

## **Pigeons' Categorization Is Exclusively Nonanalytic**

J. David Smith

Department of Psychology, The University at Buffalo, State University of New York  
346 Park Hall, Department of Psychology, University at Buffalo, The State University of New York  
716-645-0229 (voice), 716-645-3081 (fax), psysmith@buffalo.edu

F. Gregory Ashby

Department of Psychology, University of California at Santa Barbara

Mark E. Berg

Richard Stockton College of New Jersey

Matthew S. Murphy

Department of Psychology, Tufts University

Brian Spiering

Department of Psychology, University of California at Santa Barbara

Robert G. Cook

Department of Psychology, Tufts University

Randolph C. Grace

Department of Psychology, University of Canterbury, Christchurch

Recent theoretical and empirical developments in human category learning have differentiated an analytic, rule-based system of category learning from a nonanalytic system that integrates information across stimulus dimensions. The researchers applied this theoretical distinction to pigeons' category learning. Pigeons learned to categorize stimuli varying in the tilt and width of their internal striping. The matched category problems had either a unidimensional (rule-based) or multidimensional (information-integration) solution. Whereas humans and nonhuman primates strongly dimensionalize these stimuli and learn rule-based tasks far more quickly than information-integration tasks, pigeons learned the two tasks equally quickly to the same accuracy level. Pigeons likely represent a cognitive system in which the commitment to dimensional analysis and category rules was not strongly made. Their performance suggests the character of the ancestral vertebrate categorization system from which that of primates emerged.

keywords: category learning, comparative cognition, pigeons, rules, analytic/nonanalytic cognition, implicit/explicit cognition

Categorization is essential for survival. Consequently, it is a widely studied cognitive adaptation in humans (Ashby & Maddox, 2005; Knowlton & Squire, 1993; Murphy, 2003; Nosofsky, 1987; Posner, Goldsmith, & Welton, 1967; Smith & Minda, 1998) and nonhumans (Chase & Heinemann, 2001; Cook & Smith, 2006; Herrnstein, Loveland, & Cable, 1976; Lea & Ryan, 1990; Pearce, 1994; Smith, Redford, & Haas, 2008; Wasserman, Kiedinger, & Bhatt, 1988). In the human literature, an influential multiple-systems theoretical perspective (Ashby, Alfonso-Reese, Turken, & Waldron, 1998; Ashby & Ell, 2001; Ashby, Ennis, & Spiering, 2007; Erickson & Kruschke, 1998; E. E. Smith & Grossman, 2008) distinguishes analytic category learning (by which executive attention and working memory derive explicit dimensional rules) from nonanalytic learning (by which behavioral responses are implicitly mapped to unanalyzed perceptual wholes). According to the dominant neuroscience framework, humans' explicit/analytic system is mediated in part by a broad neural network that includes the anterior cingulate gyrus, prefrontal cortex, the head of the caudate nucleus, and medial temporal lobe structures that subserve declarative memory. This system is related to a broader neural complex serving the executive control of attention (Rossi, Pessoa, Desimone, & Ungerleider, 2009). The implicit/nonanalytic system depends heavily on the striatum and is catalyzed by the reinforcement-mediated strengthening of dopamine-related synapses (Ashby et al., 1998; Ashby & Ell, 2001).

Here we explore the explicit-implicit distinction from a comparative/evolutionary perspective, asking whether pigeons (*Columba livia*) also have a multiple-systems categorization capacity that includes a rule-privileged dimensional component. We test pigeons with matched category tasks differing only in their analytic/rule-based or nonanalytic/multidimensional solution. We show, through converging findings from multiple laboratories, that pigeons have no tendency toward dimensional analysis and rules. They learn both category tasks equivalently using the same nonanalytic, associative process. The results show that the dual-system, explicit/implicit control of categorization is not a generalized pattern. To the contrary, pigeons represent a species in which the commitment to dimensional analysis and category rules was not strongly made. Their performance suggests the character of the ancestral vertebrate categorization system from which that of humans emerged. The development of the capacity for dimensional analysis and explicit rule learning could have been an important step in the cognitive evolution of the primate-hominid lineage (Smith, Beran, Crossley, Boomer, & Ashby, 2010; Hauser, Weiss, & Marcus, 2002; Marcus, Vijayan, Bandi Rao, & Vishton, 1999).

