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Cultural Schemas: What They Are, How to Find Them, and What to Do Once You've Caught One

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Abstract

Cultural schemas are a central cognitive mechanism through which culture affects action. In this article, we develop a theoretical model of cultural schemas that is better able to support empirical work, including inferential, sensitizing, and operational uses. We propose a multilevel framework centered on a high-level definition of cultural schemas that is sufficiently broad to capture its major sociological applications but still sufficiently narrow to identify a set of cognitive phenomena with key functional properties in common: *cultural schemas are socially shared representations deployable in automatic cognition*. We use this conception to elaborate the main theoretical properties of cultural schemas, and to provide clear criteria that distinguish them from other cultural or cognitive elements. We then propose a series of concrete tests empirical scholarship can use to determine if these properties apply. We also demonstrate how this approach can identify potentially faulty theoretical inferences present in existing work. Moving to a lower level of analysis, we elaborate how cultural schemas can be algorithmically conceptualized in terms of their building blocks. This leads us to recommend improvements to methods for measuring cultural schemas. We conclude by outlining questions for a broader research program.

Keywords

cultural schemas, cognitive sociology, automatic cognition, connectionism, Marr's levels

Following DiMaggio's (1997) immensely influential article about "Culture and Cognition," sociologists have increasingly turned to a cognitively-minded model of how culture influences behavior. Central to this model is the concept of cultural schemas, or "knowledge structures that represent objects or events and provide default assumptions about their characteristics, relationships, and entailments under conditions of incomplete information" (DiMaggio 1997:269). In the decades since DiMaggio's work, this cognitive science-derived understanding of cultural schemas has figured centrally in some of the most prominent studies within cognitive sociology of culture (e.g., Frye 2017; Hunzaker 2016; Hunzaker and Valentino 2019; Vaisey 2009).[1] It has also been used in a vast and growing range of applications across the discipline, including in the sociologies of religion, gender, race, organizations, and demog-

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raphy, among many other subfields (e.g., Cech and Blair-Loy 2014; Clawson and Gerstel 2014; Edgell 2012; Ray 2019; see overview in Hunzaker and Valentino 2019).

In recent years, engagements with cultural schemas within cognitive sociology have become increasingly theoretically demanding, with emerging work focusing on operationalizing or formalizing the concept of cultural schemas, or attempting to discern general principles behind their operation (e.g., Bachrach 2014; Boutyline 2017; Goldberg 2011; Hunzaker 2016; Hunzaker and Valentino 2019; Shaw 2015; Shepherd and Marshall 2018; Taylor and Stoltz 2020). This wellspring of interest brings the promise of a cumulative research enterprise capable of developing a body of general scientific knowledge regarding the structure, function, and distribution of cultural schemas, which has the potential to substantially benefit the many empirical applications of this concept in sociology and other disciplines. These developments make this a fitting time to reexamine the theoretical foundation of this research program.

Our Goals

Our primary aims are pragmatic. We focus on how our theoretical conception can best support empirical work on cultural schemas, including *inferential uses* that draw on accumulated knowledge to make novel theoretical inferences about the analyst's domain; *sensitizing uses* that pose empirical questions and provide a lens for interpreting observations; and *operational uses* that construct empirical measures aimed at finding schemas in observed data.

Perhaps the main analytic utility of "cultural schemas" for sociologists comes from their powerful relationship to social behavior. As we will detail, cultural schemas can fill in unobserved or forgotten details with cultural assumptions; conceal "irrelevant" variability between objects or people by presenting them as instances of one shared category; and link situations to taken-for-granted normative prescriptions. Crucially, because internalized schemas can be invoked automatically, quickly, and implicitly, they can have these effects *outside an individual's control or awareness*. They thus cannot be simply "turned off" like volitionally controlled "cultural tools" (Frye 2012; Vaisey 2009; Wood et al. 2018). This relatively direct connection to behavior lets cultural schemas serve as an important explanatory mechanism in contemporary accounts of culture's effects on action.

A major goal of our work is to guarantee that the cultural schemas concept can robustly play this explanatory role. This requires reasonably clear limits on what counts as a cultural schema—if the concept's bounds are excessively unclear, then it is also unclear what properties cultural schemas share. Scholars in other disciplines note that the concept of schemas has historically faced the problem of accumulating too many conflicting meanings to remain analytically useful (Ghosh and Gilboa 2014). One telltale sign that this problem may be affecting sociological applications is the occasional use of "cultural schemas" as a generic term roughly synonymous with other loosely defined elements of culture like logics, meanings, or discourses (e.g., Schwarz 2018:855–56; Wilde 2004:581). If the concept can be used interchangeably with many others, it contributes little to work that uses it.

An overly ambiguous conceptualization can also lead to faulty inferences, where objects that are not cultural schemas are incorrectly inferred to possess schematic properties. For example, we will demonstrate that the common practice of using DiMaggio's (1997) and Sewell's (1992) conceptions of cultural schemas interchangeably—even though they describe different constructs—can lead to incorrect conclusions. We thus focus on developing a conception of cultural schemas that has unambiguous bounds and clear theoretical entailments. We then provide concrete empirical and conceptual tests that applied scholars can use to verify whether their objects of investigation are indeed cultural schemas. We also develop suggestions for improving schematic measurement.

Plan of Analysis

We use two prominent views of schemas as starting points. Most sociological work continues to use DiMaggio's "default assumptions" definition, but a growing number of cognitive sociologists instead conceptualize cultural schemas as networks of implicit associations accrued through experience (see Table 1). This "implicit associations" conception of cultural schemas was first prominently introduced to sociology by Vaisey (2009), who argued that it more accurately depicts their cognitive operation. Our work is the first to closely investigate the relationship between these two conceptions.

Vaisey (2009) presented the two conceptions as conflicting. However, when we trace the "implicit associations" view to its origins in formal connectionist modeling (Rumelhart, Smolensky, and McClelland 1986), we find it describes the same process of automatic pattern completion as "default assumptions," but at different levels of analysis (Marr 1982). "Default assumptions" depicts cultural schemas on the functional level, whereas "implicit associations" depicts them on the algorithmic level. As we will detail, these levels best fit different kinds of investigations: the functional-level conception answers the question "what do schemas do," and thus supports sensitizing and inferential uses; and the algorithmic-level conception answers "what are schemas composed of," and thus enables operational uses that capture schemas by detecting their individual components. To support both sets of uses, we poise our conceptualization on both levels.

Our manuscript has three parts. First, we describe the state of schemas research in cognitive science. We then lay out Marr's (1982) "levels of analysis" framework to clarify the relationships between the different levels of our conceptualization. The next section is poised on the functional level. Here, we propose a definition of cultural schemas that fits tightly around their major sociological uses and focuses attention on their theoretically central functional properties: *cultural schemas are socially shared representations deployable in automatic cognition.* After detailing the implications of this definition, we propose specific empirical and conceptual tests scholars can directly use in their work. We demonstrate our approach by applying it to Sewell's (1992) central example of commodity schemas. We then turn to the algorithmic level, which is most directly relevant to schematic measurement. Here, we clarify the "implicit associations" conception, and detail the formal properties of the cognitive model it identifies. We use this to make suggestions for future methodological scholarship.

DRAWING ON COGNITIVE SCIENCE

The cognitive conception of cultural schemas has its origins outside sociology, so it merits asking why we do not simply import a conceptualization from cognitive science instead of developing our own. The answer is that it would be far from obvious which one to import. Indeed, although the cognitive science literature on schemas has been thoroughly reviewed for sociological audiences, existing sociological treatments have not adequately stressed the fact that this multidisciplinary research program never successfully developed a common theoretical core or a single agreed-upon definition of cognitive schemas. Following the concept's emergence near the birth of modern psychology (Bartlett 1932), its re-popularization in 1970s cognitive psychology and artificial intelligence (Rumelhart and Ortony 1977), and its subsequent booming popularity in linguistics, education, anthropology, and other fields, "schema" came to refer to so many different kinds of phenomena that Mandler (1984:1) noted, "The phrase [schema theory] itself is perhaps misleading. . . . A more accurate phrase might be *schema framework*, since the principles subsumed under this view of the mind consist of very general beliefs about how this form of organization works." A decade later, D'Andrade (1995:126) echoed Mandler, adding that "the term 'schema theory' is a little grandiose."

Table 1. Two Major Conceptions of Schemas in Sociology, with Corresponding Definitions

Type Source	Definition / Explanation
Default Assumptions	
DiMaggio (1997)	First major sociological treatment to use this conception: "knowledge structures that represent objects or events and provide default assumptions about their characteristics, relationships, and entailments under conditions of incomplete information" (DiMaggio 1997:269)
Cerulo (2010)	"knowledge structures such as stereotypes, scripts, etc. that, with broad strokes, represent the characteristics of people, places, objects or events and allow us to infer what these entities do, where they fit, and what to expect of them" (Cerulo 2010:117)
Rumelhart and Ortony (1977)	Influential early usage from cognitive science: "data structures for representing the generic concepts stored in memory" (Rumelhart and Ortony 1977:101)
Implicit Associations	
Vaisey (2009)	First major sociological use of this conception: "cultural-cognitive structures . . . built up out of experience [that] allow a person to respond to stimuli in ways that are automatically generated by the weighted connections between the elements of the inputs at hand. Proponents of this view do not talk of schemas as things that are 'deployed' like tools but rather as *deep, largely unconscious networks of neural associations* that facilitate perception, interpretation, and action" (Vaisey 2009:1685–8, emphasis added)
Wood et al. (2018)	"a form of personal culture—literally, entrenched multimodal (i.e., visual, aural, tactile, olfactory, kinesthetic, etc.) *neural associations* developed via repeated embodied experience (i.e., perceptual, sensorimotor, interactional) and stored in long term memory" (Wood et al. 2018:246, emphasis added)
Frye (2017)	"Schemas influence cognition primarily through nonconscious channels; at their most basic level, they *associate related concepts* in our minds, such as coffee with warm or snake with danger" (Frye 2017:947, emphasis added)
Rumelhart, Smolensky, and McClelland (1986)	Influential early example from cognitive science: "[S]chemata emerge at the moment they are needed from the interaction of *large numbers of much simpler elements all working in concert* with one another. . . . Input comes into the system, activating a set of units. These *units are interconnected with one another, forming a sort of constraint satisfaction network*. The inputs determine the starting state of the system and the exact shape of the goodness-of-fit landscape. The system then moves toward one of the goodness maxima." (Rumelhart et al. 1986:20)

Appraisals of the trajectory that schema research took after Mandler's writing have been more pessimistic. As the number of different uses of the schema concept grew, there became ever fewer interesting things one could say about *all* cognitive schemas. As a result, Van Kesteren and colleagues (2012:212) note, "[e]nthusiasm for schema research waned since the 1980s, partly because of the overextended definition of schema that arose from the explosion of interest." Ghosh and Gilboa (2014) concur, and interpret this decline as a cautionary tale against using a definition of schemas that does not clearly delimit the concept's boundaries. Our work is partly motivated by the desire to save schema research in cognitive sociology from falling victim to the same overextension.

