CHAPTER 38

Rethinking Duality

Criticisms and Ways Forward

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The chapters in this volume are undoubtedly replete with examples of philosophers' and social scientists' historical recognition of the dual nature of human thought. Writers from the classical era through modern times have noted many times over that human behavior seems to emerge from dueling forces in the psyche (Newell, 1973), and contemporary social and cognitive psychologists have conceptualized these two forces as mental systems that can be studied empirically. In this chapter, we raise conceptual and methodological concerns about dual-mode models in the social cognitive psychological literature. In our view, the problems that fall out of a dual-mode approach to social cognitive research may outweigh its advantages.

Going beyond these concerns, we suggest new ways forward, including a reconsideration of how to think of dissociations between outcomes, and ways to understand the involvement of motivation and control in human thought. We also consider ways to test models of process and advocate for a greater emphasis on testing the independent role of the operating conditions in which a phenomenon emerges.

CRITICISMS OF DUALITY

Nomenclature

Before addressing the evidence for dual-mode models, we first note that much of the social cognitive literature could be clarified with greater precision of terminology, particularly regarding the terms *system*, *process*, and *representation* (e.g., for more discussion, see Evans, 2008; Ferguson & Fukukura, 2012; Gigerenzer & Regier, 1996; Keren & Schul, 2009; Moors & De Houwer, 2006; Newstead, 2000). One of the biggest sources of confusion, it seems to us, is the widely variable application of the term *system* and its tendency to be interchanged with *process*. This leads to confusion within and outside the field, as scholars working in areas such as cognition, neuroscience, and perception attempt to map their conception of *system* onto ours (and cannot).

Additionally, the terms *process* and *representation* are defined in typical ways that do not capture their complexity in the cognitive sciences literature. Whereas the use of *process* in the social psychological literature usually refers to associative versus rule-based operations (e.g., for definitions of these terms, see Chomsky, 1980, 1986; Hahn & Chater, 1998; Pylyshyn, 1980; Searle, 1980; Sloman, 1996; Smith, Langston, & Nisbett, 1992), the concept of representation usually refers to distributed versus symbolic (i.e., for definitions see e.g., Barsalou, 2008; Hahn & Chater, 1998; Sloman, 1996).And, these types of representation are often confounded with these types of process, in that it is assumed that rule-based processing depends solely (e.g., Sloman, 1996; but see discussion in Hahn & Chater, 1998) or partially (Smith & DeCoster, 2000) on symbolic representations, while associative processing (based on similarity or contiguity) is assumed exclusively to involve distributed representations (e.g., Bassili & Brown; Smith & DeCoster, 2000; cf. Hahn & Chater, 1998; Mitchell, Ames, Jenkins, & Banaji, 2009). In the cognitive sciences literature, however, some have argued that associative versus rule-based processing is not inherently wedded to one type of representation, and intense debate on the capacities and plausibility of each type of representation continues (e.g., Barsalou, 1999, 2008; Dietrich & Markman, 2003; Fodor, 1981; Rumelhart, 1989; Van Gelder, 1990). There is also a widespread tendency to confound what a process *does* (e.g., associative versus rule-based operations) with characteristics of its operation (e.g., awareness, intention, speed, control; Gawronski & Bodenhausen, 2009; Lieberman, 2003; Moors & De Houwer, 2006; Sherman, 2006a; Sherman et al., 2008). These continuous operating characteristics cannot be combined to form discrete (dual) processes or systems (see Keren & Schul, 2009, Logan, 1985; Moors & De Houwer, 2006) and also do not reliably or strongly correlate with process or with each other (see Bargh, 1994). For example, although it is widely assumed that associative processing occurs without awareness or control, there is in fact surprisingly little evidence for this (e.g., Berry, Shanks, Li, Rains, & Henson, 2010; Berry, Shanks, Speekenbrink, & Henson, 2012; Gawronski, Bodenhausen, & Becker, 2007; Mitchell et al., 2009).

How Convincing Are the Dissociation Data Suggesting Dual-Mode Models?

The evidence on which many dual-mode models rely consists of dissociations in which one manipulation impacts a first outcome but not a second, and a different manipulation impacts the second outcome but not the first (e.g., Gawronski & Bodenhausen, 2006; Rydell & McConnell, 2006; Rydell, McConnell, Mackie, & Strain, 2006; Wilson, Lindsey, & Schooler, 2000; for a review, see Chaiken & Trope, 1999). Such dissociation evidence is widely used at both the cognitive and the brain level to argue for separable functional processes (Dunn & Kirsner, 2003). Dissociations are consistent with two different underlying processes, but the problem is that they are also consistent with, and cannot dismiss, a single underlying process or system (Bedford, 2003; Chater, 2003; Dunn & Kirsner, 2003; Kinder & Shanks, 2001; Plaut, 1995). Such dissociations conclusively show only that some potentially small processing component is differentially sensitive to one manipulation but not another. For instance, take Chater's (2003) example of peanut allergy versus prawn allergy (two natural "manipulations"): In the first case, consumption of peanuts produces a systemic reaction but consumption of prawns does not, and in the second case, the reverse pattern emerges. Yet this dissociation proves nothing about dual digestive or immune systems. We know instead that this dissociation is produced by differential sensitivity of a single immune system to different foods (Keren & Schul, 2009; see also the not-the-liver fallacy; Bedford, 2003).