Within the enormous literature on human category learning, strong behavioral evidence for dissociable analytic and nonanalytic categorization systems comes from studies of rule-based (RB) and information-integration (II) categorization tasks. Figure 1 illustrates these tasks using sine-wave gratings varying in the dimensions of bar width and tilt. These dimensions were adopted because they are influential in vision and categorization research, well studied and calibrated in humans, and known to be highly analyzable or separable. In Figure 1A, the horizontal category boundary for the RB task shows that only the bar-width dimension carries valid category information. The subject must discover this bar-width solution using feedback provided during successive presentations of single, to-be-categorized instances. In Figure 1B, the diagonal category boundary for the II task shows that the bar-width and bar-tilt dimensions both contain partially valid category information. The subject must integrate stimulus information across both dimensions to best solve this category problem.

The RB and II tasks are elegantly matched in category size, instance variability, category separation, and a priori perceptual difficulty because they are exact geometric rotations of one another through the stimulus space. They differ only in their potential solutions. The RB task potentially affords a dimensional-rule solution whereas the II task depends on a dimensional-integration solution. Consistent with a multiple-systems perspective, humans learn RB tasks faster than II tasks by about an order of magnitude (Ashby & Ell, 2003), and do so using dimensional analysis, hypotheses, and rules. II tasks, in contrast, are acquired slowly, implicitly, and associatively.

The goal of the present research was to investigate the multiple-systems hypothesis comparatively by asking whether pigeons (*Columba livia*) share with humans a multiple-systems category-learning competence that includes both analytic, rule-based and nonanalytic, associative systems.

One possibility is that a multiple-systems organization for categorization exists broadly across vertebrates. Categorization could be an important enough cognitive capacity to deserve and receive redundant expression within cognition, and a multiple-systems architecture might have emerged early in the vertebrate lineage. Moreover, a rule-preferring system could be a particularly adaptive component within the overall categorization system for solving certain types of category problems or for flexibly maneuvering on demand among alternative solutions to category problems. If so, then pigeons would exhibit something like the RB/II performance differences that humans show, demonstrating an important continuity in categorization across vertebrate species with 250 million years of phylogenetic separation.

However, by another feasible cognitive organization, pigeons could exclusively learn by gradually associating response outputs to unanalyzed regions of perceptual space. In this case, stimuli would be treated integrally as unitary wholes, with dimensional analysis, attentional focusing, and rule formation held in abeyance during associative learning. Then, RB and II tasks would be equivalent to one another, and as a result equally coherent and learnable for pigeons. It is an intriguing theoretical possibility that pigeons represent a species in which the principal cognitive commitment was made toward associating responses to stimulus wholes and not toward dimensional analysis and rules. This would demonstrate an important discontinuity between the category-learning system of humans and pigeons, the latter possibly typifying the phylogenetically older vertebrate categorization system.

Laboratories in New Zealand (NZ-Canterbury) and the United States (USA-Tufts) independently contrasted these theoretical possibilities by giving pigeons RB/II tasks instantiated using sine-wave gratings varying in bar width and tilt. Upon discovering the strong convergence across laboratories, these independent investigations were combined for joint presentation here.

### *Method*

Naïve pigeons (11-USA; 6-NZ), maintained at 80-85% of free-feeding weight, were tested using a two-alternative symbolic matching-to-sample choice procedure using touchscreen-equipped LCD monitors. To-be-categorized stimuli were presented through a window in each chamber's front panel. These stimuli were circular sine-wave gratings varying in bar width/tilt. Choice stimuli were located to each side of the stimulus. These choice stimuli were illuminated following observing responses to the to-be-categorized stimulus. Response assignments were counterbalanced across birds and tasks. A single response to the correct or incorrect choice produced food reinforcement or a timeout, respectively, followed by an inter-trial interval. A central food hopper in the front panel delivered the grain reinforcements for correct choices. White noise masked external sounds. Daily sessions contained approximately equal numbers of samples from each category selected randomly from the available pool. Training continued until each bird reached criterial performance and began their next RB or II acquisition.

