of *Big Data in Cognitive Science: From Methods to Insights*, a book due out at the beginning of next year that contains tutorials on big data techniques from informatics for cognitive scientists. My students have won several prestigious awards, including the Marr Award, Castellan Award, and several NSF/NSERC fellowships.

Translational: I have applied my cognitive models to early detection of Alzheimer’s disease from Electronic Health Records with the IU School of Medicine. Algorithms containing my convolution-based semantic models are also used in educational tools used in classrooms (embedded in Summary Street™), and in automated methods for scoring open-ended inference questions in postsecondary education settings. My BEAGLE model is also being used to mine concepts and map them to brain activations from the full Neuroimaging literature as part of Neurosynth.org (funded by NIH).

8. Sample Grant Funding (from $5.1 million funding to date)


2010-2012: Google Research Award: “Exploring Perceptually Grounded Vector Space Models of Semantic Representation” (PI), $50,000 direct costs.
Education


Publications (sample from most recent)


**Research grants**

**Funded**

*Title: Improved accuracy for anatomical mapping and network structure of the Alzheimer’s brain. Source: Indiana Clinical and Translational Sciences Institute (CTSI) Total Award Amount: $200,000 Dates: 09/01/2015-08/31/2017*

Title: Modern diffusion-weighted MRI protocol and analyses for early profiling and
detection of reading disabilities in preschool children

Source: Indiana Clinical and Translational Sciences Institute (CTSI) Total Award
Amount: $10,000 Dates: 01/01/2016-12/31/2017 PI F. Pestilli and K. James

Pending

Title: Connectome mapping methods to study the computational significance of
largescale brain connection patterns in predicting attention, object processing and
cognitive performance. Source: Office of Naval Research Young Investigator
Program Location: Indiana University

Total Award Amount: $560,000 Dates: 09/01/16-08/31/19 PI F. Pestilli.

Title: NCS-FO: Precision connectome mapping of networks involved in attention and
object processing in individual human brains. Source: National Science Foundation
SMA - IntgStrat Undst Neurl & Cogn Sys Location: Indiana University

Total Award Amount: $871,000 ($845,000 to IU) Dates: 09/01/16-08/31/20 PI F. Pestilli.
co-PI S. Ling (Boston University), Craig Stewart (Indiana University).

Title: Advanced Computational Neuroscience Network (ACNN). Letter of Intent. Source:
National Science Foundation (Special Program from Big Data Hub in the Midwest)
Location: Collaborative Proposal. U. Michigan, Indiana University, Northwestern
University, Ohio State University, Case Western University Total Award Amount:
$1,000,000 ($332,000 to IU) Dates: 09/01/16-08/31/19 PI R. Gonzalez, U. Michigan, co-
PI Ivo Dinov and George Adler (U. Michigan), PI F. Pestilli. co-PI O. Sporns, A. Saykin,
(Indiana University), Lei Wang (Northwestern University, IL), PI S. Sahoo (Case
Western), DK Panda and X. Lu (Ohio State University)

Title: Harnessing connectome evaluation methods to map brain networks in individual
brains. Source: Brain and Behavior Foundation (NARSAD) Young Investigator
Grant Location: Indiana University Total Award Amount: $70,000

Dates: 09/01/16-08/31/19 PI F. Pestilli.

Title: AitF: A multidimensional framework for brain data representation and machine-
learning algorithms development with application to study human connectomes. Source:
National Science Foundation Location: Indiana University

Total Award Amount: $799,420 Dates: 09/01/16-08/31/20 PI F. Pestilli. co-PI M. White
(Indiana University).
Biographical Sketch

Michael S. Ryoo

School of Informatics and Computing, Indiana University Bloomington
e-mail: mryoo@indiana.edu, tel: +1-812-855-9190

Education

The University of Texas at Austin; Electrical & Computer Engineering; Ph.D., 2008
The University of Texas at Austin; Electrical & Computer Engineering; M.S., 2006
Korea Advanced Institute of Science and Technology (KAIST); Computer Science; B.S., 2004

Appointments

2015–now : Assistant Professor, School of Informatics and Computing, Indiana University Bloomington
2011–2015: Research Staff, Robotics Section, NASA’s Jet Propulsion Laboratory (JPL)
2008–2011: Research Scientist (military service), Electronics and Telecommunications Research Institute (ETRI), South Korea

Related Publications


Other Significant Publications

(among a total of 30+ conference and 10 journal publications)


Synergistic Activities


2. Tutorial Organizer. Tutorial on Emerging Topics in Human Activity Recognition, IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Columbus, OH, June 2014. (Speakers: M. S. Ryoo, Ivan Laptev, Greg Mori, Sangmin Oh)
   (Organizers: K. Kitani, Y. J. Lee, M. S. Ryoo, A. Fathi)