It is also the case that any dissociation data that emerge from the use of two different measures (e.g., implicit attitude measure vs. a Likert scale) are inherently inconclusive with regard to the involvement of two different processes (or systems) given that the (likely many) differences between any two measures can be orthogonal to process (Cunningham & Zelazo, 2007; Payne, 2005; Payne, Burkley, & Stokes, 2008; Sloman, 1996), and given recent evidence demonstrating that any measure likely captures multiple types of processes (e.g., Bishara & Payne, 2009; Conrey, Sherman, Gawronski, Hugenberg, & Groom, 2005; Sherman, 2006b). It is also important to note that even if different measures enable outcomes that seem more compatible with rule-based versus associative processes (e.g., truth testing), such evidence is equally inconclusive. As even Sloman (1996) argued, in general, it is impossible to rely on responses that manifest "associative" or "rule-like" qualities to argue for underlying process. The robustness of rules allows for any "associative" response to be modeled in terms of rules (also see Kruglanski & Dechesne, 2006; Kruglanski, Erb, Pierro, Mannetti, & Chun, 2006). Similarly, recent work with connectionist systems, which have been held up as the hardware implementing associative processing (e.g., Sloman, 1996; Smith & DeCoster, 2000), have proven capable of modeling deductive syllogisms (Rogers & McClelland, 2004), causal reasoning (Read & Montoya, 1999), executive control (Rougier, Noelle, Braver, Cohen, & O'Reilly, 2005) and serial-like processing (Spivey, 2007) all of which are usually held to characterize the rule-based system. In other words, outcomes that seem based in similarity or contiguity can still be modeled with rules, and outcomes that seem based in rule-based classification independent of similarity/contiguity can also be modeled in an associative-like structure. Outcomes might vary in different instances not because of fundamentally distinct systems or processes, but because of different parameter values within a single process (e.g., Shanks & Berry, 2012; Kruglanski et al., 2006).

Sloman (1996) argues that the best evidence that can be marshaled in support of dual-systems theories comes in the form of simultaneous contradictory belief ("Criterion S"). This refers to a conscious sense that two conflicting responses are both appropriate, *at the same moment in time.* Despite its logic, Criterion S presents a number of problems. The criterion is an inference about process drawn from introspection, which has well-documented limitations (Nisbett & Wilson, 1977). Any number of systems or processes might interact in complex ways in producing a conscious experience, which introspection likely can only imperfectly tap. It is also possible that even if beliefs are simultaneous, they may be produced by the same system. For example, it may be the case that "simultaneous contradictory beliefs" never actually occur per se; rather, people alternate quickly between different reasoning outcomes and merely report these as simultaneous (Osman, 2004). Or, a conflict could emerge from two contradictory rule-like beliefs (e.g., Chater, 2009). Or instances of manifest conflicting beliefs might truly reflect ambiguity about the application of particular rules (Betsch & Fiedler, 1999; Gigerenzer & Regier, 1996) and by some accounts should be present in any complex system that has many rules from which to select in any instance (Kelso & Engstrøm, 2006). Finally, even if one wishes to maintain that a given system must have a single output for any input, it is not clear why this output could not consist of a conscious state of ambivalence.

Finally, theorists sometimes use dissociation of brain activation to make the case for dual systems (e.g., Cushman, Young, & Greene, 2010; Lieberman, Gaunt, Gilbert, & Trope, 2002; Satpute & Lieberman, 2006; Smith & DeCoster, 2000; Spunt & Lieberman, 2013). For example, in their generalized dual-systems model, Smith and DeCoster (2000) cite the role of the hippocampus in implementing a fast-learning, effortful, symbolic processing system, and draw on lesion research to demonstrate the independence of this system from a slower, effortless one localized elsewhere. Such evidence suffers from the same issues cited earlier, such as the inability of dissociation evidence to establish two independent systems (e.g., Dunn & Kirsner, 2003). In fact, dissociations are possible in the case of lesions within nonmodular systems (Plaut, 1995).