Table 1 summarizes USA-NZ procedural differences. These procedural differences resulted from the independent planning and conduct of the original projects. They underscore the strong convergence of the pattern of findings across the NZ and USA projects.

Categories created by the randomization technique (Ashby & Gott, 1988) were defined by bivariate-normal distributions in the bar-width/bar-tilt stimulus space. Table 2 lists the distributional parameters for the category structures tested. Two RB tasks were tested (bar width with a horizontal optimal decision bound; bar tilt with a vertical decision bound). One II task was tested in which the optimal decision bound was the stimulus space's major diagonal. The II task was simply a 45° rotation of the RB tasks (see Figure 1). Nine birds were tested first with an RB task (USA—3 tilt, 3 width; NZ—3 width). Eight birds were tested first with the II task (USA-5, NZ-3). Subsequently, birds were switched to new category structures and retrained so that all birds experienced RB and II tasks.

### *Results*

Figure 2 shows the results. The leftmost panels show mean accuracy across sessions for each pigeon during their first RB or II acquisition. Pigeons significantly improved over sessions, but showed no RB/II differences in their speed of learning. The II task—profoundly more difficult for humans and nonhuman primates—was learned just as quickly as either RB task. Pigeons (USA) took on average  $30.3 \pm 3.7$  (mean  $\pm$  SEM) sessions and  $33.6 \pm 4.3$  sessions to reach criterion on the RB and II task, respectively. Pigeons (NZ) took on average  $42.5 \pm 23.5$  sessions and  $28.0 \pm 2.1$  sessions to reach criterion on the RB and II task, respectively. Combined, these means were  $33.4 \pm 5.6$  sessions (RB) and  $33.2 \pm 4.6$  sessions (II). Two NZ birds experienced RB learning difficulty and one bird never reached criterion. Neither of these birds had any difficulty learning the II task subsequently. Two USA birds were slightly slower II learners than the majority of birds, but one of these was equally slow during later RB learning. Statistical comparisons (ANOVAs, *t* tests) confirmed the improvements across sessions and confirmed the absence of RB/II learning-speed differences for each laboratory separately and for the two laboratories combined.

There was also no evidence that RB tasks supported higher terminal accuracy levels than II tasks. Comparisons of mean accuracy over the last 10 sessions for each task revealed no significant RB/II differences (USA: RB=84.85%  $\pm$  .39, II=87.15%  $\pm$  .93, NZ: RB=79.2%  $\pm$  .10, II=77.4%  $\pm$  1.3). Thus, for these 17 pigeons, the II task presented no greater learning challenge than the RB task.

Figure 2's rightmost panels show the combined acquisition results for all tasks across all pigeons. Even with multiple acquisitions and experience with both kinds of tasks, the II task was still no more difficult for the pigeons than the RB task. The mean number of sessions to criterion was equivalent across tasks. The terminal accuracy over the last 10 sessions for all acquisitions was also equivalent across tasks (USA: RB=84.95%  $\pm$  .5, II=86.54%  $\pm$  .7, NZ: RB=76.4%  $\pm$  2.0, II=76.5%  $\pm$  .1). Statistical comparisons combining all acquisitions confirmed that pigeons' RB/II performance was equivalent in both speed of learning and terminal accuracy.