The 1980s saw an end to any unified research program into cognitive schemas writ large, but productive research has continued to examine different *kinds* of schemas across various cognitive science subfields. Recent literature examines body schemas (D'Angelo et al. 2018), memory schemas (Ghosh and Gilboa 2014), image schemas (Mandler and Cánovas 2014), and narrative schemas (Kahan 2015), among many others. These research programs do not share a single common conception of schemas, and indeed have little in common beyond a focus on some kind of structured mental representation. What enables each of these "schema subtypes" to serve as focal concepts for successful research enterprises is a *clear delineation of each field's specific object of study*. Research into cultural schemas in cognitive sociology has reached a point where it requires the same kind of delineation.

A search through major cognitive science journals reveals recent work on many types of *cognitive* schemas, but a near-complete absence of work on *cultural* schemas (i.e., cognitive schemas that diffuse through social learning).[2] Cultural schemas received little systematic attention in cognitive science after the decline of the "cultural models school" of cognitive anthropology (e.g., D'Andrade 1995; Quinn 2011; Strauss and Quinn 1997). Indeed, no discipline aside from sociology appears to currently have an active research program focused specifically on cultural schemas. Cognitive sociologists may thus be doubly amiss to defer to a "schema theory" from cognitive science. First, by treating these disconnected research programs as a single coherent theoretical conception, sociological work risks recapitulating the excessive breadth that doomed the original research program into cognitive schemas. And second, failing to delineate *cultural* schemas from other types of cognitive schemas conceals an opening in interdisciplinary cognitive science that cognitive sociologists are well-positioned to fill.[3]

Cognitive Meta-Theory: Levels of Analysis

We organize our conceptualization around Marr's (1982) "levels of analysis," which is an influential meta-theoretical framework for cognitive explanation (Brighton and Gigerenzer 2008; for sociological introduction, see Foster 2018). Its crux is the idea that it is possible to provide qualitatively distinct descriptions of the same cognitive process that are simultaneously correct but useful for different investigations because they answer different questions about the process.

At the highest level are *functional or behavioral* explanations, in terms of the process's consequences for the organism's behavior (or "downstream" cognitive processes).[4] We can illustrate this level by analogy to an article printed in an old-fashioned physical newspaper. On this level, a newspaper article is a vehicle allowing a small number of observers (journalists) to quickly convey information about important events to a vast geographically dispersed public. Most sociological research takes place on this level.

Next is the *representational/algorithmic* level, which provides parsimonious, analytically fruitful models of the computational task underlying the process. This usually involves an analytic separation between cognitive contents (*representations*) and the operations performed on them (*algorithms*). On this level, newspaper articles are narrative descriptions of events represented as written text. The main algorithms that allow these representations to fulfill their function are writing, which encodes narrative into written text, and reading, which decodes it back into narrative. The structuralist idea that a concept's cultural meaning comes from its pattern of similarities and differences to other concepts (Mohr 1998) is one representational/algorithmic-level idea that is well known in cultural sociology. The majority of cognitive science research has been poised at this level (Thagard 2005).

Finally, it is possible to describe the same cognitive system in terms of its *biological or physical implementation*. On this level, the newspaper article consists of ink on wood-pulp paper. Explanations in terms of brain regions or neural wiring are poised at this level, which is most closely associated with neuroscience (and most distant from sociology[5]). For simplicity, we will call the three levels *functional, algorithmic*, and *biological*, respectively.

This framework can help us make sense of which sociological applications the two conceptualizations of schemas best support. Many applied users are primarily interested in *what schemas do* (i.e., how they affect behavior) and *what schematic cognition looks like* (i.e., how schemas can be observed in an empirical setting). These questions stand firmly on the functional level. The conception introduced by DiMaggio (1997) and elaborated by Cerulo (2010) offers ready answers to these questions because it is based around a functional-level definition of schemas as "providing default assumptions" (DiMaggio 1997:269) that "allow us to infer what [places, people, or objects] do, where they fit, and what to expect of them" (Cerulo 2010:117). Because this conceptualization is poised on the level of human behavior, it clearly suggests how schemas can be spotted "in the wild"—for example, when a waiter chooses whether to hand the bill to the male or female diner. This direct applicability to social behavior may help explain why this conception made cultural schemas such a ubiquitous part of the sociological lexicon.

In contrast, the newer conception of schemas as "largely unconscious networks of neural associations" (Vaisey 2009:1686) that are "developed via repeated embodied experience (i.e., perceptual, sensorimotor, interactional) and stored in long term memory" (Wood et al. 2018:246) is poised at the algorithmic/representational level, and thus does not provide straightforward answers to these functional-level questions. For example, it is far from clear how these associations could be identified when observing a naturalistic social setting. However, as a description of an algorithmic/representational scheme, it answers the lower-level, cognitive-scientific question about *what schemas consist of.* This makes it usable as the basis of various measurement techniques that aim to capture schemas by detecting their building blocks (Boutyline 2017; Goldberg 2011; Hunzaker and Valentino 2019; Schröder and Thagard 2013; Shepherd and Marshall 2018; Tsoukalas 2006). Such operational uses are a fundamentally important advance toward a robust research program into cultural schemas.[6]

Neither current conception thus fulfills all the needs of sociological research if taken alone. To meet both sets of needs, the conceptualization we develop here is poised on both levels. On the functional level, we develop a conception that provides clear guidance about what schemas are, what they do, and how they can be spotted "in the wild." On the algorithmic level, we develop a conception that clarifies which components of schemas should be measured. On each level, we leverage our conception to produce concrete suggestions for empirical and methodological work.

FUNCTIONAL LEVEL

Existing Sociological Uses

The best-known cognitive conception of cultural schemas in sociology is DiMaggio's (1997) functional-level treatment. Drawing on an interdisciplinary research program in cognitive psychology, cognitive linguistics, artificial intelligence, and—most directly—cognitive anthropology (D'Andrade 1995), DiMaggio (1997:269) defines schemas as "knowledge structures that represent objects or events and provide default assumptions about their characteristics, relationships, and entailments under conditions of incomplete information" (see also Cerulo 2010). We call this the "default assumptions" conception (see Table 1).

The "default assumptions" conception is a clear and parsimonious depiction of schemas as *pattern completion engines* that fill in missing pieces of knowledge with culturally learned defaults. The following vignette from Rumelhart (1980:43) demonstrates such schemas in action:

> Business has been slow since the oil crisis. Nobody seemed to want anything really elegant anymore. Suddenly the door opened

> and a well-dressed man entered the showroom floor. John put on his friendliest and most sincere expression and walked towards the man.

Although this passage does not explicitly reference automobiles, many readers effortlessly recognize that it is set in a car dealership (possibly one that sells large U.S.-made sedans); John is a salesman; and the well-dressed man is a customer. The relevant schemas fill in missing information, letting us perceive the disjointed sentences that make up this vignette as a meaningful whole (D'Andrade 1995). This pattern completion property enables cultural schemas to automatically and often unconsciously fill in the gaps in perceived information with cultural assumptions—drawn, for example, from well-known stereotypes of various social groups (Hunzaker 2016).[7]

The "default assumptions" definition thus has an excellent fit to many key sociological applications. However, as an analytic definition, it has two sets of drawbacks. First, it does not draw a clear boundary around what counts as a cultural schema. To observe one clear indication of this imprecision, note that the definition states that schemas "represent objects and events" (DiMaggio 1997:269). If read literally, this wording seemingly rules out schemas that represent people, organizations, or social norms—phenomena of central interest to sociology. This obviously unintentional restriction suggests this definition must be read somewhat loosely, which limits its ability to precisely delineate the concept's boundaries.

Second, DiMaggio's assertion that schematic cognition occurs "under conditions of *incomplete* information" describes the operation of schemas that work through *pattern completion*, but it excludes other sociologically important functions of cultural schemas. These functions involve *pattern matching* (i.e., identifying which of a set of known representations best fits the observed pattern), which does not require incomplete information to be useful. This includes using *implicit categories* to automatically classify people into genders and races, or businesses and services into market categories (Kovács and Hannan 2010; Lewis 2003; Ridgeway and Correll 2004);[8] and invoking *cultural scripts* that provide automatic rules of thumb for appropriate behavior in certain situations, whether as implicit norms used in determining correct, moral, appropriate, or ideologically prescribed behavior, or as cultural "recipes" for achieving certain goals (Blair-Loy 2001; Frye 2012; Martin and Desmond 2010; Vaisey 2009; Vaisey and Lizardo 2010).

Although implicit categories can have a role in pattern completion, their use in pattern matching instead fulfills a different purpose: *ignoring irrelevant variation* between stimuli (Brubaker, Loveman, and Stamatov 2004; Goldstone, Kersten, and Carvalho 2018; Rosch 1978; Zerubavel 1996). For example, automatically identifying an electric sedan, a family minivan, and a massive SUV as three instances of the category "cars" enables us to simplify a perceived situation to "there are three cars ahead of us in line at the drive-thru." This backgrounds irrelevant variation and frees up our cognitive resources for other tasks.

Like implicit categories, internalized cultural scripts also have a function that goes beyond pattern completion. Cultural scripts consist of *pattern matching* followed by *an extra inference step* (e.g., "lower your voice if you are indoors"). This differs from pattern completion because the inference is not an unobserved part of the pattern but rather something external to it, and can thus similarly take place whether or not information is incomplete.[9]

Categories and cultural scripts are thus two examples of cultural schemas that do not fully fit under the "default assumptions" conception. To accommodate these functions of schematic cognition, our conceptualization will be broader than "default assumptions."[10] But just how broad should our conception be? Clearly, it would be unproductive to make it coterminous with everything sociologists have described as "cultural schemas," since some sociologists use it as a shorthand for nearly *any* piece of culture—a conception that is too broad to carry much weight.