Other evidence that is problematic for notions of independent systems at the level of neural hardware comes from what Anderson (2010) terms *neural reuse.* Under Anderson's (2007a, 2007b, 2010) conception, new functions are implemented in the brain by drawing on dispersed areas of cortex that previously participated in other functioning, such that localized brain regions come to participate in a variety of functions. In other words, a particular function (e.g., syllogistic reasoning) would be implemented not by a *dedicated* section or circuit of cortex, but by a pattern of activity among cortical elements that each participate in other functions when active in other combinations. These findings make it difficult to substantiate evidence that particular brain areas are the exclusive domain of any one particular type of processing, and they cast further doubt on the idea that even apparent cortical dissociations support dual-systems claims.

WAYS FORWARD

We believe the dual-mode approach has gotten entrenched, and its tentative status due to controversial data and theory is thus often obscured. For example, some of the key assumptions on which many social cognitive dual-mode theories are based are undermined by empirical findings and conceptual argument. These examples also stand as critiques of dual-mode theory, but they additionally point to new ways to conceptualize some general issues in the literature. We consider below two examples of such assumptions, then consider alternative ways to explain dissociated outcomes and the role of motivation.

Rethinking Learning

One of the most widely agreed upon differences between associative and rule-based processing, or between "System 1" and "System 2," is the rate or ease of learning. System 1 (or, associative processing) and System 2 (or, rule-based processing) are commonly referred to as the "slow" versus "fast" learning systems, respectively (for a review, see Conrey & Smith, 2007; cf. Gawronski & Bodenhausen, 2006, 2011; Gawronski & Bodenhausen, 2006, 2007, 2011). Many dual-mode theories assume that associative processes are slow learning because they consist of processes in the implicit memory system, and the implicit memory system has been historically characterized as slow learning. Rule-based processing, on the other hand, is thought to be fast learning, because it is enabled by the explicit memory system, which in turn is thought to be fast learning. In the social psychological literature, associative (or implicit) processing is therefore assumed to enable learning about a new event or pairing only after a long time, and after a large amount of experience. Rule-based, or symbolic or explicit processes, on the other hand, are assumed to enable learning after a single trial.

It is important to note that this assumption of learning is one of the most central criteria of most dual-mode models. This is because much of the argument for the necessity (functionality) of two independent systems consists of human and nonhuman animals' purported needs for both fast and slow learning (see Sherry & Schacter, 1987, for a discussion of the imperative for independent fast and slow learning systems in humans and other species). Thus, the evolutionary or functional explanation for two separate systems is based directly on (incompatible) learning needs.

Despite the centrality of the assumption of differential learning rates in many dual-mode models, much work calls this assumption into question in ways that highlight both the need to move beyond such conceptions and, importantly, strategies for doing so. First, contrary to widespread assumptions in the social cognitive literature, many scholars argue that implicit memory is actually composed of various kinds of processes that have fundamentally different characteristics, including learning rate (see Amodio & Ratner, 2011; Poldrack & Foerde, 2007; Squire & Kandel, 1999). For example, whereas semantic memory is often characterized as slow to develop (McClelland, McNaughton, & O'Reilly, 1995), aversive as well as appetitive conditioning can be acquired across animal models and in humans very rapidly, sometimes in a single trial (e.g., Cahill & McGaugh, 1990; Fanselow, 1990; Garcia, Kimeldorf, & Koelling, 1955; Hermer-Vazquez et al., 2005; LeDoux, 2000; Lossner & Rose, 1983; Rutishauser, Mamelak, & Schuman, 2006; Yin & Knowlton, 2006). Amodio and Ratner (2011) argue that it is misleading to assume that implicit (associative, "System 1") processes in social psychological phenomena rely on a single system that is characterized by one kind of learning. This conception (existing largely outside of social psychological literature) of memory and learning then directly challenges one of the most commonly accepted assumptions of almost all dual-mode models (for an exception, see Gawronski & Bodenhausen, 2006, 2011).

In addition to the data showing that appetitive and aversive conditioning (i.e., often assumed to be based on associative processing) can happen rapidly, there also exists another type of evidence of fast learning. Studies from the social cognitive attitudes literature show that participants can develop implicit (or System 1, associative-based) attitudes toward objects on the basis of new verbal (propositionally based) information learned only minutes earlier (Ashburn-

Nardo, Voils, & Monteith, 2001; Castelli, Zogmaister, Smith, & Arcuri, 2004; Gawronski et al., 2007; Gawronski & LeBel, 2008; Gregg, Seibt, & Banaji, 2006). This is especially interesting given that such verbal instructions are often presumed to depend on System 2 processing (Epstein, 1994; Rydell & McConnell, 2006). Gregg and colleagues (2006), for instance, asked participants to suppose that two novel groups, the Niffites and the Luppites, comprised good versus evil people. In an Implicit Association Test (IAT; Greenwald, McGhee, & Schwartz, 1998) administered 1 or 2 minutes later, they showed greater implicit preference for whichever group was described as good.