Specific-item memorization was not a factor as pigeons tested for subsequent discrimination transfer with novel stimuli (created using the same distributional parameters as in training, tested USA only) showed perfect transfer. Pigeons had statistically equivalent mean accuracies for novel stimuli (91.02%  $\pm$  1.4) and training stimuli (90.1%  $\pm$  .72). There were also no RB/II performance differences for novel stimuli (RB-91.01%  $\pm$  1.42; II-91.0%  $\pm$  1.97). Thus, the pigeons were responding based on the general perceptual distributions that defined the categories in stimulus space and that encompassed both training and novel, transfer stimuli.

### *Discussion*

The present results provide the crucial new observation that pigeons show no tendency to learn rules or to apply dimensional analysis when tested with highly controlled and diagnostic category tasks. In sharp contrast to humans and nonhuman primates, the pigeons showed complete indifference to the task's rotation in perceptual space, learning RB and II tasks equally quickly and to the same level of accuracy. Note that this result also suggests that there is no inherent difficulty difference between the two categorization tasks shown in Figure 1. The fact that humans find the dimensional task in the top panel so much easier must therefore be due to differences in how we learn the two tasks, rather than due to a fundamental difference in the two tasks themselves.

The indifference of the pigeons to the task's rotation in perceptual space is exactly the same indifference that humans show to task rotations within non-separable/integral perceptual spaces (Foard & Kemler Nelson, 1984; L. B. Smith & Kemler Nelson, 1978). Pigeons' data pattern is also strongly isomorphic with that produced by humans' implicit-striatal category-learning system that is judged to be nonanalytic. Indeed, all aspects of their performance are consistent with a cognitive organization by which they gradually associate behavioral responses to unanalyzed stimulus wholes or to regions of perceptual space, while holding in abeyance stimulus analysis, selective attention, and rule formation. The hypothesis that pigeons rely on nonanalytic, integrated perception during learning is also supported by the finding that these animals can associate responses to large numbers of dissimilar or randomly assigned pictorial stimuli (Fagot & Cook, 2006; Cook, Levison, Gillett, & Blaisdell, 2005; Vaughn & Greene, 1984). This hypothesis and the current results are even consistent with the finding that pigeons sometimes show a gradual reorienting of attention over many trials (Leith & Maki, 1975). Even nonanalytic systems can learn, gradually and associatively, to orient or reorient the decision boundary within a perceptual space, and they can sometimes respond undimensionally though implicitly (Wills et al., 2009).

A unitary, exclusively nonanalytic category system has some distinct advantages. Such a system could have a neural economy that might especially suit nervous systems constrained in size by the weight limitations of flight. Moreover, pigeons could avoid strategy competition during category learning and avoid the maladaptive, adventitious rules that humans often invent and exhibit during learning (Jitsumori, 1993). They might also be adept at learning non-linear category boundaries that would defeat a rule-based system. There is a parsimony, breadth and power to a category-learning system that always, simply associates responses to stimuli, without overlaying axes, dimensions, and rules. We therefore suggest that pigeons' category learning could illuminate a phylogenetically ancient associative categorization system that is widely distributed across the vertebrates.

In turn, one considers when and why in vertebrate evolution the privilege of dimensional analysis and category rules emerged. Rule-based category systems are not a species-unique human endowment,

grounded in humans' language, symbolic functioning, or frontal-cortical brain development. Macaques (*Macaca mulatta*) also learn RB tasks faster and to higher terminal performance levels than they do II tasks, probably because they perceive analytically the stimulus dimensions composing the stimuli (Smith et al., 2010). Macaques present an illuminating comparative contrast to pigeons. They also help date the phylogenetic emergence of dimensionally-analytic categorization. This emergence in the primates was surely gradual—related research (Smith, Minda, & Washburn, 2004) shows that macaques do not have the full suite of dimensionally analytic categorization abilities.

The multiple-systems organization also has distinct advantages. It allows for economical, quickly learned, and easy-to-generalize category representations (i.e., rules). It brings cognitive flexibility and attentional agility arising from dimensional analysis. Perhaps most important, it opens up the possibilities for cognitive analysis, rules, inferences, symbolic representations, and eventually even language. Therefore, the privilege that developed regarding explicit dimensional analysis and category rules may have been among the crucial pre-adaptations that promoted cognitive evolution within the primate-hominid lineage.