   (Speakers: M. S. Ryoo, Anthony Hoogs, Arslan Basharat, Sangmin Oh)

   (Speakers: J. K. Aggarwal, M. S. Ryoo, K. Kitani)

6. Workshop Organizer. ICPR Contest on Semantic Description of Human Activities (SDHA), International Conference on Pattern Recognition (ICPR), August 2010.  
   (Organizers: M. S. Ryoo, J. K. Aggarwal, A. K. Roy-Chowdhury)

**Funding - Current grants and contracts**

1. **(PI)** ICT R&D program of South Korean Ministry of Science, “Recognizing Objects and Events from Videos for XD-Media Special Effects”, 2016.01˜2018.12, ∼$330,000 for 36 months, with Electronics and Telecommunications Research Institute (ETRI, Korea).

2. **(co-PI)** DARPA’s Simplifying Complexity in Scientific Discovery (SIMPLEX), Task “Action Recognition and Learning from a First-Person View,” 2015.03˜2018.05, ∼$250,000 for 39 months, with S.-C. Zhu (UCLA).

3. **(PI)** ARL’s Robotics Collaborative Technology Alliance (RCTA), Sub-task P5-5 “Human Activity Recognition with Context Learning,” 2016.01˜2016.12, $60,000 (2017˜2019 funding amount TBD).

**Funding - Past funding**

1. **(PI)** NVIDIA hardware donation program, September 2015.


**Collaborators & Other Affiliations**

**Collaborators and Co-Editors:**
Alireza Fathi (Apple Co.); Thomas J. Fuchs (Memorial Sloan Kettering Cancer Center); Yumi Iwashita (Kyushu University, Japan); Christopher Kanan (Rochester Institute of Technology); Kris Kitani (Carnegie Mellon University); Yong Jae Lee (UC Davis); Larry Matthies (Jet Propulsion Laboratory); Brandon Rothrock (Jet Propulsion Laboratory); Lu Xia (Amazon Co.); Song-Chun Zhu (UCLA)

**Graduate Advisors:** J. K. Aggarwal (University of Texas at Austin)

**Graduate Advisees:** Alexander Seewald (Indiana University - PhD student); AJ Piergiovanni (Indiana University - PhD student); Jangwon Lee (Indiana University - PhD student)
1. Professional preparation

- B.S., Mathematics, University of Alberta, Edmonton, Canada, 2008.
- B.S., Computing Science, University of Alberta, Edmonton, Canada, 2008.
- Ph.D., Computing Science, University of Alberta, Edmonton, Canada, 2015.

2. Appointments

01/2015 — present Assistant Professor, Department of Computer Science, School of Informatics and Computing, Indiana University, Bloomington

3. Products

Selected relevant publications


Other relevant publications

Clement Gehring, Yangchen Pan and **M. White**. Incremental Truncated LSTD. In Proceedings of the Twenty-First International Joint Conference on Artificial Intelligence (IJCAI), 2016.


4. Synergistic activities

- Served on panels for graduate and undergraduate students, through Women in Technology (CeWIT) at Indiana University
- Tutored native american students under Frontier College, Edmonton, AB, Canada (2014)
- Workshops for youth, including workshops with Women in Scholarship, Engineering, Science and Technology (WISEST) and Women in Technology (WIT) promoting diversity in Computing Science (2011, 2007)

5. Collaborators (past 5 years, alphabetical by last name), total = 10
Bowling Michael (U. of Alberta), Degris Thomas (Google Deepmind), Gyorgy Andras (U. of Alberta), Pestilli Franco (Indiana U.), Radivojac Predrag (Indiana U.), Schuurmans Dale (U. of Alberta), Sutton Richard (U. of Alberta), Trosset Michael (Indiana U.), Veness Joel (Google Deepmind), Zhang Xinhua (NICTA)

6. Current advisees
Ph.D.: Tasneem Alowaisheq, Lei Le, Raksha Kumaraswamy, Yangchen Pan.

7. Ph.D. Advisors
Michael Bowling and Dale Schuurmans, University of Alberta
BIOGRAPHICAL SKETCH

Provide the following information for the Senior/key personnel and other significant contributors. Follow this format for each person. DO NOT EXCEED FIVE PAGES.

NAME: Yu, Chen

eRA COMMONS USER NAME (credential, e.g., agency login): chenyu@indiana.edu

POSITION TITLE: Professor, Psychological and Brain Sciences, Indiana University at Bloomington

EDUCATION/TRAINING (Begin with baccalaureate or other initial professional education, such as nursing, include postdoctoral training and residency training if applicable. Add/delete rows as necessary.)