Luckily, the bulk of sociological uses of schemas do not require such overextension. As we will detail, default assumptions, implicit categories, and internalized cultural scripts *do* have key properties in common that set them apart from other pieces of culture, other types of cognitive schemas, and other types of nondeclarative culture. First, these sociologically central examples differ from discourses, narratives, and other consciously deployable cultural "tools" in that they are pieces of nondeclarative culture (Lizardo 2017; Lizardo and Strand 2010; Vaisey 2009; Wood et al. 2018). Second, unlike many other kinds of learned cognitive contents, they are socially shared. And finally, they are instances of "higher-order mental representations" (Evans 2008:259), as opposed to the directly embodied structures used in "lower-order" cognition (e.g., the basic motor program of walking) (see also Railton 2017; Ryder 2009; Thagard 2012). We develop these distinctions in the next section, where we use them to propose a conception of schemas with precise bounds and clear theoretical entailments.

Our Functional-Level Conceptualization

In light of these considerations, we propose this functional-level definition: *cultural schemas are socially shared representations deployable in automatic cognition.* Table 2 provides a diagrammatic guide to the three criteria contained in this definition: social sharedness, automaticity, and representational character. In this section, we explain each of these concepts and detail what its inclusion accomplishes.

To help ground our discussion, we begin with an imagined scenario of schematic cognition, featuring an adolescent masculinity schema that could be roughly phrased as "boys shouldn't work hard for their grades" (cf. DiPrete and Buchmann 2013):

> Billy, an eighth-grade student, is sitting at his desk while a teacher is returning graded homework essays. As the teacher hands him his assignment, she exclaims, "Great job, Billy! This must have taken a lot of work!" Billy quickly tells the teacher that she is mistaken and that it took him only a few hours. Although Billy had, in fact, spent all weekend working on the assignment, *he is intuitively aware that this hard work is in violation of the image of indifference* he and the other boys try to project in their relations with the school. To Billy's horror, the teacher responds with "No way! This is really well written, and you even wrote three pages more than you were required. You should be proud!" before turning her back to him to move on to the next student, oblivious to the quiet snickering that her praise elicited in the boy sitting next to Billy.

Automatic cognition. In this scenario, the schema is activated when Billy hears the teacher's praise. The speed with which Billy identifies the praise as a violation of masculine norms, and the fact that Billy spots it without intentionally searching for such violations, are characteristics of *automatic cognition*.[11] As Railton (2006) points out, because fluent conversation is highly taxing on resources required for controlled cognition, many important interactional norms are likely largely automatic.

Like other recent sociological and cognitive treatments, we make automaticity central to our definition because it accounts for a key reason why cultural schemas are important to sociologists: schemas' close relationship to action.[12] Cultural schemas can influence behavior via at least three relatively direct routes (DiMaggio 1997; Frye 2017; Gorman 2005; Hsu and Grodal 2015; Lizardo 2017; Vaisey 2009; Wood et al. 2018): (1) as sets of default assumptions, they work under conditions of incomplete information, automatically filling in the gaps in what people perceive, remember, or understand others to be saying with familiar defaults (pattern completion). Then, (2) as implicit categories, they help manage excessive complexity by automatically identifying different observed stimuli as instances of a known type

Table 2. What Types of Mental Contents Meet (or Do Not Meet) Each of Our Three Criteria for Cultural Schemas: Automaticity, Representational Character, and Social Sharedness

Three Criteria for Cultural Schemas				
Automatic	Represent-ational	Socially Shared	Type of Mental Contents	Example
Yes	Yes	Yes	Cultural schema	Common implicit stereotype (e.g., "girls are studious")
		No	Non-cultural schema	Idiosyncratic implicit stereotype (e.g., "men love tomatoes")
	No	Yes	Non-schematic nondeclarative culture	Mere association (e.g., association of "cat" with "bat," which is due to rhyme alone)
		No	Nondeclarative non-culture	Most motor schemas (e.g., ability to rapidly stabilize yourself when you sense you are beginning to slip on ice)
No	Yes	Yes	Declarative culture	Many products of classroom learning (e.g., steps for integration by parts; a Chaucer poem memorized for class)
		No	Declarative non-culture	Specific personal beliefs (e.g., knowledge of contents of my bag; my plans for next weekend)
	No	Yes		
		No		

Note: Cultural schemas meet all three criteria (automatic = yes, representational = yes, shared = yes). Five other entries refer to a different kind of mental content. The two bottom rows are left blank because non-automatic (Type II) cognitive contents must be representational, making the corresponding combinations impossible.

(pattern matching)—a categorization exercise that then allows their individual details to be ignored, simplifying reasoning and memorization. Finally, (3) as automatic cultural scripts (including internalized norms and common cultural prescriptions), they can directly produce actions or emotions by triggering habitual responses to familiar situations. Cultural schemas thus provide an avenue by which culture can alter the inputs to conscious thought, or produce behavior without conscious intention. Schemas' autonomous character thus makes them more closely linked to action than discourses, justifications, memorized facts, and other consciously deployable "cultural tools" that influence behavior only by "providing resources" for action (Swidler 1986:273; Vaisey 2009).

This is exactly the distinction between Type I "automatic" and Type II "controlled" cognitive processes. As we will describe, the defining feature of Type I cognitive processes is their *autonomy*: when their triggering stimuli are encountered, these processes are deployed without requiring conscious attention or control (Evans and Stanovich 2013:236).[13] The autonomous/controlled distinction has a number of important correlates: Type I processes are usually implicit, unconscious, nondeclarative, and fast; Type II cognitive processes are usually explicit, conscious, declarative, and slow (Evans 2008; for extensive sociological treatments, see Lizardo 2017; Lizardo et al. 2016). As we will detail, the automatic character of cultural schemas has far-reaching implications for their properties.[14]

Socially shared. Social sharedness of schemas refers to their acquisition from other people—be it directly from other living human beings, or indirectly via some form of media. We can surmise that Billy's model of masculinity is *socially shared* because the norm violation is readily recognized by both Billy and the snickering student. More broadly, anything that can properly be called a social norm must be socially shared. Sharedness is central to our definition because it delineates *cultural* schemas from non-cultural ones (Foster 2018; Sperber 1996). Categories, default assumptions, and scripts become cultural when they are replicated from person to person, for example, through interaction or from mass media (e.g., stereotypes for groups one has never met). This replication enables some schemas to diffuse over macro-scale populations and outlive the people with whom they originated.

Our focus on social sharedness departs from the recent treatment of schemas by Wood and colleagues (2018). We agree with Wood and colleagues that most schemas are likely shared to some extent, but we disagree that this renders the term "cultural schema" meaningless. Schemas vary greatly in the extent of their sharedness. For example, some schematic representations of masculinity may be learned from mainstream cinema, and are thus widely shared, whereas others may come from idiosyncratic family experiences and only be shared with a few others (if at all). Schemas also vary in the importance of *social* learning to their acquisition. For example, motor schemas for walking on icy ground may be widely shared by people living in cold climates, but this sharedness is largely unrelated to social activity. This connection to social learning distinguishes cultural schemas from non-cultural cognitive schemas (see Table 2). There are also edge cases where this classification is less clear—for example, when social influences partly alter the results of individual learning. We thus follow Foster (2018:146) and Sperber (1996:82) in thinking of "cultural-ness" as a gradient: the more closely a schema is tied to the transfer of representations between people, the more cultural it is.

This perspective lets us reexamine the status of "image schemas" (Lakoff 1990 [1997]): cognitive representations that arise from sensory-motor experiences and are used to understand abstract concepts by metaphorically mapping their structure onto that of the experience (Hampe 2005:1–2). Wood and colleagues (2018) present image schemas as a key example of cultural schemas. However, image schemas originate in immediate bodily experience and common brain structures, rather than social learning, and may be human universals (Dodge and Lakoff 2008). Thus, while we agree that image schemas are a promising conceptual tool for cultural analysis, we disagree that they are themselves *cultural* schemas—because they are not socially learned.

Representations. Cultural schemas carry information about the world: default assumptions describe characteristics of people, objects, and events; categories convey how they should be grouped; and normative scripts prescribe appropriate judgments or actions. All three are thus fundamentally *representational* concepts (Pitt 2020; Ryder 2009). Following Sperber (2006:25) and Foster (2018), we hold that something is representational when it carries *interpretable information* about real or imagined states of the world. Representations are thus meaningful—or, more strictly, *semantically or morally evaluable*: if X is a representation, it should be possible to ask questions like "What does X describe?" "Is it true that X?" or "Do we find it morally acceptable that X?" (Ryder 2009). This "minimalist" conceptualization lets us sidestep some thorny theoretical debates around the term "representation."[15]

Billy's stereotype clearly carries information about the world: that boys don't and shouldn't work hard in school. This enables us to ask questions like: Is it *true* that boys don't work hard in school? Does Billy (or ought we) *endorse* the idea that boys should behave this way? Does this stereotype *refer to* all forms of school-relevant effort, or are some learning situations exempt? What matters here is not that these questions are answered in any particular way, but that we can meaningfully ask them about Billy's stereotype.

This representational character distinguishes cultural schemas from lower-order cognitive constructs like motor programs, which make up a substantial portion of Type I learning (e.g., acclimatization to cold climates, which involves directly embodied learning like durable changes in metabolic heat production, skin blood flow, resting oxygen consumption, and hormonal production [Castellani and Young 2016]). Furthermore, it distinguishes cultural schemas from *mere associations* in the technical connectionist usage, where "association" strictly refers to the strength of connection between two elements (Pitt 2020). For example, due to the title of the U.S. national anthem, many Americans may automatically perceive the word "spangled" to have a patriotic connotation that is entirely missing from "sprinkled," "glittery," or "covered in spangles"—despite the near synonymy of these terms. Although the *presence* of a cultural association between "spangled" and patriotism may be widely recognized among Americans, we can at most inquire why or how it is that the two concepts came to be associated, how strong the association is, or what further consequences the association has. We cannot meaningfully ask whether the *content* of this association is true. This association is thus cultural and likely automatic, but it is not representational.

We suspect that applied sociological users of the "cultural schemas" concept will rarely run afoul of this representational criterion. However, the criterion is vital for delimiting the concept of cultural schemas: without it, "cultural schemas" would be coterminous with all of nondeclarative culture (see Table 2). This would leave it too overextended for either theoretical or methodological uses.

Implications of the Functional-Level Account

As noted earlier, our goal was to develop a conception of cultural schemas that fits tightly around the three central sociological examples: implicit categories (e.g., those used to automatically categorize a person by race or gender); default assumptions (e.g., stereotypes); and internalized cultural scripts (e.g., those used to effortlessly recognize behavior as appropriate or inappropriate). As intended, all three constructs clearly fit under the above conceptualization: they are automatically accessible, widely shared, and representational in character.