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*Author Notes*

J. David Smith, Department of Psychology, University at Buffalo, The State University of New York; F. Gregory Ashby and Brian Spiering, Department of Psychology, University of California at Santa Barbara; Mark E. Berg, Richard Stockton College of New Jersey; Robert G. Cook and Matthew S. Murphy, Department of Psychology, Tufts University; Randolph C. Grace, Department of Psychology, University of Canterbury, Christchurch.

Correspondence concerning this article should be addressed to J. David Smith, Park Hall, Department of Psychology, 346 Park Hall, University at Buffalo, The State University of New York, Buffalo, NY, 14260, or to [psysmith@buffalo.edu](mailto:psysmith@buffalo.edu).

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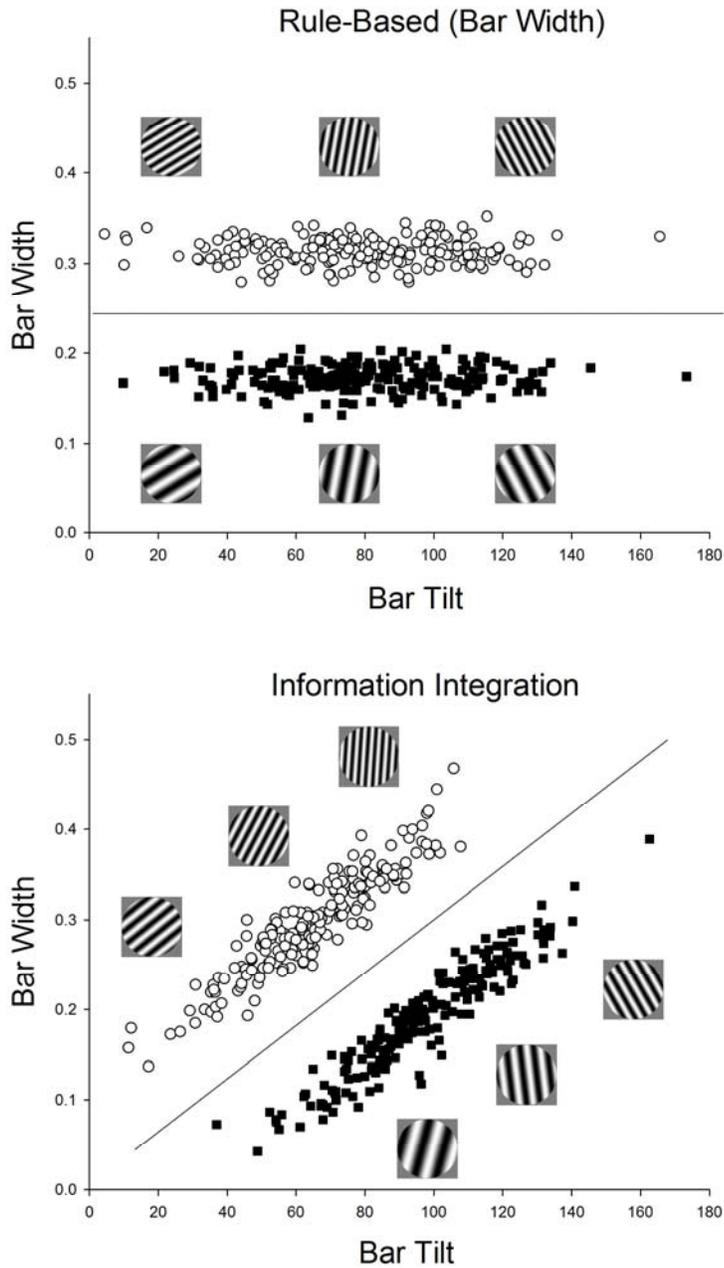
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**Table 1. Procedural differences—USA and NZ projects.**