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<tr>
<th>INSTITUTION AND LOCATION</th>
<th>DEGREE</th>
<th>Completion Date</th>
<th>FIELD OF STUDY</th>
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<td>Beijing University of Technology</td>
<td>B.E.</td>
<td>07/96</td>
<td>Automation/Robotics</td>
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<td>Beijing University of Technology</td>
<td>M.S.</td>
<td>07/99</td>
<td>Automation/Robotics</td>
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<td>University of Rochester</td>
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<td>06/01</td>
<td>Computer Science</td>
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<td>University of Rochester</td>
<td>Ph.D.</td>
<td>06/04</td>
<td>Computer Science</td>
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B. Positions and Selected Honors

Positions:
2015-now Professor, Department of Psychological and Brian Sciences, Cognitive Science Program, School of Informatics and Computing, Indiana University
2010-2015: Associate Professor, Department of Psychological and Brian Sciences, Cognitive Science Program, School of Informatics, Indiana University
2004-2009: Assistant Professor, Department of Psychological and Brian Sciences, Department of Computer Science, Cognitive Science Program, Indiana University.

Other Experience and Professional Memberships

• Panelist of NIH Cognition and Perception, 2013; NIH R24 Study Session, 2012; NIH F12 Study Session, 2009
• Panelist of NSF Robust Intelligence, 2010; NSF Cyber-Enable Discovery and Innovation (CDI), 2008; NSF Perception, Action and Cognition (PAC), 2006-2008; NSF Human Social Dynamics (HSD), 2006
• Editorial Board, IEEE Transactions on Autonomous Mental Development, 2014-current
• Editorial Board, Infancy, 2013-current
• Associate Editor, the Journal Frontiers in Neurorobotics, 2007-current
• Associate Editor, the Journal Frontiers in Psychology, 2009 – now

Honors and Awards:

• Intel Best Paper Award, 3rd IEEE International Workshop on Egocentric Vision 2014
• Robert L. Fantz Memorial Award, American Psychological Foundation 2013
• Best Paper of Experiment Combined with Computational Model, IEEE ICDL Conference 2012
• David Marr Prize for the Best Paper, Cognitive Science Society 2012
• Early Distinguished Contribution Award, International Society of Infant Studies 2008
• Outstanding Junior Faculty Award, Indiana University 2008
• Marr Prize for the Best Student-Authored Paper, Cognitive Science Society 2003
C. Contribution to Science

My first contribution focuses on studying statistical word learning – how human learners, both adults, infants and young children, are capable of aggregating statistical information across multiple encounters of words and referents.


My second contribution concerns word learning in social contexts.


My third contribution is in the domain of perception-action coupling in parent-child social interactions. In a set of studies, we used a novel method that seeks to describe the visual learning environment from a young child's point of view and measures the visual information that a child perceives in real-time toy play with a parent. The novel method involves measuring, in high temporal resolutions, eye gaze, hand and head movements, and the visual field from the child’s point of view (using head cameras).


D. Research Support

- “An Information-Theoretic Approach to Coordinated Behavior” (AFOSR FA9550-09-1-0665) (PI: Chen Yu, co-PIs: Olaf Sporns and Linda Smith), $300,000 September 2009-August 2011
- “Embodied attention in toddlers” (co-PI, PI: Linda B. Smith, NICHD R21) $348,000, December 2011 – March 2013.
Letters of Support:

Dean of the College of Arts and Sciences –to be submitted directly
Chair of Psychological and Brain Sciences – to be submitted directly

Administrator Letters included here:

1. Dean of the School of Informatics and Computer Science
2. Chair of Informatics
3. Director of the Program of Cognitive Science

Expert outside letters:

**Jay McClelland**
Lucie Stern Professor in the Social Sciences
Director, Center for Mind, Brain and Computation
Department of Psychology, Stanford University

Bio. Member of the National Academy of Sciences, American Academy of Arts and Sciences. Jay McClelland received his Ph.D. in Cognitive Psychology from the University of Pennsylvania in 1975. Over his career, McClelland has contributed to both the experimental and theoretical literatures in a number of areas, most notably in the application of connectionist/parallel distributed processing models to problems in perception, cognitive development, language learning, and the neurobiology of memory. He was a co-founder with David E. Rumelhart of the Parallel Distributed Processing (PDP) research group, and together with Rumelhart he led the effort leading to the publication in 1986 of the two-volume book, *Parallel Distributed Processing*, in which the parallel distributed processing framework was laid out and applied to a wide range of topics in cognitive psychology and cognitive neuroscience. McClelland and Rumelhart jointly received the 1993 Howard Crosby Warren Medal from the Society of Experimental Psychologists, the 1996 Distinguished Scientific Contribution Award from the American Psychological Association, the 2001 Grawemeyer Prize in Psychology, and the 2002 IEEE Neural Networks Pioneer Award for this work.