Given the perennial threat of overextension faced by schema research, the opposite question is equally important: what *is not* a cultural schema? We cannot, of course, provide an exhaustive list of things that are not schemas. However, our definition lends itself to a number of straightforward empirical and conceptual tests to answer whether any given cultural construct could be a schema. We discuss these below, organizing our account around keywords in our conceptualization (representation, sharedness, automaticity) and further consequences of automaticity (conscious control, resource limits, nonverbal character and domain-specificity).

Representation. First, something would fail to be a schema if it is not representational. As we noted earlier, to qualify as a representation, a schema must carry information about the world. To test this, we may ask ourselves whether we can meaningfully posit questions like "is X true," "do we endorse X," "when does X apply," "what does X refer to," and "do people believe X" (Ryder 2009). Lower-order cognitive constructs and mere associations will fail this test; default assumptions, categories, and other higher-order constructs will pass.

Sharedness. To qualify as cultural, an automatic representation must be widely (but not universally) shared. We could imagine an automatic mental representation that is schematic but is too idiosyncratic to qualify as cultural (e.g., if a girl's experiences with her father and brother lead her to develop the idiosyncratic stereotype "men love tomatoes," it would not be a *cultural* schema). Accordingly, the critical test question is this: is this schema common to some social group—for example, occupants of a certain social position or geographic area, members of an organization or friend network, or participants in some social activity?

Sharedness can be witnessed directly, by examining activity within a collective setting such as a focus group (see McDonnell 2014). Scholars may also be able to test sharedness by looking for taken-for-granted character or intelligibility. For example, Rumelhart's "oil crisis" vignette described earlier is only easily comprehensible to readers who possess cognitive schemas for car showrooms and salespeople. If that passage came from an interview transcript, it could be evidence that the respondent assumes the listener shares the schemas in question. For other types of schemas—especially those with normative contents—it may be possible to observe whether the violation of the schema is understandable to others. For example, if someone violates an unstated behavioral prescription, would this violation be clear to others in the relevant community, without the need for explanation?

Conversely, some mental representations appear to be universally shared among humans—for example, image schemas grounded in common biological structures (Dodge and Lakoff 2008). Because universal sharedness would point to origins in something other than social learning, to qualify as cultural, the sharedness must also not be universal. Thus, scholars should be able to point to a non-idiosyncratic social group who do not share the schema in question.

Automaticity. Finally, something would fail to be a cultural schema if it is not automatically deployable, that is, it cannot operate within Type I cognition. The Type I character of cultural schemas has been noted in many sociological treatments, but we go beyond this existing work by proposing that empirical scholars use the distinctive characteristics of Type I and II cognition to judge whether something could be a schema.

Major recent dual-process accounts in cognitive psychology distinguish between sets of *defining features* characteristic of each type of cognitive process, and *common correlates* that generally (but not universally) accompany these defining features (Evans 2012; Evans and Stanovich 2013; Pennycook et al. 2018; Stanovich and Toplak 2012). There is consensus that the defining feature of Type I cognition is *autonomy*: the deployment of Type I processes does not require controlled attention or working-memory resources. Rather, Type I processes are automatically invoked when their triggering stimulus is encountered, unless something intervenes to prevent their deployment (Evans and Stanovich 2013:236; Stanovich and Toplak 2012). Autonomy is often accompanied by a number of key correlates, including high speed, high capacity, unconscious character, parallel deployment, and domain- or context-specificity. Type II cognition, in contrast, is *not* autonomous or automatic; rather, Type II processes are defined by their *reliance on working memory*—a limited-capacity cognitive resource that is available to conscious introspection and related to inhibitory control (Engle 2002; Evans and Stanovich 2013).[16] This is accompanied by a host of frequently-discussed correlates: Type II processes are generally conscious, effortful, slow, serial, low capacity, domain- or context-general, and declarative (Evans 2008; Lizardo 2017; Lizardo et al. 2016; Smith and DeCoster 2000).

Importantly, a number of the "typical correlates" of automatic cognition are imperfect indicators of autonomy. For example, high speed is a necessary but not sufficient indicator of Type I processing, as some Type II processes are also fast. In the empirical and conceptual tests we propose, we note whenever a test rests on these imperfect correlates. In such cases, empirical researchers should additionally validate their claims of automaticity or autonomy using other methods.

Conscious control. Cultural schemas must be deployable automatically, that is, without conscious control, so any cognitive mechanism that we can always effortlessly "turn off"—or choose not to engage—is not a schema. Stanovich and Toplak (2012) and Evans and Stanovich (2013) see this as the defining distinction between Type I and II processes: Type I processes are automatically executed when their triggering stimuli are encountered (unless overridden by Type II processes), whereas Type II processes are effortful and subject to conscious control. Type II processes take effort to deploy, whereas Type I processes take effort *not* to deploy. For example, many social norms and habits (e.g., our tendency to turn our bodies fully toward someone with more authority than ourselves [Railton 2006]) are extremely difficult to turn off. In contrast, it is often easy to forget to follow the social norms of an unfamiliar culture, which we have not yet internalized deeply enough for automaticity. Scholars should ask which category the cultural construct they are examining falls into. If it is always deployed intentionally, it is likely an element of culture accessible only to Type II cognition rather than a schema.

Resource limits. Due to their autonomy, Type I processes can be deployed in parallel: many can run at the same time, and they can operate even while we do other demanding tasks. This is not the case for Type II processes, which are dependent on access to a single conscious, limited-capacity, central working-memory system (Evans 2008, 2012; Evans and Stanovich 2013). Because this working-memory system can only handle one substantive conscious task at a time, Type II processes are similarly limited. Accordingly, something is unlikely to be a schema if it cannot be successfully deployed while performing other demanding cognitive tasks (e.g., being engrossed in a debate).

These differences are used as the basis for various *cognitive load* exercises (Feldon 2007). For example, to examine whether some focal task is automatic, a "digit memory" exercise requires one group of subjects to remember a long string of random numbers, which necessitates active rehearsal (see Wegner, Erber, and Zanakos 1993). If their performance on the focal task suffers compared to "un-loaded" participants, then the task requires working-memory resources.

A simpler but less robust test simply requires participants to complete the focal task under severe time pressure (e.g., Payne, Lambert, and Jacoby 2002), which may deny Type II processes the time and effort they require. Sociologists sometimes also simply observe whether subjects performed a given task quickly to determine whether participants used Type I cognition. However, we caution that speed is an imperfect correlate of Type I cognition: while Type II processes are indeed usually slower than Type I processes, some Type II processes are very fast (Evans 2012). A test resting entirely on speed may thus sometimes produce incorrect results, and therefore requires careful validation.

Although behavioral experiments provide the best test of automaticity, they are not always realistically feasible for sociological research. In such cases, researchers could conceptually test automaticity by asking whether a representation could successfully be deployed simultaneously with some other cognitively demanding task. Everyday tasks that mimic heavy cognitive load exercises include trying to remember a grocery list, engaging in an intellectually challenging argument, or speaking in a foreign language one has only recently begun to learn. If it seems implausible that someone could generally invoke a representation concurrently with uninterrupted participation in such concurrent tasks, that representation is unlikely to be a cultural schema.

With many schemas, automaticity can also be tested by constructing vignettes that require this schema to be effortlessly understood. For example, Rumelhart's (1980) oil crisis example describes a car dealership without ever directly referencing cars or dealers (mentioning only related terms like "oil crisis" and "showroom floor"). If understanding this passage is so undemanding that subjects can do so even under severe time pressure or while otherwise distracted, then their mental representation of car dealerships may indeed be a schema. We provide a more detailed example of this conceptual exercise below, where we apply this approach to Sewell's (1992) "commodification" schema.

Nonverbal character and domain-specificity. Verbal character is a correlate of Type II cognition: whereas paradigmatic examples of Type II cognition are linguistic or discursive, most Type I processes are nonverbal (Evans 2008:259). Accordingly, constructs are less likely to be schemas if they involve complex verbiage. For example, discourses, complete narratives, or highly detailed ideologies are unlikely to be schemas: their deployment requires too many cognitive resources to be successfully used in parallel with other taxing processes. Nevertheless, understanding and producing them likely involves applying many smaller, more specific schemas (e.g., default assumptions about narrative structure or core ideological rules of thumb). This may put an upper limit on a cultural schema's complexity: although language enables slow discursive cognition to support precise and intricate descriptions, the fast nonverbal character of schemas suggests they are relatively simple representations of gist (see also Lizardo and Strand 2010:205–6; Martin 2010; Stanovich and Toplak 2012:10).

A related correlate of Type I cognition is *domain-specificity*. Type II knowledge can be context-independent and abstract—qualities enabled in part via the powerful expressive characteristics of language—and tied to general-purpose intelligence and logical or hypothetical reasoning. Indeed, Stanovich and Toplak (2012) propose this capacity for hypothetical reasoning as the defining characteristic of Type II cognition (see also Evans and Stanovich 2013). In contrast, Type I knowledge is often *domain-specific*—thoroughly tied to, and specifically functioning within, contexts closely resembling the one in which it was learned (Evans 2008, 2012). Type II knowledge (e.g., mathematical or rhetorical tools) can be transposed with relative ease across diverse contexts, but the principles that underlie Type I inferences may not be transferrable to other domains without the help of Type II processes. As Wilson (2002) notes, tasks that involve novel interactions with unfamiliar environments require people to construct new mental representations: a cognitively demanding process that often requires conscious, Type II cognition. Automatic cognition is instead "responsible for forming stable . . . representations of the typical properties of the environment" (Smith and DeCoster 2000:110). For related reasons, Type I skills and habits may be helpful in the familiar social contexts in which they were developed, but may prove useless or counterproductive in other environments (Foster 2018).