Even more recent work shows that people can even rapidly *revise* newly formed implicit attitudes based on very little propositional information. Cone and Ferguson (2012) predicted that people should show revision in their newly formed implicit attitudes for minimally self-relevant novel objects. When participants were assigned to groups based on (a bogus) personality test, they showed an implicit preference toward their ingroup only minutes later, providing further evidence that implicit attitudes can form extremely rapidly. However, the authors then told some of them that there was a mistake in their ingroup assignment and they actually belonged to the *other* group. Their implicit attitudes nevertheless then immediately showed a significant shift toward the other group, showing fast revision. Whereas previous work had found no evidence of fast revision of attitudes toward fictional groups that had no relevance to participants, this recent work shows that such revision commonly occurs when the novel attitude objects have some minimal relevance, such as one's ingroup. We also demonstrated that *revised* implicit attitudes toward a novel object were just as strong as their newly formed attitudes had been, suggesting that the evidence for fast revision was not implicit ambivalence (Petty, Tormala, Briñol, & Jarvis, 2006).

In summary, evidence from two different literatures (conditioning in animals and humans; social cognitive attitudes in humans) points strongly against the slow learning claims for System 1 types of processes, at least in the realm of attitudes. This kind of evidence may be interpreted in various ways: It can be seen as casting doubt on the learning rates typically linked with the two different modes, casting doubt on the assumption that there are only two modes, or challenging the need for separate systems or processes altogether. Relative to the last possibility, although the evidence for two (relatively independent) memory systems has been seen as strong, there are tenable challenges. Not only is there a fair amount of criticism of the evidence for two memory systems (e.g., Hintzman, 1990; Howe, Rabinowitz, & Grant, 1993; Ostergaard, 1992; see Poldrack, 1996, for a review), but also researchers have started to examine computational models to test the claims of a single versus multiple systems. Shanks and Berry and their colleagues (Berry, Shanks, & Henson, 2008a, 2008b; Berry et al., 2012; Shanks & Berry, 2012; Shanks & Perruchet, 2002) have developed mathematical models of single memory systems based on signal detection theory (SDT), and have found strong support for a single- versus dual-memory system (see also Craik, 1983; Kolers & Roediger, 1984). This work (see Shanks & Berry, 2012) assumes that the dissociation data (from priming vs. recognition tasks) interpreted as support for separate implicit and explicit memory systems can be modeled using a simple SDT model that assumes a single process. One of the key ideas here is that in both priming (i.e., implicit) and recognition (i.e., explicit) tasks, there is the *same* underlying source of memory trace (one process), but the tasks differ in the type and amount of nonmemorial noise. They argue that dissociations between these types of tasks in fact emerge from these different types of noise that obscure to varying degrees the same underlying signal of the memory trace. The progression and implications of this work are obviously highly relevant for social cognitive theorizing.

In summary, we have outlined some evidence and theory that challenge one of the major foundations upon which most of the dual-mode theory is built, the existence of two memory systems and the different learning rate between them. What remains is a comprehensive examination of the conditions under which implicit attitudes and processes more generally show fast versus slow change (see Ferguson & Fukukura, 2012). For example, there are obviously differences in the types of manipulations that produce change on implicit versus explicit measures (e.g., see Gawronski & Bodenhausen, 2006), and the reasons for such dissociations remain unclear. Our point here is that we may not necessarily have to go to a dual-mode model in order to explain such differences. We have outlined the various nonprocess reasons that could potentially explain such dissociation data, and the burden is now on theorists to generate single-system alternatives to the current crop of dual-mode explanations.

Rethinking "Symbolic" Thought in "System 1"

Perhaps one of the strongest arguments for "System 2" processes and representations is that some kinds of cognition seem to require symbolic, syntactically structured thought, such as language, probability, logic, and math (Dietrich & Markman, 2003; Fodor & Pylyshyn, 1988). This debate has often centered on the requirements of language and its observed productivity, systematicity, and compositionality. In terms of productivity, whereas associative thought is assumed by many to be merely reproductive, in that it is limited to whatever we have experienced in the past, we must also have some form of thinking that is productive so as to be able to deal with totally novel situations. For instance, as Chomsky (1968) speculated, we can generate an infinite number of propositions (claims), and this unboundedness could not come from associative thought. *Systematicity* refers to the fact that our ability to understand that "Mary loves John" implies our ability to understand that "John loves Mary." And *compositionality* refers to the fact that our ability to understand that "Mary loves John" is a function of our understanding of its constituent parts, "Mary," "loves," and "John."