**Jeffrey Elman**
Distinguished Professor of Cognitive Science
University of California- San Diego

Member of American Academy of Arts Sciences, Winner Rumelhart Prize. Jeffrey L. Elman received in PhD from the University of Texas in Linguistics. He has made multiple major contributions to the theoretical foundations of human cognition, most notably in the areas of language and development. His work has had an immense impact across fields as diverse as cognitive science, psycholinguistics, developmental psychology, evolutionary theory, computer
science and linguistics. Elman’s 1990 paper *Finding Structure in Time* introduced a new way of thinking about language knowledge, language processing, and language learning based on distributed representations in connectionist networks. The paper is listed as one of the 10 most-cited papers in the field of psychology. He is a fellow of Cognitive Science Society, American Psychological Society, was President of the Cognitive Science Society, and co-founder of the Kavli Institute at UCSD. He served as Dean of the School of Social Science at UCSD for a decade. His book *Rethinking Innateness*, funded by the MacArthur Foundation, is considered a landmark contribution to the study of human development.

**James Rehg**  
Professor  College of Computing  
Georgia Institute of Technology

Dr. Rehg is a leading figure in egocentric vision, wearable sensors and behavioral imaging. His research interests include computer vision, computer graphics, machine learning, robotics, and distributed computing. He co-directs the Computational Perception Laboratory (CPL) and is affiliated with the GVU Center, Aware Home Research Institute, and the Center for Experimental Research in Computer Science. He received his Ph.D. from CMU in 1995. He received an NSF CAREER award in 2001. Dr. Rehg received the 2005 Raytheon Faculty Fellowship Award from the College of Computing. Dr. Rehg is also leading a multi-institution effort, funded by an NSF Expedition award, to develop the science and technology of Behavioral Imaging—the capture and analysis of social and communicative behavior using multi-modal sensing, to support the study and treatment of developmental disorders such as autism. He is the Deputy Director of the NIH Center of Excellence on Mobile Sensor Data-to-Knowledge (MD2K), which is developing novel on-body sensing and predictive analytics for improving health outcomes.
Dear Professor Rick Van Kooten,

I am writing to express my enthusiastic support for the Learning: Machines, Brains and Children proposal to be submitted to IU’s EAR program. The proposed research is well aligned with current SOIC research and education in data science, vision, and machine learning. I strongly believe that the combination of faculty expertise, research and capability is excellent not just at IU, but nationally. This proposal represents an excellent opportunity not just to impact this important field nationally, but to provide critical insights to IU to help it achieve successful outcomes for students, faculty and the university as a whole, using state of the art data science with unique interplay between computer science, cognitive psychology, and neuroscience.

SoIC already hosts world leading researchers in data science and machine learning disciplines spanning the theoretical to the applied, that will be of direct use in this project.

SoIC has created a cross-campus data science graduate education program with one of the broadest curricula, strong industry engagements and highest levels of intellectual diversity in the country. Founded in 2014, the program now has over 500 graduate students; many of these students will directly benefit from the research proposed in this project. Undergraduate opportunities are now being explored. The program has attracted attention due to its innovative online and residential options, very strong relationship with industry including Silicon Valley companies, and a curriculum encompassing technical and “decision maker” paths. Its student body includes many high ranked industry professionals as well as traditional STEM students. At a recent NSF workshop, IU was recognized as a leader in defining the curricular scope for Data Science nationally and internationally.
The proposal focuses on visual learning that requires an interdisciplinary approach to solve the problem. The potential transfer of knowledge from human visual system to machine vision is a very compelling strategy. The proposal puts forth a plan to study the mechanisms of how children learn and mimic it in non-biological machines. IU has strong existing strength in the interdisciplinary fields it bridges. The proposal requests faculty in three complimentary areas that can enhance the strength of IU in this domain.

Professors Smith, Crandall, Goldstone, and James are an impressive team of faculty to lead this very strong proposal. They are outstanding scientists with impeccable reputations. I very strongly support this proposal.

Sincerely,

Raj Acharya

Raj Acharya
To whom it may concern:

On behalf of the Informatics Division of the School of Informatics and Computing (SOIC), I write in strong support of the proposal “Learning: Brains, Machines, and Children,” led by Co-PIs Linda Smith, David Crandall, Rob Goldstone, and Karin James to the OVPR Emerging Areas of Research (EAR) program.