Some classical research paradigms illustrate this difference. For example, in the Wason Selection Task, participants decide which of four cards with a letter on one side and a number on the other—displaying D, 3, B, and 7—they must flip over to assess whether the following statement is true: "If there is a D on any side of a card, then there is a 3 on the other side." The logically correct answer is to flip the D to assess *modus ponens* (if P then Q; P; therefore Q), and the 7 to assess *modus tollens* (if P then Q; not-Q; therefore not-P). Participants generally correctly select the D, but most fail to select the 7. Yet when a structurally identical task is placed in a familiar domain, participants fare much better: given the rule "if a person is drinking beer, then he must be over 20 years old" and presented with cards reading "drinking beer," "drinking coke," "25 years old," and "16 years old," participants generally successfully identify "drinking beer" and "16 years old" as the cards to flip (Cosmides 1989). Subjects' intuitions concerning the commonly invoked social rule about drinking age enable them to correctly answer the contextualized "underage drinker" question, but they cannot easily transpose these intuitions to the decontextualized domain of formal logic, especially under time pressure (Roberts and Newton 2001). Relatedly, multiple studies show that people may implicitly learn to automatically follow a statistical principle within one domain, but are unable to translate it to other contexts without conscious consideration (Evans 2012).

Domain-specificity is an imperfect correlate of automaticity. We thus do not assume a priori that all cultural schemas are domain-specific. However, we urge extra scrutiny toward the claim that a given cultural schema generally functions across domains. This highlights a conflict between the cognitive conception of "cultural schemas" and their older non-cognitive incarnation in cultural sociology famously articulated by Sewell (1992), who conceived of cultural schemas as easily functioning across highly varied domains.

Example: Sewell's Schemas as "Deep Structures"

To demonstrate our approach, we apply it to Sewell's (1992:22) commodity (or commodification) schema, which he used as a primary example of his notion of highly transposable "deep structural" schemas.[17] Our analysis will also illustrate how using the cognitive and cultural conceptions of cultural schemas interchangeably (as sociologists often do) can lead to faulty inferences.

To conceptually examine whether the commodity schema could indeed be a cultural schema in our cognitive sense of the term, we start by noting that this schema can be phrased roughly as *"if X is useful, then X can be bought and sold for money."* This construct is obviously representational and socially shared. We thus focus on verifying whether it could plausibly be deployed in implicit, automatic cognition. We construct a passage that could only be effortlessly interpreted with such a schema: *"I really wanted one too, but when I got to the store, I realized my credit card was already maxed out."* This lets us verify that we can effortlessly interpret this passage, and recognize—without even realizing we are filling in blanks—that "I really wanted one too" probably refers to an object that can be bought at the store in question. This effortlessness and lack of conscious awareness suggest we indeed possess a commodity schema.

Sewell (1992:25), however, argues this commodity schema "is exceptionally transposable. It knows no natural limits; it can be applied not only to cloth, tobacco, or cooking pans, but to land, housework, bread, sex, advertising, emotions, or knowledge, each of which can be converted into any other by means of money." Our preceding test passage, however, referenced only the sale of goods in a store—a thoroughly familiar setting closely associated with commodities. To examine whether we can indeed effortlessly transpose it to less familiar settings, we next construct a passage set in a context that has seen many recent innovations in commodification: *"I really wanted to get to my airplane seat quickly, but when I got to the check-in counter, I realized my credit card was already maxed out."* To seamlessly interpret this passage, we would need to recognize that, because boarding early is a useful service, it is possible to purchase it with money (by buying a boarding group upgrade). Unlike the first passage, we suspect most readers could not *effortlessly* interpret this second passage. Moreover, we suspect readers had this difficulty even if they knew that such boarding group upgrades exist. The automatic transposition of this schema to *truly* novel domains appears even less likely (e.g., if the example concerned the novel practice of paying your neighbors to say "hi" rather than look the other way when they pass you by).

We similarly expect airline management did not effortlessly and unintentionally invent the idea of charging money for earlier boarding. Rather, it is more likely that this novel instance of commodification was *consciously* and *intentionally* devised by airline employees whose job was to seek out new revenue streams. Thus, while we can readily apply the commodity schema to known settings, we may not be able to transpose it to new domains without Type II cognition—that is, unless we deploy it not as a schema, but as a consciously accessible, declarative cultural construct (Lizardo 2017).

This conclusion agrees with the literature on domain-specificity of Type I cognition we reviewed earlier. And it does not present a problem for Sewell's (1992) account, as Sewell does not require cultural schemas to be implicit. However, it demonstrates that the cognitive and non-cognitive conceptions are sometimes incompatible, which can be a problem for scholars who use them interchangeably. One prominent recent example of this practice is found in Ray's (2019) theory of racial schemas. Ray (2019:32) follows Sewell in arguing that "racial schemas, like the commodity form, are easily applied to new organizational resources." At the same time, Ray (2019:35) argues that cultural schemas can be used outside of actors' intention or awareness: "Placing broadly shared racial schemas at the center of a structural theory of race renders conscious coordination unnecessary. . . . In novel situations, people transpose existing racialized schemas to a new set of organizational resources. This transposition need not be conscious or intentional." Our reasoning suggests this inference may be incorrect. We agree with Ray that schematic cognition may explain situations where people unconsciously apply existing schemas to new situations *that have the same key features as familiar situations*, but we suspect racial schemas, like the commodity form, are likely applied to *truly* novel situations primarily via conscious, intentional transposition.

In the preceding sections, we developed our functional-level conception of schemas, which covers the main types of schemas of interest to sociologists but excludes pieces of culture that do not share important characteristics with them. We linked our definition to concrete tests—some empirical, others conceptual—that scholars can use to decide whether the construct they are investigating is likely to be a cultural schema. We then demonstrated this approach by applying it to Sewell's commodity schema. We now proceed to the algorithmic level of our conception.

ALGORITHMIC LEVEL

Schemas as Networks of Implicit Associations

Over the past decade, the "default assumptions" conception of schemas in sociology has gradually given way to a newer definition we call "implicit associations." This view was first prominently articulated in sociology by Vaisey (2009), whose influence on how sociologists conceptualize schemas is an underappreciated aspect of this otherwise-famous work. Drawing on cognitive anthropologists Strauss and Quinn (1997), who in turn based their conception on Rumelhart and colleagues (1986), Vaisey (2009:1686) talks of schemas as "cultural-cognitive structures [that] are built up out of experience and allow a person to respond to stimuli in ways that are automatically generated by the weighted connections between the elements of the inputs at hand" and "deep, largely unconscious networks of neural associations that facilitate perception, interpretation, and action." Table 1 also includes a related conceptualization from Wood and colleagues (2018).

This conception can be interpreted as either a biological- or an algorithmic-level claim. First, because the definition references neurons, some scholars may read it as a biological-level statement about brain wiring (i.e., the network of axons interconnecting literal neurons). But under this interpretation, this conception simply states that schemas are structures of interconnected neurons developed through experience, which can describe *any* product of individual learning. This conception is clearly too broad to carry analytic weight.

We therefore focus on the second interpretation, which is implied by the phrase "spreading activation" (and is likely the intended meaning). In this reading, it is a *representational/algorithmic* claim that schemas can be computationally modeled as artificial "neural networks"—a class of highly abstract dynamic network models with only a loose metaphorical relationship to biological neurons (Thagard 2012).[18] These neural network (or "connectionist") models represent cognition as the diffusion of activation states across weighted networks of simple computational units called "neurons." Connectionist models capture some important aspects of brain biology: for example, the brain indeed contains a vast number of relatively simple processing units (neurons) and interconnections between them. These models abstract away many other important biological details, such as the role of neurotransmitters and hormones and variation between different types of neurons (Buckner and Garson 2019).

While cogent, the assertion that schemas can be represented as neural networks is still excessively broad. Variations in the wiring architecture, representational scheme, learning algorithm, and activation functions yield a vast range of connectionist networks useful for examining diverse cognitive processes, including grammar, speech, concept learning, vision, and movement (Smolensky 1988). Advocates of a type of connectionism called "predictive coding" have gone as far as suggesting it "provides a unified account of all cognitive phenomena, including perception, reasoning, planning and motor control" (Buckner and Garson 2019). Connectionist networks can also perform *any* computation doable by a computer (Graves, Wayne, and Danihelka 2014). Thus, our algorithmic-level conception of cultural schemas must be more specific.

In fact, a number of sociologists already tacitly use a more specific connectionist conception of schemas (e.g., Frye 2017; see Table 1), which we call the "implicit concept network" (ICN), and which we will demonstrate is substantially more analytically useful. Whereas Vaisey's "implicit networks" conception does not specify the nature of the individual nodes, all nodes in an ICN correspond specifically to concepts, ideas, attitudes, and other *meaningful* cognitive objects (hereafter, "concepts" as shorthand). ICNs have a simple overall structure: they consist entirely of concepts tied together via pairwise implicit associations. The meaning of concepts is thus captured entirely via their relationship to other (meaningful) concepts. This is exactly the type of network that recently developed quantitative methods for schematic measurement in sociology tend to construct (e.g., Boutyline 2017; Hunzaker and Valentino 2019; Taylor and Stoltz 2020). It is also the semantic structure simulated by Goldberg and Stein (2018).

The description of ICNs may at first appear very similar to Vaisey's (2009) conception, but the subtle difference here is crucial: whereas Vaisey's conception does not clearly identify how the network represents concepts, the definition of ICNs implies they use *localist representations*—a simple, intuitive representational scheme where each individual node corresponds to one (meaningful) concept. Most connectionist network models instead use *distributed representations* (e.g., Figure 2). In their simplest form, these *distributed networks* add layers of "hidden nodes" that represent "fine-grained features below the level of the concepts consciously used to describe the task domain" (Smolensky 1988:1) rather than their own separate meaningful concepts. Instead of capturing the meaning of concepts via their direct relationships to other meaningful concepts (as localist ICNs do), distributed networks capture the meaning of concepts via their relationships to these networks of lower-level, fine-grained, non-conscious features. ICNs do not capture these aspects of semantic meaning—an important limitation we detail below.