<i>Contrast</i>	<i>USA</i>	<i>NZ</i>
<i>Number of Birds</i>	11	6
<i>RB Task First</i>	6	3
<i>II Task First</i>	5	3
<i>Screen Resolution</i>	1024 x 786	640 x 480
<i>Choice Assignment</i>	Visual	Spatial / Visual
<i>Choice Colors</i>	Blue / Red	Green / Red
<i>Stimuli per Category</i>	200	40
<i>Stimulus Size</i>	3 x 3 cm	9.5 x 12 cm
<i>Task</i>	Simultaneous	Zero-Delay
<i>Warning Signal</i>	Yes	No
<i>Trial-Start Response</i>	Yes	No
<i>Observing Response</i>	Variable 13-15 pecks	Fixed 5 pecks
<i>Sample Illuminated during Response</i>	Yes	No
<i>Inter-Trial Interval</i>	3 s	9 s
<i>Timeout</i>	Dark 8 s	Flashing 10 s
<i>Reinforcement Time</i>	2.5 s	3 s
<i>Grain</i>	Mixed	Wheat
<i>Daily Trials</i>	80	90
<i>Criterion Performance</i>	5 sessions > 80%	4 sessions > 80%

Table 2. Population parameters for the distributions tested in the category tasks.

<b>Rule-Based (Bar Width)</b>					
	<i>Category A</i>		<i>Category B</i>		
	<i>Tilt</i>	<i>Width</i>	<i>Tilt</i>	<i>Width</i>	
<b>USA</b>					
<i>Minimum</i>	4.41	0.279	9.79	0.128	
<i>Maximum</i>	165.58	0.351	173.31	0.204	
<i>Standard Deviation</i>	27.91	0.014	26.96	0.013	
<i>Mean</i>	78.76	0.313	79.97	0.172	
<b>NZ</b>					
<i>Minimum</i>	-26.67	0.037	-6.96	0.048	
<i>Maximum</i>	119.26	0.042	109.36	0.052	
<i>Standard Deviation</i>	33.86	0.009	29.65	0.009	
<i>Mean</i>	41.91	0.040	41.38	0.049	
<b>Rule-Based (Bar Tilt)</b>					
	<i>Category A</i>		<i>Category B</i>		
	<i>Tilt</i>	<i>Width</i>	<i>Tilt</i>	<i>Width</i>	
<b>USA</b>					
<i>Minimum</i>	41.02	0.012	91.38	0.046	
<i>Maximum</i>	70.35	0.503	116.02	0.510	
<i>Standard Deviation</i>	5.13	0.082	4.94	0.086	
<i>Mean</i>	55.97	0.243	104.57	0.247	
<b>Information Integration</b>					
	<i>Category A</i>		<i>Category B</i>		
	<i>Tilt</i>	<i>Width</i>	<i>Tilt</i>	<i>Width</i>	
<b>USA</b>					
<i>Minimum</i>	11.34	0.136	36.95	0.042	
<i>Maximum</i>	107.77	0.468	162.60	0.388	
<i>Standard Deviation</i>	18.55	0.055	20.62	0.060	
<i>Mean</i>	65.31	0.299	97.61	0.192	
<b>NZ</b>					
<i>Minimum</i>	5.15	0.025	-2.43	0.036	
<i>Maximum</i>	107.35	0.058	80.09	0.063	
<i>Standard Deviation</i>	23.65	0.016	21.13	0.015	
<i>Mean</i>	52.08	0.041	31.21	0.047	



*Figure 1.* A rule-based (RB) category structure (A). An information-integration (II) category structure (B). Category tasks are depicted using the USA project’s stimulus space. The NZ project examined an analogous stimulus space. In both projects, stimuli were circular sine-wave gratings varying in bar-width and bar-tilt. The horizontal decision bound (A) shows that only the bar-width dimension carried diagnostic category information, so that a one-dimensional, bar-width decision bound or rule produced optimal performance. The diagonal decision bound (B) shows that both the bar-width and bar-tilt dimensions carried partially diagnostic category information, so that information needed to be integrated across dimensions for optimal performance.