However, the claims that these characteristics can only be generated by rule-based thinking have been refuted in a number of ways, through either argument (Chalmers, 1990, 1993; Smolensky, 1988; Van Gelder, 1990) or examples of connectionist models that show these characteristics (Chalmers, 1990; Elman, 1990; Pollack, 1990; Smolensky, 1990). (Note that even Sloman, 1996, did not agree with the claim that associative processing is merely reproductive.) There is now an impressive body of evidence demonstrating, for example, that various characteristics of language can be modeled successfully with connectionist networks (e.g., Christiansen & Chater, 2001, 2009; McClelland, Plaut, Gotts, & Maia, 2003). Thus, the common claims that System 2 is more "verbal" or language-based seem unwarranted.

There are related and frequently asserted claims that only (conscious) rule-based processing could enable the reading of multiword phrases and abstract mathematics (e.g., Deutsch, Gawronski, & Strack, 2006; Greenwald & Liu, 1985, 1992; Baumeister & Masicampo, 2010; Morewedge & Kahneman, 2010; Winkielman, 2008; but see, e.g., Anderson, Spoehr, & Bennett, 1994). However, recent work challenges this assumption by showing that people can solve math problems and read multiword phrases nonconsciously (Sklar, Levy, Goldstein, Mandel, Maril, & Hassin, 2012). Sklar and colleagues used a recently developed method called continuous flash suppression (Tsuchiya & Koch, 2005), which consists of presentation of material (e.g., an equation) to one eye with a simultaneous presentation of rapidly changing masks (noise) to the other eye. The continuous flashes of noise to the one eye keep the static information to the other eye below conscious awareness, for up to 2 seconds. For nonconscious reading, Sklar and colleagues (2012) showed that participants were able to nonconsciously process whether the meaning of three-word sentences constituted a semantic violation (e.g., "I ironed coffee") or not ("I ironed clothes"). As for evidence of nonconscious arithmetic, when presented with equations (e.g., 2 + 3 + 5 = . . .), participants responded significantly faster to solutions of those equations (e.g., 10) than to nonsolutions (e.g., 11). The findings show that cognitive operations that classically are assumed to be uniquely enabled by rule-based thinking can occur nonconsciously.

These findings are a perfect example of how the notion of process (in this case, rule-based vs. associative) could potentially be confounded with a characteristic of the operation of the process (consciousness). To the extent that one believes that rule-based processing has to be conscious (confounding the two), these findings would indicate that the process at play here cannot be rule-based (and could, instead, be associative). However, if one believes, as we do, that the operating characteristics of a process are orthogonal to what it is the process is doing (following rules vs. operating by similarity and contiguity), then one would not necessarily believe that rule-based processing has to be accompanied by consciousness (e.g., Sloman, 1996). So, therefore, these data are agnostic about what the process is, and instead tell us simply that these outcomes that have been historically branded as consciousness-dependent (reading, doing math), however they are enabled or solved, can in fact operate without consciousness.

Rethinking Dissociated Outcomes

We noted earlier that many scholars interpret empirical dissociations across (implicit vs. explicit) behavioral measures as evidence for two different systems, or processes. We also noted that a dual-mode model is certainly consistent with such dissociation. But such evidence could also be consistent with a single-system/process model. What type of single-system model might explain such dissociations? Let's consider a prototypical case of dissociation in social psychology: the difference in attitudes toward racial/ethnic groups as a function of whether an implicit versus explicit measure is used. For example, when racial outgroup attitudes are measured after relatively short cognitive processing durations (e.g., on the IAT), they often appear negative, whereas when the same attitudes are measured after relatively long processing durations (e.g., through self-report), they often appear more positive, or egalitarian (e.g., Dovidio, Kawakami, & Gaertner, 2002).

The dual-mode interpretation of these data is that whereas the "fast" attitudes are explained by System 1, the endorsed responses are often explained by System 2 (or a combination of System 1 and System 2; see Gawronski & Bodenhausen, 2006; Strack & Deutsch, 2004). A single-system interpretation, on the other hand, comes from the mathematical modeling of dynamical systems (Hirsch & Smale, 1974). *Dynamical systems models* (technically, coupled differential equations) describe the dynamics of a group of multiple interacting components. Dynamical systems frequently exhibit a property of *self-organization* (e.g., Kelso 1995); that is, the system's components gradually assemble themselves from a disordered state into an ordered state, and they do so without a central executive directing those changes. The key idea here rests on the mathematical concept of an "attractor." To put the key concepts together, the dynamical system comprises multiple components that interact.The *state* of the system is a pattern of numbers that describe each component's value at some particular time. After the system has been externally perturbed, for example, by a stimulus, (this is called an *initial condition*), the "dynamics" describe how the system moves itself, toward particular states (called the *stable states* or "attractors" of the system).