This contrast with distributed networks highlights that ICNs are *a specific kind* of connectionist model. Figure 1 depicts a typical ICN, which resembles the example from Rumelhart and colleagues' (1986) pioneering treatment. Here, each node represents a piece of furniture. During training, the network is "shown" a series of rooms by simultaneously activating sets of nodes corresponding to the furniture seen in each room. For example, the network may be shown a "typical bedroom" by activating *dresser*, *bed*, and *nightstand*.[19] The network then learns by following

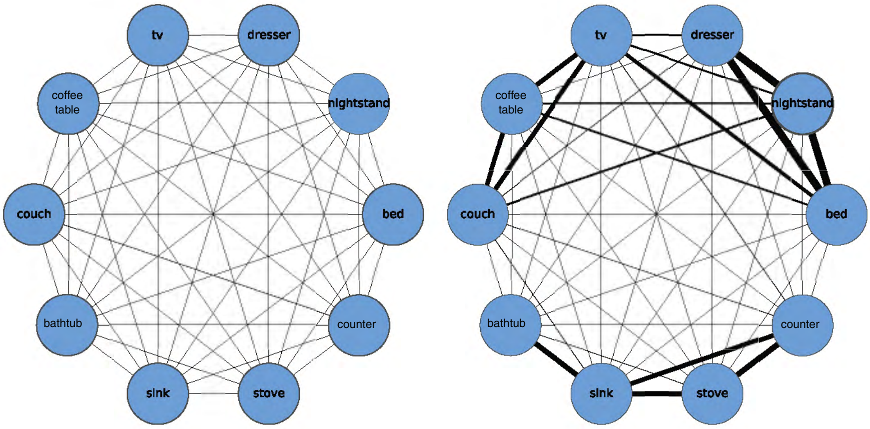

Figure 1. Example of Typical Implicit Concept Network (ICN): An ICN for Rooms (cf. Rumelhart et al. 1986) Before Training (left) and After Being Trained on a Series of Rooms (right)
Note: Line width represents tie weight.

the Hebbian principle of "neurons that fire together wire together," that is, if two nodes are activated simultaneously, their pairwise connection strength increases.

After training, the network is able to make guesses about rooms. In this mode, after a set of nodes is activated, this activation cascades between nodes in rough proportion to the tie strengths between them. In a key early finding, Hopfield (1982) showed that, if there are stable patterns in the environment, such networks will learn to reproduce them. For example, if the network had been exposed to enough "typical bedrooms" during training and is subsequently shown only *dresser* and *nightstand*, the network would then automatically activate *bed*. This pattern-completion property is why Rumelhart and colleagues (1986) first proposed that connectionist networks provide a good model for schemas.

This elaborated model provides a clearer description of the algorithmic-level building blocks of schemas than do prior sociological conceptions. Below, we develop the implications of this model for schematic measurement. Then, in the following section, we focus on this model's limitations and contrast it with an alternative algorithmic-level model of schemas as networks with distributed representations. We conclude that both of these models should be part of the sociological toolkit.

Implications of the Clarified Model

Relationship to functional level. First, ICNs learn schemas in exactly the sense that they internalize default assumptions about the learning environment. Thus, although Vaisey (2009) introduced "implicit associations" as a competing conception to "default associations," they in fact appear to describe one and the same phenomenon: schemas that enable pattern completion.[20] The two descriptions sit at different levels of analysis and thus best support different kinds of investigations—but because they refer to the same type of schemas, these investigations can supplement and guide one another. Indeed, this complementarity is central to the interrelationship between levels of analysis envisioned by Marr (1982): the functional-level conception determines what properties the algorithmic-level model must explain, and the algorithmic-level model, in turn, provides a deeper understanding of these properties.

Associations versus schemas. Relatedly, connectionism-inspired sociological work often uses "implicit associations" and "schemas" interchangeably, but there is an important functional difference between them: as Rumelhart and colleagues (1986:31) note, ICNs only come to represent schemas *after* they have successfully learned to predict the stable features of the environment. A schema is thus *one possible product* of associative learning, which arises only when an ICN has internalized a predictable environmental pattern. At that point, the ICN stops simply associating concepts and starts successfully "filling in the blank" in partially observed phenomena (see also Schröder and Thagard 2013:258)—a property closely related to our functional-level assertion that schemas are *representations*. Thus, although pattern completion schemas can indeed be modeled as sets of associations between concepts, *not every set of associations is a schema*.

This has direct implications for recent sociological work that aims to uncover cultural schemas by measuring subjects' associations between the concepts in the domain of interest (Hunzaker and Valentino 2019). To capture schemas of poverty and welfare, Hunzaker and Valentino measure respondents' associations among a set of conceptually related ideas, including "being a welfare recipient," "becoming a teen parent," and "racism." The above logic suggests this approach may indeed uncover schemas, but it is not *guaranteed* to uncover a schema in any instance.[21] Answering whether a given estimated ICN captures a schema requires "zooming out" from the algorithmic level and demonstrating it can fulfill the relevant function of a schema. An especially convincing validation could use the estimated network structure to make testable predictions about how subjects will perform automatic pattern completion or pattern matching within the given domain (see, e.g., Hunzaker 2016).

The same need for additional empirical validation applies to cultural schemas surfaced by recent techniques for estimated schemas from survey data (e.g., Boutyline 2017; Goldberg 2011), which similarly assume (rather than test) the ability of the estimated structure to function as a schema. Indeed, because these methods infer individual-level associations between concepts rather than measuring them directly, the assumptions they require are substantially stronger. Taylor and Stoltz's (2020) inventive technique for identifying cultural schemas in documents rests partly on the same strong assumptions as these survey-based methods, and thus shares their need for empirical validation.[22]

Types of connections. This model also clarifies what kinds of ties these connectionist-inspired methods need to measure. Because each tie in an ICN is produced through Hebbian learning (i.e., simultaneous activation), its weight T(A,B) is determined by how often A and B coincide in the learning environment. This tie then has a single function: it determines how much the activation of one node should increase or decrease in response to changes in activation of the other node. Roughly speaking, if you think of concept A, T(A,B) determines how much more (or less) likely this makes you to think of concept B. The ties have no other meaning.

The weight T(A,B) can thus be measured by sequential priming, which tests how much faster (or more likely) a person is to recognize concept B after they are presented with concept A (e.g., Shepherd and Marshall 2018). It can also be measured by the Implicit Association Test (IAT), which captures the relative ease of keeping A and B simultaneously activated in mind. In contrast, when attempting to measure the connectionist network behind schemas of poverty, Hunzaker and Valentino (2019:956) measure each T(A,B) by asking respondents to report whether A and B are "related '(1) because one causes the others or (2) because they commonly go together in this context [of poverty in the US] for some other reason' (i.e., the relationship between the concepts need not be causal)." This procedure thus captures individuals' *perception* of causal or correlational relationships between A and B. Although it is plausible that this perception may be related to T(A,B), this relationship is not guaranteed. Future work building on Hunzaker and Valentino's approach should thus validate this tie strength measure (e.g., by examining its relationship to IAT scores or other established measures of implicit association). An even better solution may be to incorporate these established measures of T(A,B) directly into the broader methodological procedure.[23]

Relational versus connectionist models. Connectionism-inspired methodologies in sociology often seek to construct network representations of their target domains. This approach is highly promising, but existing work elides important differences between these networks and connectionist models. Relational views of culture long predate connectionism. For example, in mid-twentieth-century structural linguistics and anthropology, "word meaning was reduced to just those features that define the differences between words" (Quinn 2011:32). The final product was a *static* relational map of a domain, where the meaning of a word or symbol is captured by its semantic relationships to other words (e.g., relations of similarity or opposition; see Mohr 1998). Psychological approaches to semantics in the 1960s similarly envisioned conceptual knowledge as a static hierarchy "that is structured according to abstract relations between concepts" (Yee, Chrysikou, and Thompson-Schill 2014:356). The connectionist revolution in cognitive science advanced beyond these earlier relational approaches by focusing not on the *position* of nodes in a network but rather the *flow of activation* between nodes. Connectionist methods examine cognitively realistic ways that knowledge can be learned and deployed (e.g., how an ICN learns to complete the gaps in partially observed "bedrooms"). The networks they construct are dynamic models rather than static images.

In contrast, connectionist-inspired approaches in sociology generally construct static network images that lack this key dynamic component (e.g., Boutyline 2017; Goldberg 2011; Hunzaker and Valentino 2019; Taylor and Stoltz 2020; but see Arseniev-Koehler and Foster 2020). Unlike connectionist models, these static images neither measure nor articulate which cognitive tasks the estimated schemas can perform. These models are thus representations without an algorithm, and their cognitive importance is assumed rather than demonstrated. In contrast, connectionist networks explicitly model both contents and process: they depict the representation and literally implement the algorithm. This enables connectionist models to serve as their own proofs-of-concept, thus making their theoretical import far clearer, richer, and more convincing. We therefore urge this important line of sociological work to go beyond modeling schemas as static relational networks, and to prioritize capturing their crucial dynamic components.

Limitations of ICNs

As noted earlier, connectionist models are not literal depictions of neural-synaptic processes. Rather, they are higher-level, analytically useful approximations that capture some realistic features of brain function while eliding others. But even among connectionist models, localist networks like the ICN offer some of the loosest approximations of these underlying cognitive mechanisms. Although they can capture the pattern-completion properties of schemas, there are other features of schematic cognition they do not realistically or usefully capture. As we will demonstrate, this means the ICN is not always the appropriate model for cognitive schemas, especially for analyses of large numbers of interrelated schemas.

An important limitation of ICNs arises because they represent the meaning of concepts entirely via their associations with other discrete, consciously accessible concepts. This localist representation is only a coarse-grained approximation of semantic memory (i.e., memory for concepts). As Kumar (2021:52) notes, "the formation of direct associations [between concepts] is most likely an initial step in the computation of meaning. However, it also appears that the complex semantic memory system does

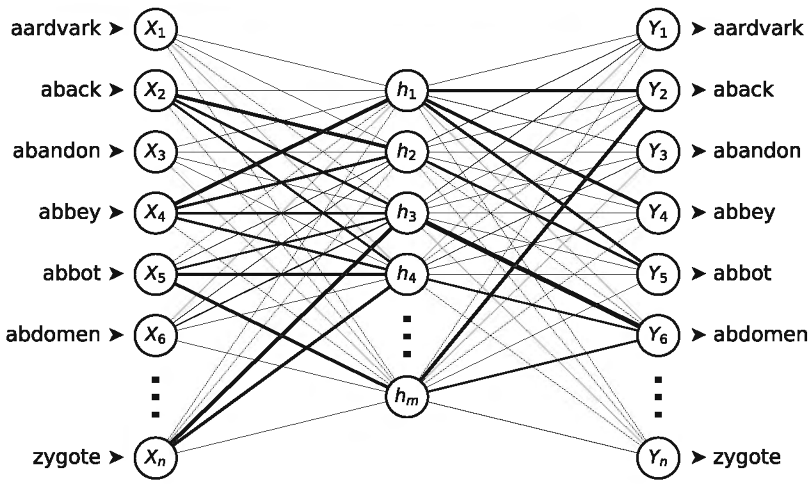

Figure 2. Part of a Possible Word2Vec Distributed-Representation Neural Network
Note: Omitted network sections are indicated by '. . .'. Nodes X represent inputs (observations); nodes Y represent outputs (guesses/pattern completions); nodes h ("hidden nodes") represent non-conscious fine-grained features. There are often $m = 50$ to $m = 300$ hidden nodes and $n = 10{,}000$ to $n = 500{,}000$ input and output nodes. Line width represents tie weight (here shown prior to training, when weights are random). Activation flows from left to right.

not simply rely on these direct associations." Instead, it abstracts and generalizes from the observed co-occurrences, constructing non-conscious lower-level mental models of the concepts' shared characteristics—a deeper cognitive step that distinguishes semantic memory from simpler episodic memory (i.e., memory for events; see Günther, Rinaldi, and Marelli 2019:1011). ICNs represent only the direct associations that come from the initial learning step.