The proposal is an ambitious and innovative project to study learning from both computational and human perspectives, and has the promise to significantly impact both of these fields, and even to help establish a new multidisciplinary field of the science of learning. On the computational side, the Co-PIs and collaborators from SOIC include David Crandall, Michael Ryoo, Sriraam Natarjan, and Martha White, all of whom are highly active researchers with expertise in machine learning, including the emerging areas of deep learning, reinforcement learning, and computer vision. All three have very successful external funding records with a total of several million dollars of external grants and contracts from NSF, NIH, DARPA, IARPA, and the military. On the human side, Linda Smith, Rob Goldstone, Karin James, Mihcael Jones, David Landy, Franco Pestilli, Olaf Sporns, and Chen Yu are well-known experts in their fields with strong research records, including histories of successful long-running collaborations and involvement with SOIC.

The highly interdisciplinary nature of the proposed project aligns well with our Department’s vision for the future of computing research and education. In fact, this is the type of forward-thinking project that might not be possible in more traditional computer science departments that were not established on a foundation of interdisciplinarity. This unique characteristic of IU and SOIC in particular, and the fact that the project would build on three of the university’s most well-respected programs (Psychological and Brain Sciences, Cognitive Science, and Informatics and
Computing), and the strong research records of the Co-PIs and collaborators put IU on a strong trajectory to be the leader in this new emerging field of the science of learning. If awarded, this EAR proposal would make it possible for IU to realize this potential promise, by for example hiring three faculty and three postdocs with interdisciplinary training in machine and human learning.

Please feel free to contact me should you have any questions.

Sincerely,

Erik Stolterman
Chair of Informatics and Professor in Informatics
School of Informatics and Computing
Indiana University, Bloomington
919 E 10th Street, Bloomington, IN, 47408

estolter@indiana.edu
812 856 5803
Dear colleagues:

I write as Director of the IU Cognitive Science Program in strong support of the EAR proposal on Learning: Machines, Brains, and Children. This proposal embodies the interdisciplinary approach to tackling important new research challenges from multiple perspectives that Cognitive Science is all about. It combines three of the core fields of Cognitive Science: neuroscience, cognitive psychology, and AI/computer science—and in fact all but two of the team members are faculty long affiliated with our Cognitive Science Program (and I expect those two will soon be affiliated as well). Thus the Cognitive Science Program is already deeply involved in this proposal, and will support the efforts of this team going forward with the resources we have available. But we also stand to gain greatly from this proposal: The new faculty, postdoctoral researchers, and graduate students to be hired and supported will all be in fields central to Cognitive Science and will contribute significantly to the thriving collaborative culture and research productivity of our top-rated program.

The basic premise of this proposal is original, exciting, and impactful: to further our understanding of learning systems, and increase our ability to build new such systems, by studying the principles driving the most advanced learning system we know—the developing human brain. Humans grow to be better and better at learning by reusing existing cognitive mechanisms in new domains, by selecting for themselves the inputs that they will learn from, and by learning to perceive and form concepts at the same time. The research proposed here will uncover the way these principles work, and will use those principles to guide the development of new machine learning algorithms that increasingly drive our information technology and economy.

The team behind this proposal comprises internationally-renowned leaders in their fields, many of whom have already collaborated extensively, and together they have laid a considerable foundation for the research to be done. But to make the necessary big push on these important questions, the three new faculty hires are needed in areas of machine learning and computational neuroscience that are not currently covered here at IU. The postdocs and graduate students to be funded will further make connections between PIs and labs that are certain to generate even more new research avenues in unanticipated directions. Our existing Cognitive Science Program infrastructure will assist in their training and introduction to the rest of the IU community.
I fully expect the research from this proposal to make a profound impact on our basic scientific understanding of learning in human and artificial systems, and to make lasting contributions to applications of machine learning in a wide range of domains including education and commerce. It will also make IU a go-to hub for this kind of vital work. I most strongly recommend this proposal for your consideration and support.

Sincerely,

[Signature]

Dr. Peter M. Todd  
Director of the Cognitive Science Program  
Provost Professor, Cognitive Science, Psychology, and Informatics
Dear Committee:

I am delighted to write in support of the Emerging Area Research proposal titled “Learning: Machines, Brains and Children.” The proposal puts forward a strong case for university investment in a new science of learning, one emergent in the overlapping domains of cognitive modeling, computational neuroscience, and machine learning. The intersecting advances in these areas promise even greater advances to come. This past year, at conferences and workshops around the world, there has been much discussion about how far we have come and what might be next. There is a growing sense that the big advances have just begun and that we are the tipping point for truly barrier breaking advances in a unified understanding of neural and algorithmic learning mechanisms. That said, there are hard problems that remain unsolved. As argued in the proposal, solving these problems will require that cognitive scientists, neuroscientists, and computer scientists jointly direct their attention to the common theoretical underpinnings of learning as it is studied from these different perspectives. I strongly support the plan to hire and train scientists and theorists who integrate advances in biological and machine learning.