In cognitive science, the brain has been considered a dynamical *system* by many theorists (e.g., Beer, 1995; Kelso, 1995; Spivey, 2007). The brain comprises multiple interacting components (brain regions, or neurons), and it is continuously perturbed by external forces (stimulation from sensory receptors), but it responds to these perturbations according to its own internal principles for componentwise interactions (the brain regions or neurons interact due to patterns of synaptic connectivity between spiking neurons; see, e.g., Hopfield, 1984; Izhikevich, 2007). Now what might an attractor be in the brain? Let's first illustrate the concept of an attractor in a simple one-dimensional system. Consider a "system" that is simply the height of a tennis ball above the ground. Imagine that someone drops a tennis ball from the Space Needle (650 ft. above the ground) with zero velocity. That state (of being 650 ft. above the ground) is highly unstable, and the ball is pushed to the ground (by the force of gravity). Thus, the "attractor" in that simple system is the ground (more specifically, the height of 0 ft.). Dynamical systems approaches to neural cognition extend this concept to the brain by considering it as a high-dimensional system whose components are neurons and whose state is, for example, the current firing rate of each neuron. The dynamical systems perspective observes that certain firing configurations could be highly unstable, because of the network effect of communication between neurons: Learned patterns of synaptic connectivity cause one neuron's firing to influence, whether directly or indirectly, the firing of other neurons in the network. Recurrent connectivity between neuronal regions, and or lateral inhibition, can cause the neural firing patterns eventually to "settle" or converge into certain predetermined, interpretable neural patterns (e.g., Wang, 2001). Thus, the brain is pushed into relatively stable firing patterns, representing relatively coherent, interpretable representations (e.g., "I see Professor Spivey," rather than "I see a person 40% likely to be Professor Spivey, 35% likely to be my brother-in-law, and so forth"; see Spivey, 2007). Indeed, there is evidence for the existence of attractors in many neural systems (e.g., the olfactory system: Mazor & Laurent, 2005; the hippocampus: Wills, Lever, Cacucci, Burgess, & O'Keefe, 2005; the prefrontal cortex: Durstewitz, Kelc, & Gunturkun, 1999; the lateral intraparietal (LIP) area: Ganguli et al., 2008).

What are the implications for attitudes toward groups of people? Dynamical systems can explain some basic dissociation phenomena (e.g., how early negative biases morph into personally endorsed positive decisions), without stipulating two deciders. Early biases may be exhibited as a single mental system transitions through multiple intermediate decision states en route to its finalized decision. This notion of intermediate tentative decision states is common in the mathematical modeling of neural decisions (see Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006), even in the simple drift-diffusion models that accumulate sensory evidence over time. But the more neurobiologically detailed decision-making models are often endowed with recurrent feedback and/or lateral inhibition, two fundamental features of neurobiological processing (O'Reilly, 1998). These decision-making models are no longer just accumulators of evidence; they are now dynamical systems harboring attractors. That is, these dynamical systems do not stop processing when the incoming evidence is shut off; they gravitate automatically from certain regions of space (the "unstable" regions of space, usually representing blends of multiple decisions or interpretations) into other regions of space (the "stable" regions of space, usually representing coherent singular interpretations or decisions). Many detailed models of neural decision making incorporate these features: for example, the competing accumulator model (Usher & McClelland, 2001), the normalized recurrence model (Spivey, 2007), the recurrent neural circuit model (e.g., Wong & Wang, 2006), and the dynamical field theory model (Erlhagen & Schöner, 2002).

The important observation is that just as a bird can fly toward its nest through multiple pathways, a dynamical neural system can transition into its eventual decision (stable firing pattern) according to potentially very many different trajectories (its continuously evolving firing patterns over the preceding temporal period). Let us imagine from a macro-scale (as does normalized recurrence; Spivey, 2007) that the typical brain comprises a number of informational sources (personal memories, semantic information, emotional associations, future goals, etc.), each of which provides partial probabilistic support for a certain evaluative decision (e.g., liking vs. disliking white or black Americans). From a dynamical systems perspective, the decision is made when the conflict distributed across the cacophonous system is resolved into a single harmonious decision. A dynamical systems model (e.g., any of the ones listed earlier) describes the dynamics of this decision process; in particular, it describes how a certain initial set of conflicts across informational sources dynamically resolves into a decision. Let us first assume that, as self-reports suggest, white people in general possess greater overall informational support for "liking" rather "disliking" both black people and white people. However, let us further assume that, as IAT findings suggest, white people nevertheless harbor greater conflict among their information sources when they have to decide whether they like black people then when they do the same about white people. Then a stochastic dynamical systems model makes very particular predictions about the dynamics of the decision—qualitative predictions that can be "read off" the equations of the previous models (see, e.g., the introduction to Wojnowicz, Ferguson, Dale, & Spivey, 2009). In particular, such models predict that the decision would exhibit *deviation* (a general trend of moving through regions of decision space with greater input of dislike in the transitional moments of mental processing), *disorder* (brief excursions toward a dislike interpretation rather than a like interpretation), and *acceleration* (i.e., processing of the decision would accelerate over time; the simultaneous activation of multiple alternative decisions causes excess activation in the neural system, thus artificially slowing processing due to lateral inhibition).