This limits ICNs' ability to realistically learn large sets of interrelated schemas. For example, consider how an ICN containing 15,000 different concepts would represent learning one additional concept X. Because ICNs do not generalize across the concepts they represent, learning the meaning of X requires the ICN to estimate X's relationship to *each one* of the 15,000 concepts. This requires a vast number of observations of the target concept. This is cognitively unrealistic, as actual humans can learn new concepts after just a handful of examples (Günther et al. 2019; Lazaridou, Marelli, and Baroni 2017). It also means that, given even a very large input corpus, an ICN-based method would only be able to extract a relatively small number of cultural schemas. This limits ICNs' practical applicability as empirical tools for uncovering large collections of interrelated schemas from "big data."

Networks with distributed representations overcome these limitations. Recall that, in a distributed network, concepts are represented by weighted ties to "hidden nodes" that correspond to concepts' fine-grained features below the level of terms we consciously use to reason about the domain (see Figure 2). Importantly, the number of hidden nodes is generally small (e.g., 300 hidden nodes for a vocabulary of 500,000 concepts). Perhaps counterintuitively, using a *small* number of hidden nodes is what gives distributed networks their expressive power, as this "compression" forces each hidden node to efficiently represent the shared features of *many* different concepts. Because different concepts share the same hidden nodes, learning something new about one concept makes a distributed network in effect update its knowledge of all related concepts (Hinton, McClelland, and Rumelhart 1986). This also enables distributed networks to share humans' ability to successfully learn new concepts from just a small number of examples (Günther et al. 2019; Lazaridou et al. 2017).

One example of a distributed network that makes use of this richer expressive power sits "under the hood" of Word2Vec (Mikolov et al. 2013). Recent work in cognitive science and sociology has successfully used *word embedding models* estimated (or "trained") by Word2Vec to study the cultural schemas suggested by million- or even billion-word text corpora, such as the complete Google News corpus (Arseniev-Koehler and Foster 2020; Caliskan, Bryson, and Narayanan 2017; for a sociological introduction, see Kozlowski, Taddy, and Evans 2018). In its most common usage, Word2Vec trains a neural network with $m = 50$ to $m = 500$ hidden nodes to represent a vocabulary of $n = 10{,}000$ to $n = 500{,}000$ different words (see Figure 2; for simplicity, we use $m = 300$ and $n = 500{,}000$). In each training step, it takes a short passage from the corpus, omits one *focal* word, and activates input nodes (X in figure 2) that correspond to each remaining word in the passage. For example, for the passage "weather today is sunny and hot," it may omit the focal word "sunny" and activate the input nodes "weather," "today," "is," "and," "hot." The activation then diffuses along weighted ties from the input nodes to the hidden nodes (h) and then to the output nodes (Y), where it represents the network's guesses about the omitted word.[24] If it guesses incorrectly, it *backpropagates* the error, adjusting the weights of the ties used to make the incorrect guess so that, in the future, it would be more likely to guess correctly. By performing these steps on each passage in the corpus, Word2Vec inductively learns $m = 300$ fine-grained features, and expresses each of the $n = 500{,}000$ words in its vocabulary as a combination of these 300 features.

Word2Vec thus learns concepts by perfecting its ability to guess missing words. This, as Arseniev-Koehler and Foster (2020) point out, closely matches DiMaggio's functional-level conception of cultural schemas as pattern-completion engines that fill in the gaps in incomplete observations with cultural defaults. Moreover, Word2Vec uses a distributed neural network that itself is a highly plausible algorithmic-level model of schematic cognition (Günther et al. 2019). A Word2Vec word embedding is thus a cognitively realistic model of the cultural schemas that a naïve learner would learn from reading through its corpus (Arseniev-Koehler and Foster 2020). A growing range of validation studies confirms that these word embeddings indeed mirror various assumptions, biases, and stereotypes that are displayed by general members of the population, including the implicit associations tracked by the IAT (Caliskan et al. 2017; Lewis and Lupyan 2020). This makes word embeddings an extremely powerful tool for examining cultural schemas on the macro scale. Indeed, we believe this method carries enormous promise for future scholarship.

To be clear, we are not arguing that Word2Vec or other distributed networks are *always* preferrable to ICNs. Distributed representations are more cognitively realistic and computationally capable, but they require enormous amounts of input data, which may restrict their practical application to only studies of very large populations (Günther et al. 2019). Relatedly, we argued that ICN-based methods should estimate tie weights using validated tools for measuring implicit associations behaviorally (e.g., the IAT). In contrast, it is not clear how the tie weights that make up a distributed representation could be practically measured from actual observed behaviors. Instead, they need to be estimated indirectly, from the traces of these associations found in large corpora. We thus believe ICNs and distributed networks should both be parts of this sociological toolkit, much as localist and distributed networks both still see active use in cognitive semantics (e.g., Günther et al. 2019; Kumar 2021; Zemla and Austerweil 2018).

More broadly, we believe no single "one-size-fits-all" algorithmic-level solution is appropriate for answering all questions about schemas. Rather, methodologists developing new techniques for measuring schemas should begin by determining which functional-level features are the most theoretically central to the schemas they investigate. Researchers should then select an algorithmic-level model that (1) clearly and parsimoniously expresses these relevant features and (2) can be estimated from the empirical data at hand. The resulting method should be validated empirically by demonstrating that the schemas it estimates indeed correspond to observed instances of schematic cognition (e.g., automatic pattern matching or pattern completion).

CONCLUDING DISCUSSION

In the previous section, we laid out a clarified algorithmic-level conception of schemas as networks of implicit association between concepts. We used this conception to propose how future methodological scholarship could improve the measurement of cultural schemas. We now return to our functional-level conception of cultural schemas as *socially shared representations deployable in automatic cognition* to outline a series of questions for a broader research program. Work in cognitive sociology of culture often focuses on two sets of phenomena that are relatively neglected in cognitive psychology and other cognitive disciplines: (1) macro-social processes that span large societal or historical scales, and (2) real micro-social behaviors that take place in naturalistic settings. The research program we outline draws on these traditional strengths.

Within existing sociological work on cultural schemas, attention to macro-scale processes is perhaps most characteristic of Sewell (1992) and related contemporary treatments (e.g., Ray 2019). This work has observed that, as social and economic circumstances change across decades or centuries, the same cultural schemas (e.g., the treatment of goods and services as commodities, or practices of racial segregation) can come to apply to settings they did not previously encompass. However, we argued that there is a tension between this observation and the cognitive conception of cultural schemas as *automatically deployable* representations: automatic cognition is often characterized as predominantly specific to domains where it was learned (Evans 2008, 2012), with the application of existing knowledge to new domains understood as a feature of effortful, controlled cognition. Indeed, as we demonstrated, the commodity schema did not appear to be automatically deployable within unfamiliar domains. How, then, can we explain the historical observation of cultural schemas' apparent transposability?

We believe the answer lies with another functional-level property of cultural schemas we stressed here: schemas are a form of *representation.* Unlike many other types of shared cognitive contents (e.g., motor skills or mere associations), a cultural schema conveys something meaningful about the world. This "something" is the schema's *mode-independent representational contents*. As Sperber (1996:78–79) points out, a person does "not discover the world unaided, and then make public her privately developed representations of it; rather, a great many of her representations of the world are acquired vicariously." The social origins of automatically deployable cognitive representations are thus a natural topic for cognitive sociology.

The representational contents of a schema can be *externalized* into public expression and *internalized* into personal culture—although, in their public form, they would be public representations rather than schemas (Lizardo 2017; Sperber 1996).[25] For example, consider an experienced driver who successfully makes a left turn while engrossed in a demanding conversation. Without consciously thinking about her driving, this driver could still automatically turn on her blinker, move to the leftmost lane, stop at the red light, and complete her turn after it turns green. These rules are shared, automatically-deployable representations—but, when she first learned them from a DMV handbook, they initially required substantial conscious effort to follow correctly. These rules eventually become routinized into cultural schemas, but people first have to internalize them as explicit deliberative knowledge. What persists across the three modalities—public representations in the DMV handbook, personal declarative culture, and finally personal nondeclarative culture—are the schema's representational contents.

Other pieces of culture may follow similar paths. For example, as Kruglanski and Gigerenzer (2011) note, some "rules" of social life may similarly be first learned deliberatively, and then transformed into intuitively accessible structures by routinization. Vaisey and Frye (2019) make a similar point about explicitly learned physical skills. More broadly, Stanovich and Toplak (2012:8) and Evans (2008) argue that automatic cognition encompasses both the products of implicit learning and the explicitly-learned cognitive contents "that have been practiced to automaticity." And, as Foster (2018) points out, narratives may be first learned as explicit declarative culture, but can later yield implicit nondeclarative culture by learners "replaying" the narratives in their mind.[26]

But it is the reverse pathway—from nondeclarative to declarative personal culture—that may hold the answer to the contradiction we highlighted here. Karmiloff-Smith (1994:693, emphasis in original) calls this pathway "representational redescription . . . [a] process by which information that is [implicit] *in* a cognitive system becomes progressively explicit knowledge *to* that system." Karmiloff-Smith theorizes that representational redescription may play a key role in human cognition because it makes the largely automatic knowledge acquired through implicit or heavily embodied learning (e.g., musicians' "behavioral mastery" over playing the piano [Karmiloff-Smith 1994] or chefs' sensory understanding of the taste of various ingredient combinations [Leschziner and Brett 2019]) available to the kinds of detailed introspection, intentional manipulation, and hypothetical thinking that are important parts of analytic engagement, creativity, and agency.

This process could make the representational contents of a cultural schema available to effortful conscious cognition, which we suspect may be generally necessary to translate these representations to novel domains. After they are transformed to encompass new settings, the representational contents could then travel the reverse pathway, becoming routinized through repeated application into automatic cognition. The end product of this process would be a cultural schema that largely resembles the original schema, but now applies to a broader set of domains.