This proposal focuses on cognitive development and on how learning builds on itself over developmental time. This sets it apart from usual discussions of next steps in this area, and is visionary in this aspect of its approach. There is no better place than Indiana for putting development into the study of learning. The parallel experiments with children and deep learning networks coupled with analyses of the internal brain networks and the machine learning networks are elegant and truly pioneering. The faculty submitting this proposal have put forth a thoughtful and compelling analysis of the hard problems that need to be solved and they have laid out novel and well-argued research programs to solve them. Together these elements constitute a strong base on which to build the new area. Certainly, the current strengths in developmental science (Smith, Yu), computational neuroscience (Sporns, Pestilli), large data analysis (Jones), and the cognition of learning (Goldstone) are world class, and the stable of smart young machine learning researchers appears excellent. I can also attest to Smith’s outstanding leadership skills — I see this program as in excellent hands with Smith at the forefront of this leadership team.
In sum, the likelihood of high impact – indeed, international leadership – in this exciting new area is excellent. The payoff to Indiana and to new knowledge should be substantial.

Sincerely yours,

[Signature]

James L. McClelland  
Director, Center for Mind, Brain, and Computation  
Lucie Stern Professor of the Social Sciences  
Department of Psychology
September 4, 2016

Dear Emerging Area Review Committee,

Linda Smith asked me to write a letter of support for her team’s Emerging Area proposal, which I understand is a university-wide competition to support hiring and research in new high impact fields of inquiry. To anticipate the punchline: This is one of the most exciting proposals of this sort I have ever seen. It is outstanding, ambitious, and makes enormous sense. The proposal comes from a group of scientists at the top of their fields, and I think has a real likelihood of leading to high impact work that could change cognitive science. I realize this is an unusually exuberant endorsement, so let me explain.

The proposal argues persuasively that cognitive modeling, computational neuroscience and machine learning need to take development seriously. Given the focus on learning that those two fields have traditionally had, it is odd that there has been such a disconnect between them and developmental research. I say this as someone who came rather late in my own career to appreciating that development holds the key to understanding how complex behaviors emerge from often non-obvious origins.

The planned approach has three components, and they fit together in a way that is insightful. The first set of projects uses deep-learning networks to understand reuse and the developmental cascade. The approach is unprecedented in its use of training sets in machine learning that are based on the statistical structure children’s visual experiences as they progress from infancy to early childhood. The approach is also innovative in its parallel experiments with children and deep-learning networks and its ability in both cases to “look under the hood” through the use of neuroimaging and analyses of the internal workings of the networks.

The second project builds on the pioneering developmental research at Indiana, which I consider to be some of the most exciting in the world. This project attempts to capture the multi-scale dynamics of real-world learning experiences, over both the macro-scale of development and the micro-scale of fractions of seconds. The planned machine-learning component requires multiple time scales in the algorithms, which in turn requires a major (and much anticipated) advance in machine learning.

Finally, the third component of the proposal goes after what is perhaps the biggest gap in contemporary understanding in human cognition and machine learning, which is how perceptual development with its increasing narrowing, precision, and categorization prepares the way for more advanced abstract learning and concepts.

The proposal is stunning in its conceptualization of the problem to be solved and clear in its plan to solve that problem.
The unique strategy of injecting developmental approaches and research into computational modeling in neuroscience, cognitive modeling and machine learning has the potential for field-changing advances in each of these areas. It also has the potential to bring these separate areas together to create a field of research that seamlessly combines all three to find the general principles of learning that all these areas have been working to discover, but hitherto in isolation.

Perhaps most importantly, I believe that this research program has consequences for the lives of children. The evidence is now quite clear that early inequalities in children’s environments have effects—in brain, in cognition, in behavior—by the third birthday and that by this point some children’s futures may already be firmly constrained as these early inequalities appear to set the path for success in school. What we do not know is the mechanistic pathway: How are those early experiences changing internal processes? What is the pathway from the early effects to later learning? These are the larger questions that motivate this whole program and without answers we cannot begin address this critical societal problem.

Indiana is unique in its complex systems perspective on development. The cognitive science program at IU is one of the best in the world. The program has a long history of landmark contributions that combine computational, cognitive, and neuroscience approaches. I am enthusiastic and confident that this team—with additional investments from Indiana University--can lead the field in this new approach.

Finally, the time is right for universities to invest in a big way in this research. Many believe that the truly amazing advances in human neuroscience and in machine learning put us at a tipping point for a new insights into how systems learn. Recent calls from federal funding agencies certainly exhibit this belief. But if we want systems that learn like people, then development has to be in the mix as well.