The dynamical perspective on explicit attitude formation was supported by recent research analyzing hand movement trajectories taken by participants during their like versus dislike evaluations of racial groups (Wojnowicz et al., 2009). Participants were asked to click on "LIKE" or "DISLIKE" response boxes (in the upper corners of the computer screen) to report their evaluations of a series of stimuli. The key stimuli, "black people" and "white people" were embedded within a large set of distractor stimuli, such as "ice cream" and "Hitler." The results were that participants tended to select "LIKE" for both white people and black people. However, while participants were selecting "LIKE" for black people, their hands exhibited significant greater curvature toward the "DISLIKE" response box. Moreover, their hand movement patterns exhibited greater disorder and greater acceleration.

These results suggest that the dissociated measurements of racial evaluations (more specifically, the fact that among white participants a "black people" stimulus yields negative evaluations on IAT measures and positive evaluations on self-reports, whereas a "white people" stimulus yields positive evaluations on both) may be explained, at least in part, by the way in which a dynamical cognitive system processes high levels of conflict. According to dynamical systems theory, when a person must choose between two possible options, and when there is relatively high conflict distributed across multiple sources of informational support (memories of personal experiences, emotional associations, semantic knowledge, etc.), then the system will deliver relatively strong support for the nonendorsed option during early moments of mental processing. This is precisely what is observed in implicit measures of racial evaluation. Critically, this perspective can be interpreted as a single system or process. In particular, from the dynamical systems perspective, mental processing is described according to a single set of neurobiologically plausible principles that are common to many brain regions (O'Reilly, 1998), so there is no "ontological gulf" between two incommensurate systems (i.e., System 1 and System 2). That is, both the early implicit biases and the later endorsed decision are part and parcel of a single process—the dynamic evolution of a distributed parallel mental representation.

There is increasing research in social psychology that shows how a dynamical systems perspective can be applied to classical social psychological questions (for reviews, see Freeman & Ambady, 2010; Freeman, Dale, & Farmer, 2011). One important contribution is that this work allows an examination of real-time processing by using the motor movements of a hand, for example, as a proxy for ongoing cognition. This provides an incredibly fine-grained temporal profile of how decisions unfold in real time, and can reveal outcomes that differ from the typical implicit measures of response times (e.g., Song & Nakayama, 2006, 2008; Wojnowicz et al., 2009). However, another contribution is that this work can address the single- versus multiple-mode question. Whenever there are claims about how one system or process transitions to another (in a discrete or continuous fashion), the dynamical systems perspective and its associated methodological tools (mouse tracking, eye tracking) can directly test those claims. We view this as an exciting new direction in social cognition work, particularly given its applicability to theory about (the number of) systems and processes.

Rethinking Goals and Control

The dynamical systems perspective is also currently being used to help explain goal pursuit and executive control while invoking brain systems as interacting parallel distributed processing networks, although this work is more recent. Modeling the functionalities of goal pursuit and executive control generally require multiple brain systems (the prefrontal cortex, basal ganglia, posterior cortex, etc., are regions that have functionally meaningful specializations in terms of neuromodulation, connectivity patterns, firing rate stability, etc.), but at the same time, these multiple brain systems are well defined

as parallel distributed processing networks, whose cognitive processing is characterized by interaction both inside and between brain regions, and conform to a single set of shared processing principles, such as distributed processing, lateral inhibition, and recurrent feedback (O'Reilly, 1998).

One major question is how people pursue distant goals through a parallel distributed processing network—an approach differing from that of some of the dual-mode theories that see the pursuit of distant goals as requiring inherently discrete logical rules in a serial processing system (e.g., Strack & Deutsch, 2004). As a solution to this problem, recent work in computational neuroscience has investigated how the basal ganglia serve as an "adaptive critic" of the rest of the brain, instantiating a type of learning known as reinforcement learning (e.g., Montague, Dayan & Sejnowski, 1996). The term *reinforcement learning*, unfortunately, sounds antiquated, conjuring up Skinner's no longer influential notion that higher-order cognition can be explained by very simple procedures for learning knee-jerk reactions to the environment. However, the label is misleading. Contemporary reinforcement learning approaches are relatively quite sophisticated (see Fukukura, Helzer, & Ferguson, 2013), and they demonstrate how "merely associative" stimulus–response mechanisms could subserve the complex, strategic pursuit of distant goals. According to this literature, brains contain an internal critic that tracks the "value" of transitions between various environmental states (or their cortical representations; see Montague et al., 1996). Whenever the person reaches a more highly valued state than expected, the critic sends out an internally manufactured dopaminergic reward signal. Using these dopaminergic reward signals, the "adaptive critic" (located in the basal ganglia) determines the value of being in a particular state. Using these value assessments, the adaptive critic trains the rest of the brain to choose behaviors that subserve a person's strategic goals, even when pursuing the goal will require repeated deliberation at multiple junctures deep into the future. What these findings mean, in effect, is that the frequently derided notion of stimulus–response associations can be actually quite intelligent. These associations are far more sophisticated than brutish knee-jerk reactions to immediate pleasure and pain; instead, the strength of these associations can capture, in a single quantity, complex information about how to maximize the expected value of an arbitrarily distant future. In fact, when stimulus–response associations are sculpted by an internal critic, they can guide an agent to successful performance even in penultimate logical, rule-based tasks, such as backgammon or chess games (see Sutton & Barto, 1998). Although assessing the value of an action in the face of such dynamic iterative stochastic loops is complicated, recent work in reinforcement learning has determined that it is possibly in theory (e.g., Houk, Adams, & Barto, 1995), and that the brain seems to be making such computations (e.g., Dayan & Daw, 2008).