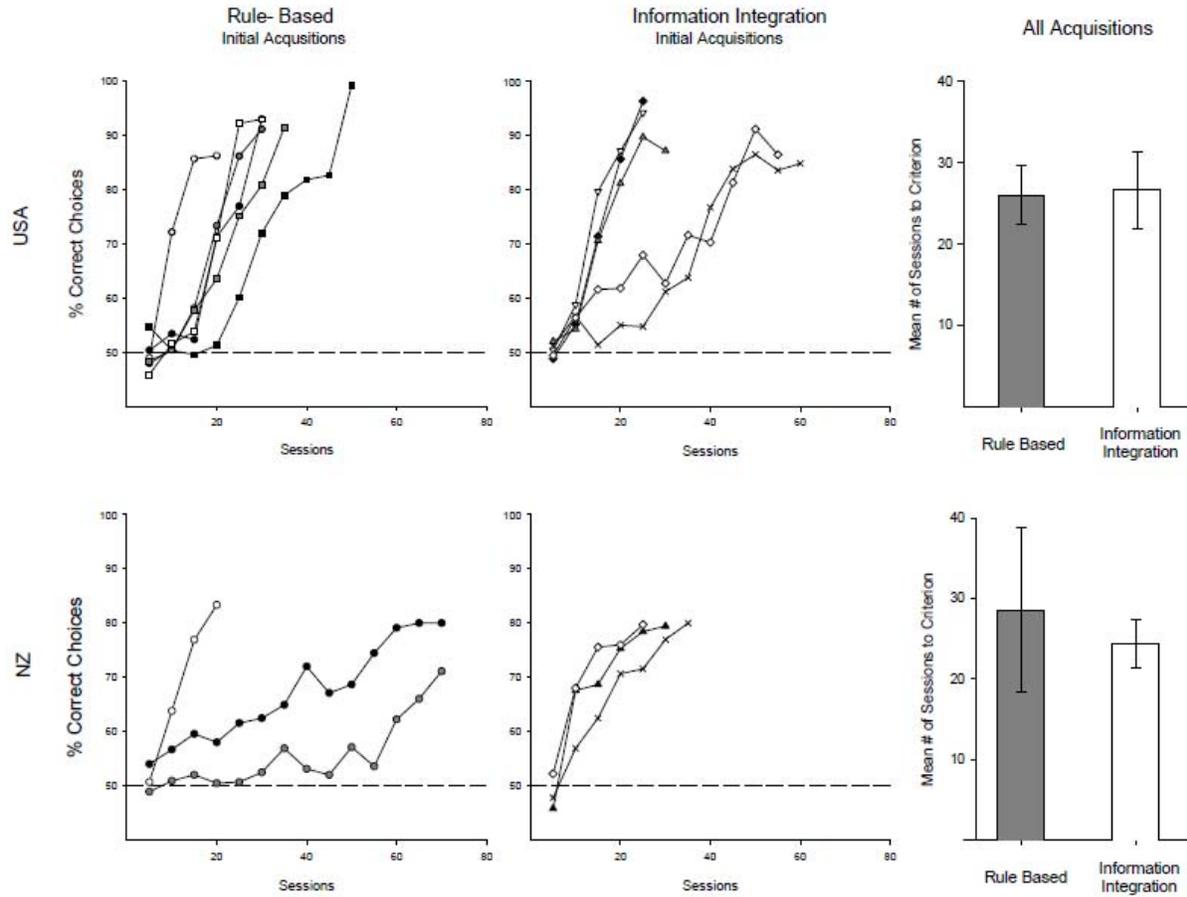


Figure 2. The leftmost panels show mean accuracy across sessions for individual pigeons tested first in a rule-based (RB) task. The central panels show mean accuracy across sessions for individual pigeons tested first in an information-integration (II) task. The rightmost panels show the mean number of sessions to criterion for all RB and II acquisitions. The top and bottom rows, respectively, show results from the USA and NZ projects.