In sum, this is a tremendously exciting proposal. There are very few other universities that are as well positioned to undertake such an ambitious program as Indiana University. I look forward to the discoveries that will come from this new collaborative research area.

Yours truly,

Jeffrey L. Elman
Chancellor’s Associates Distinguished Professor of Cognitive Science
Founding Co-Director, Kavli Institute for Brain & Mind
Dean Emeritus, Division of Social Sciences
Dear Emerging Area Review Committee,

This letter is written in support of the proposal titled “Learning: Brains, Machines and Children” by Linda Smith and a team of interdisciplinary faculty at Indiana. I understand that the proposal is being submitted to an internal Emerging Area competition to decide new investments by the university in new high impact research areas. In brief, this is a visionary proposal with the potential field-changing impacts in the study of human visual learning and in machine vision. I should say at the outset that I have a vested interest in all of this. Linda Smith, Chen Yu and I are currently funded by a collaborative NSF grant that specifically seeks to use deep learning nets (DNNs) to understand how changes in toddlers’ visual experiences around the first birthday, and changes in visual object recognition, may be rate-limiting factors in the ability of toddlers to break into object name learning. Already, our findings challenge current machine learning approaches which cannot readily exploit the structure in toddler visual experiences.

The overall plan of this ambitious proposal is to support and cultivate collaborative research focused on visual cognition as it relates to object recognition, early word learning, symbol learning and mathematics. These goals raise the bar for machine vision considerably. The proposed approach is novel and innovative in at least three ways: (1) in use of training sets in machine learning based on the statistical structure children’s visual experiences; (2) in its parallel experiments with children and deep-learning networks and its use of neuroimaging to look under the hood” in human learning; (3) its focus on how DNNs learn –with analyses of learning trajectories within and across layers. Goal three is ambitious with likely far reaching consequences and quite rightly this is the focus of the proposal for three new hires, all in or connected to machine learning. The goal is to move the field from simply demonstrating useable algorithms (although the benefits of these gains in machine learning to society are notable in their own right) to an understanding of the principles –expressable as algorithms – that underlie both human and machine learning. Understanding the similarities and differences – and aligning them – of learning by humans and machines is highly relevant to building networks of humans and machines that can work (and learn) seamlessly together and from each other.

There are now emerging a quite exciting cohort of computational theorists and machine learners working across human and machine learning and explicitly in exploiting recent advances in neurocomputation and human learning. This proposal, and most critically the proposed hires, will put Indiana in the game, a game that I sincerely believe will dominate all of science (as well as social science) over the next decade. I believe it’s important to emphasize the need to take steps now to grow capabilities in this emerging area. There is an opportunity to act which will not last indefinitely.

Indiana has unique and remarkable strengths in its developmental perspective and a unique opportunity to lead in this new field. I am enthusiastic and confident that this team –with additional investments from Indiana University -- can lead the field in this new approach. In sum, this is a very exciting proposal. I look forward to the discoveries that will come from this new collaborative research area.

Sincerely,

Dr. James M. Rehg,
Professor, School of Interactive Computing
Director, Center for Behavior Imaging
September 9, 2016

Rick Van Kooten, Vice Provost for Research
Office of the Vice Provost for Research
Carmichael Center, Suite 202-204
530 E. Kirkwood Avenue
Bloomington, IN 47408

Dear Vice Provost Van Kooten,

The three divisions and the three schools in the College of Arts and Sciences put forward a total of 39 pre-proposal abstracts. Of these 39 pre-proposals, 17 were developed into full proposals. The majority of the 17 investigators met with at least one dean in the College prior to submitting their proposals. We will focus on these 17 proposals in this letter of support.

Below is a ranking of proposals into 3 categories. Three proposals were ranked in the highest category. To be ranked in the highest category the proposal had to demonstrate a coherent strategy to meet fully the EAR objectives to “support investigators and teams of investigators who are prepared to undertake a significant and complex investigation involving fresh approaches to research. The research or creative activity that is emerging or under development should capitalize on existing strengths on campus; have the potential for enhancing the volume, quality, impact and reputation of research at IU Bloomington; and lead to federal, corporate, or private funding.” Thus, the primary criterion to be ranked in the high category is research excellence and we favored proposals led by faculty who have an established record of excellence in research or creative activity.

In addition, the highest category proposals also met wider College objectives. In particular, we favored proposals that came not only from strong individual faculty members, but those from strong departments where a new emerging area of research builds on our current strengths and where there is demonstrated success in collective vision and action. In addition to research excellence, we also supported proposals where
there are excellent graduate and undergraduate programs that place their graduate students in top institutions and where there is high demand for undergraduate enrollment.