Similar work has extended these findings to explain how the prefrontal cortex can subserve executive control functionalities, without depending upon explicit logical rules (Rougier et al., 2005) or employing a distinct form of computation (e.g., discrete logical symbolic thought). Aligning one's behavior with respect to transient goals is part of what is meant by psychological control —in particular by the capacity of "flexible top-down processing." O'Reilly and Frank (2006) argue that flexible top-down processing is subserved by the prefrontal cortex due to that region's distinct neurocomputational features. In particular, prefrontal cortical neurons are characterized (compared to, say, posterior cortical neurons) by their abilities (1) to actively maintain goal-related information, (2) to flexibly update representations in response to dopaminergic signals (of value), and (3) to send widespread feedback to the rest of the brain. In this way, the prefrontal cortex can strategically bias lower-level sensory representations or attentional resources in a way that subserves goal-related needs (e.g., Miller & Cohen, 2001). The way that this "flexible top-down processing" region can interactively influence the brain is described in O'Reilly and Frank's (2006) dynamic gating model of prefrontal control. Importantly, this model implements motivated control through multiple interacting parallel-processing brain regions, fundamentally characterized by interaction both inside and between brain regions. What justifies the use of the term *multiple* systems or brain regions is not distinct computational formats (i.e., symbolic vs. distributed representations) or a wall of separation between the systems (whereby communication is unclear), but rather the fact that the nature of the parallel distributed processing inside has important fundamental differences (neuromodulators, network centrality, etc.). Recent theoretical work on multiple interacting systems (Ferguson & Wojnowicz, 2011) has examined how this "multiple interacting systems" model of executive control could explain the social psychological phenomenon of evaluative readiness (Ferguson, 2008). The primary idea is that the prefrontal cortex serves to dynamically project the high-dimensional dynamics of the posterior cortical system in such a way that it best subserves motivational needs (see Ferguson & Wojnowicz, 2011).

CONCLUSION

We have outlined some criticisms of dual-mode theory, as well as ways to move beyond the criticisms. We now conclude by making two suggestions. The first is that, in our view, the question of rule-based versus associative processing can only be convincingly tested using computational model testing. Computational models consist of assigning computational programs that specify algorithms (e.g., rule-following) for cognitive functions. Critically, these computational programs are then runnable and can be tested for how they fit behavioral data. We view computational models as the most informative type of model testing (e.g., Hintzman, 1990; Newell, 1990; Sun, 2008), because they provide highly specified (both procedurally and conceptually) predictions that can be formally tested and compared with human (or animal) data. Most of the computational work in social psychology over the last few decades has consisted of connectionist models (Read & Monroe, 2008). There is almost no application of symbolic models such as Adaptive Character of Thought–Rational (ACT-R; Anderson, 1993; Anderson & Lebiere, 1998) or CLARION (Sun, Slusarz, & Terry, 2005), or hybrid models (e.g., Smolensky, 1988) to social psychological phenomena. This is possibly a missed opportunity given that social cognitive dual-process models strongly postulate rule-based processing (and/or symbolic representations).

Our second suggestion is to advocate for greater testing of the operating characteristics of a process—in other words, the dimensions such as awareness, resources, control, speed, and intention, according to which phenomena emerge (e.g., see Moors & De Houwer, 2006). In our view, such information is valuable, necessary, and informative, and might even be of greater interest to our field than the identification of rule-based versus associative processing. In fact, the operating characteristics that are studied most often in the context of dual-mode theories include awareness, intention, control, and effort. The common currency of subjective experience among these characteristics most often studied by social psychologists is undoubtedly no accident, and knowledge about the extent and nature of phenomena that can emerge outside of, or only with, our subjective consent or awareness will probably continue to be of interest to our field, and to those outside of it (e.g., Ross, Lepper, & Ward, 2010).

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