Representational redescription may thus be key to social reproduction, wherein familiar social arrangements backed by widely shared cultural schemas (e.g., racial segregation [Ray 2019] or exchange of objects and services for money [Sewell 1992]) are adapted so they may continue under new circumstances. But because implicit cultural schemas enable routine behaviors—a foundational component of social structure—and representational redescription exposes these schemas to possible transformation, it may also paradoxically be an important conduit for social change. We thus believe the different routes that the representational contents of different cultural schemas take across the "cultural triangle" (Lizardo 2017) of public representation, personal declarative culture, and personal nondeclarative culture should be a central area of study for cognitive sociology.

Future scholarship should attempt to identify whether different types of cultural schemas vary in their likelihood of following different pathways between public representation and automatic cognition, and how this affects their eventual social spread. For example, the public-to-explicit-to-implicit (PEI) pathway we outlined may enable some schemas to diffuse over mass media, which could lead to a much broader spread than schemas that require the slow, sustained exposure characteristic of the public-to-implicit (PI) pathway. This could result in long-term patterns of cultural change where PEI-diffusing schemas gradually displace PI-diffusing ones (see also Sperber [1996] on "cultural attractors"). Conversely, because the spread through mass media is likely to be less demographically patterned, PEI schemas may be less useful as cultural capital than

PI schemas (Bourdieu 1987; Lizardo 2006), which could create social reasons for their continued persistence.

Indeed, the relationship between different parts of the cultural triangle has recently been the focus of a number of innovative micro-sociological studies (e.g., Cerulo 2018; Leschziner and Brett 2019; Winchester 2016). This work demonstrates how, in naturalistic settings, Type I and Type II cognition are not as radically separate as they were often portrayed in older dual-process sociology. Rather, the two types of culture and cognition frequently draw on and reinforce one another. The theoretical account we outlined in this section similarly implies a complementary relationship between cultural modalities.

To advance sociological research into cultural schemas, scholars should turn this micro-sociological attention to processes of schematic transposition.[27] For example, when entrepreneurs apply the commodity schema to previously uncommodified goods or services, does this transposition sometimes take place implicitly and unintentionally, or does it generally follow the kind of conscious, intentional process we posited here? Conversely, when consumers first encounter truly novel instances of commodification, are they able to seamlessly deploy their existing schemas to reason about them without effort or conscious control? If these micro-sociological investigations then successfully merge with macro-sociological efforts to understand the trajectories cultural schemas take across large-scale societies and the longue durée of history, the combined research program could yield valuable and uniquely sociological insights into cultural schemas, thus potentially creating a long-sought avenue by which sociological insights about culture can come to bear on the interdisciplinary study of cognition (e.g., Cerulo 2010; Lizardo 2014; Vaisey and Valentino 2018).

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Notes

1. Following Wood and colleagues (2018), we distinguish between the cognitive conceptions of cultural schemas (e.g., DiMaggio 1997; Vaisey 2009) and the older non-cognitive conception from Sewell (1992). In cognitive conceptions, schemas are concrete mental structures inside individuals' minds, whereas for Sewell (1992:8) they are "virtual" objects without "any particular location in space or time." Aside from our analysis of Sewell's commodity schema, and our discussion of schematic transposition in the conclusion, we follow Wood and colleagues in restricting our scope to cognitive conceptions.
2. Some social psychology scholarship, however, has examined cultural schemas (e.g., Markus and Kitayama 2010).
3. For a related discussion of sociology's relationship to judgment and decision-making (JDM) scholarship—a close relative of cognitive science—see Vaisey and Valentino (2018).
4. Marr confusingly named this level "computational." Like Brighton and Gigerenzer (2008), we use more intuitively interpretable level names.
5. Indeed, sociological scholarship has little to gain from engaging directly with biological-level explanations—although, as Lizardo and colleagues (2019) argue, cognitive neuroscience also yields higher-level insights that carry promise for cultural sociology.
6. But neither level has a monopoly on conceptual or operational uses. For example, Hunzaker (2016) operationalizes schemas entirely via their pattern-completion function, whereas Arseniev-Koehler and Foster's (2020) theoretical argument focuses on algorithmic-level building blocks.
7. Following Hunzaker (2016), we use "stereotype" to refer to a common set of interlinked implicit assumptions about members of a social group. For example, a stereotype of a gang member may be an implicit representation of a young man with a specific race, criminal record, personality, and clothing style (MacLin and Herrera 2006). This stereotype then enables automatic pattern completion.
8. Note that we use the term "*implicit* categories" to specifically denote only categories that can be

deployed in automatic cognition. Familiar categories invoked in daily speech would generally qualify. However, other categories (e.g., those invoked solely in bureaucratic classification) may be too complex or unwieldy to be deployed automatically.

9. To clarify, recognizing that one's current situation matches the pattern "I am indoors" triggers the automatic inference "I should lower my voice."
10. These three types of cultural schemas correspond to analytically distinguishable functions of schematic cognition. We enumerate them to ascertain that our functional-level conception is sufficiently broad to cover all three. Note that these differences in *function* may not correspond to meaningful differences in *representations* on the algorithmic level. Rather, they may describe different algorithms performed on the same (or similar) representations—bottom-up in the case of pattern matching, and top-down for pattern completion. Thus, when we contrast racial stereotyping (i.e., *drawing inferences* about someone based on their race—an example of pattern completion) and racial categorization (i.e., *grouping* someone according to their race—an example of pattern matching), our goal is to specifically distinguish between two different *uses* of schemas. We are not arguing that these terms identify different sets of cognitive structures on lower levels of analysis. Indeed, we expect both of these uses generally draw on some of the same lower-level cognitive representations.
11. Discourse itself is paradigmatic of deliberative cognition, but conversation also involves many fast automatic processes (e.g., completion of partially unheard utterances, associative memory retrieval). Note, though, that this example also involves some non-automatic cognition (e.g., Billy's decision to lie about how much work he has done).
12. Automaticity did not always play a central role in older accounts. For example, in D'Andrade's (1995:122–49) 27-page treatment, automaticity is not referenced until the 23rd page—and it is unclear whether D'Andrade is describing *all* cultural schemas as automatic, or only some. Similarly, automaticity does not feature in Shore's (1998:53) definition of "foundational schemas" and is referenced only rarely and ambiguously in his account (e.g., p. 368). Some of Shore's central examples are also incompatible with automaticity: for instance, Shore (1998:212) proposes that "walkabout" narratives *themselves* "serve as foundational schemas." Yet, as we will discuss, narrative is a central example of *non*-automatic cognition.
13. To make our definition of cultural schemas more intuitively intelligible, we use the widely familiar term "automatic cognition" to reference Type I processes. However, Evans and Stanovich (2013:228) note that the concept of "automaticity" has become overextended and is often taken to include features that are only *correlates* of autonomous cognition, such as high speed. Thus, we follow them in holding that the only defining feature of Type I cognition is *autonomy*, and we use this as the sole meaning of "automatic" in this article.
14. Importantly, the Type I character of schemas implies that all schemas *can* function without a person's control, but it does not imply that all schemas *must always* function in this manner. Type II processes can trigger Type I processes, which means some Type I processes can be invoked volitionally (e.g., Leschziner and Brett 2019). The automatic character thus does not necessarily imply a complete absence of control, although it implies schemas should not *require* it.
15. Ryder (2009:234) notes that this "minimalist" conception is uncontroversial: "On this minimalist notion, only a radical eliminativist would deny that there are mental representations. It is not clear that there are any such radical eliminativists." Our treatment requires only this minimalist notion, but recent research on model-based learning provides compelling reasons to believe that schemas may also be representational in other cognitive senses of the term (see, e.g., Railton 2017).
16. The other primary defining feature of Type II cognition is cognitive decoupling (Evans and Stanovich 2013; Stanovich and Toplak 2012). We restrict our focus to working memory because this is sufficient for empirically delineating Type I cognition.
17. Sewell terms this transposable schema "commodification." However, because "commodification" is the act of turning non-commodities into commodities, it appears more accurate to term the *transposable* schema "commodity." Commodification is then the *transposition* of this schema to new domains.
18. To avoid confusion, we use "neural network" to refer only to these computational models (and never to literal networks of neurons).
19. This could represent exposure to real rooms or to their depictions (e.g., in narrative or film).
20. Rumelhart and colleagues (1986:21) thus argue that the "language of schemata and schema theories should be considered an approximation to the language of [connectionism]."
21. This is especially concerning because the method requires the analyst to know a priori which concepts make up the network—a task that in practice involves substantial guesswork. Future work should aim to overcome this major limitation by identifying the concepts inductively.
22. Note that more straightforward applications of Word2Vec to cultural schemas (e.g., Arseniev-Koehler and Foster 2020) do not make these assumptions.
23. Indeed, the IAT and related measures have already been adapted to diverse sociological uses (e.g., Melamed et al. 2019; Miles, Charron-Chénier, and Schleifer 2019; Silva 2018; Srivastava and Banaji 2011).

24. Specifically, the activation of each node Y_i represents the estimated probability that *i* is the omitted word.
25. By public representation, we mean representations that are externally observable by people. They must exist in some physical medium outside a person's mind (e.g., as spoken language, observable behavior, or physical artifacts). Social institutions (e.g., marriage) and public codes are only public representations to the extent that they correspond to externally observable phenomena. We consider their shared *subjective* components (e.g., peoples' knowledge of the codes) as personal culture rather than public representation.
26. Note that our argument here contrasts with Lizardo and colleagues (2016), Lizardo (2017), and Wood and colleagues (2018), who suggest the route from public to nondeclarative personal culture happens primarily through implicit slow learning enabled by long-term sustained exposure. We agree this is likely one route taken by cultural schemas; however, our examples suggest cultural schemas may also be first rapidly learned as explicit representations rather than through repeated personal experience, and then made implicit through repeated application.
27. Sociologists have examined the use of conceptual metaphor to transpose image schemas (Rotolo 2020; Winchester 2016). Although theoretically related, we do not believe findings from this scholarship directly apply to cultural schemas, for three reasons. First, we noted that image schemas are human universals, and are thus not *cultural* schemas. Second, image schemas consist of simple experiential primitives for elementary concepts like containers, paths, and balance—"the most basic forms and relations we sense and perceive" (Rotolo 2020:170)—and thus may be qualitatively simpler than "typical" cultural schemas (e.g., the car dealership schema, the studying-is-for-girls schema). Finally, there are only a few dozen different image schemas, suggesting they are not subject to the same dynamics of innovation and diffusion as cultural schemas.

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