Proposals in the second category are interesting and provocative in their approach to emerging areas of research and have our support, but holistically are not as strong as those in the first category in at least one EAR or broader College objectives category. All of the proposals in the third category we find to have significant merits, but are not evaluated as high on the EAR or College objectives categories as those in the first 2 groups.

❖ Category 1 (highest ranked, in no particular order)

I am happy to provide my strongest support to the following Emerging Areas of Research proposals:

**Learning: Machines, Brains, and Children,** submitted by a group led by Professor Linda Smith of the Department of Psychological and Brain Sciences. The program outlined in this proposal promises to place IU at the forefront in a growing area of convergence in the disciplines of machine learning and developmental psychology. It builds upon strong existing programs in both developmental psychology in the College and machine learning and computer science in the SoIC; a number of our most accomplished researchers are team members. Unlike many EAR proposals, this proposal arose organically from discussions between team members on this topic which began well before the EAR call, which speaks to the likely long term sustainability of this effort. The additional faculty and post-doc hires funded through the EAR program would take a strong research effort that has already made impressive strides towards forging the necessary cross-disciplinary ties, and make IU a world leader in the development of machine learning tools derived from advances in early childhood development.

Please let me know if you have questions about any of this. Let me take this opportunity to thank you for this great opportunity.

Sincerely yours,

Larry D. Singell
Executive Dean
September 8, 2016

Dear Vice Provost Van Kooten and members of the EAR Review Committee,

I’m writing to offer my strong and enthusiastic support for the Emerging Areas of Research (EAR) proposal titled “Learning: Machines, Brains, and Children.” I have discussed this proposal with Linda Smith, one of the Co-PIs to consider the direction of this proposal, its alignment with our department’s strengths and ambitions, and the involvement of our faculty and students. On all these fronts, I see tremendous opportunities for synergy with department priorities. In addition, I see extraordinary opportunity to position Indiana University as a national leader in this important and cutting-edge area of scholarship. In my humble opinion this proposal would be an excellent investment for buttressing connections to SoIC and the nascent Department of Intelligent Systems Engineering through the traditional areas of strengths in our department represented in this proposal. The result would be a highly innovative program that would certainly establish IU as a national leader in this area.

**Significance and funding potential.** As described in the proposal, this emerging area of research is positioned to have huge impacts on artificial intelligence, decision science, big data, industry, and human well-being. And, there is increasing awareness that the big breakthroughs will, as the proposal states, come from research at the intersection of human learning, neuroscience, and machine learning—three research domains that have, unfortunately, drifted apart at many institutions. IU has an opportunity here to compellingly unify these areas using this stellar team as a foundation. The proposed hires would propel this area of research at IU to national prominence. Moreover, this team, given their strong history of external funding and the importance of this work, will be well-positioned to garner external funding from the National Science Foundation, Department of Defense, Office of Naval Research, and the Defense Advanced Research Projects Agency (DARPA).

**Alignment to our department’s goals and strengths.** The IU Department of Psychological and Brain Sciences is deeply committed to the study of learning from multiple perspectives: behavioral, cognitive, developmental, neural, and computational. Our strengths in this area are manifest in the strong research
programs of the PBS co-authors of this proposal: Linda Smith, Chen Yu, Karin James, Rob Goldstone, David Land, Mike Jones, and Olaf Sporns. In addition, our strengths in this area will be a terrific recruiting tool and incentive for prospective hires to come to IU. Linda Smith and Rob Goldstone are members of the American Academy of Science and Olaf Sporns is one of the most renowned computational neuroscientists in the world. But please don’t get me wrong, this team proposes is to leverage these strengths to build something that doesn’t currently exist here at IU and that addresses a major knowledge and methodological gap in the field. And, this proposal is much bigger and ambitious than anything that could be done within any unit or department on campus and cleverly leverages a transdisciplinary approach.

Support for proposed hire(s) in PBS. For the reasons described above, I strongly support the proposed faculty hire(s) in the Department of Psychological and Brain Sciences (PBS). One hire is slated for PBS and another will be in SoIC. The team proposes that the third hire will be split between the PBS/College or placed entirely in one or the other unit—depending on fit. These PBS-related hires are entirely consistent with our department’s vision for strategic hiring and research. Moreover, given the research focus of the targeted hires, these hires will build even stronger interdisciplinary bridges between PBS/College and the SoIC.

Additional PBS support for infrastructure. PBS is also committed to making space available for the Smart Room and assisting with renovation costs.

Conclusion. This project has my strongest and most enthusiastic support. If you have questions that I might be able to answer, please do not hesitate to email (whetrick@indiana.edu) or call (812-855-2620).

Sincerely,

William P. Hetrick, PhD.
Professor and Department Chair
Department of Psychological and Brain Sciences
College of Arts and Sciences
Indiana University Bloomington