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Toward an Evolutionary Approach to Social Cognition

Abstract

We discuss the benefits of combining evolutionary and traditional cognitive approaches in the study of social cognition. A central goal of applying a traditional cognitive approach is to develop a computational theory (through task analysis) of the domain under study. A task analysis includes a specification of the computational problems that the system must solve for it to operate successfully. Evolutionary psychological theory provides a useful guide in developing a computational theory because it allows a top-down analysis of the constraints that a complex, information processing system must meet to exist in its current form, and because it provides principled criteria for evaluating the success of the system. Research on grandparental investment is used to illustrate the advantages of using evolutionary principles within a task analysis. We conclude that evolutionary approaches to social phenomena can be made more rigorous by adding a computational layer of analysis, and functionally agnostic approaches within psychology can better avoid blind alleys of investigation by adding a rigorous evolutionary approach.

Key words

Theory of evolution, evolutionary psychology, psychology, social cognition, grandparenting, altruism.

Humans are intensely social, and thus it is reasonable to assume that a large proportion of the human cognitive architecture is dedicated to social tasks (see FISKE 1991; HIRSCHFELD/GELMAN 1994; LESLIE 1987; TOOBY/COSMIDES 1992). The investigation of social cognitive mechanisms is not easy, however, because they are sensitive to contextual variation, and because multiple mechanisms are simultaneously engaged by the same social task (TOOBY/COSMIDES 1992). As a result, many of the most powerful conceptual tools developed by cognitive scientists have not been immediately useful to social psychologists (but see HASTIE 1988, and SMITH/ZARATE 1992, for applications to person perception and simple social judgement). Recent advances in evolutionary psychology can help social psychologists develop a rigorous top-down approach to social cognition by adding a layer of analysis to the 'top' of the traditional approach employed in cognitive science.

In this article, we first re-introduce to psychologists the multilevel approach often used in cognitive science, and we argue that this approach can strengthen social psychological research and theory. Second, we argue that the effective use of a multilevel approach in social domains will require the addition of an evolutionary level of analysis. Finally, we argue that current work in evolutionary psychology, especially work on social phenomena, can be made more rigorous if evolutionary theory is used in conjunction with the multilevel approach of cognitive science.

In his work on visual perception, David MARR (1977, 1982; MARR/POGGIO 1977) proposed that any information processing system can be understood at three levels of analysis (see Table 1). The first level, the computational theory, specifies the problem to be solved, the information available for solving the problem, and the sub-tasks that must be completed to solve the problem, given the informational constraints imposed on the system. Developing a computational theory entails decomposing a larger problem (e.g., visual perception) into the sub-problems (e.g., edge detection, computation of surface orientation) that must be solved, in a real-world environment, to accomplish the larger task.

The second level, the algorithm, specifies the rules used by the system for solving the problem. The algorithm is specified in abstract terms, independent of the physical system on which it is implemented. The algorithm specifies the nature of

I. Computational theory (Task Analysis)
What is the goal of the computation, why is the computation appropriate, and what is the logic of the strategy by which the computation can be carried out?
II. Algorithm (Cognition)
How can the computational theory be implemented? In particular, what is the representation for the input and output, and what is the algorithm for the transformation of input to output?
III. Implementation (Hardware)
How can the algorithm and representation be realized physically?

Table 1: MARR's Three Levels of Analysis. Adapted from MARR (1982, p25).

the input into the system, in addition to the operations performed by the system that solve the subproblems specified by the computational theory (e.g., for edge detection, computing the second derivative of light intensity, and using zero-crossings to indicate edges; MARR 1982).

The third level, the implementation (or hardware), concerns the physical instantiation of the algorithms specified at the second level. Detailing algorithmic implementation amounts to a description of the mechanical processes by which the system carries out the operations specified abstractly at the second level (e.g., for edge detection, 2 geniculate X-cells, one on-center and one off-center, connected by an 'and' gate; MARR 1982).

For cognitive scientists, and most psychologists, a primary goal is to understand the abstract rules according to which the mind works. This corresponds to MARR's second level of analysis and captures what psychologists mean by cognition—the ways in which information is used by the mind. The algorithmic level of analysis captures a unique class of generalizations not reflected in purely physical or purely behavioral descriptions. It is the algorithmic level of analysis that is typically of primary interest to psychologists (CHOMSKY 1957; FODOR 1968; PYLYSHYN 1984).

According to MARR (1977, 1982), the most profitable strategy for identifying the algorithms used by the mind is to adopt a top-down strategy by first developing a computational theory for the domain in question. Careful consideration of the specific sub-tasks required in a domain, together with a consideration of the information available for accomplishing these tasks, limits the potentially viable algorithms. Only algorithms capable of successfully completing the series of required sub-tasks, using information available to the system in real-world situations, are worth consideration. Employing a computational theory prevents the researcher from considering the huge array of algorithms that are impossible given the real-world constraints on the system.

The set of viable algorithms is relatively unconstrained, however, by the physical hardware on which the algorithms are implemented. Given a complete description of the physical elements of a system, in addition to a complete description of how those physical elements are connected, the researcher remains uninformed as to the abstract rules that are instantiated in that physical system. In MARR's words:

"Although algorithms and mechanisms are empirically more accessible, it is the top level, the level of computational theory, which is critically important from an information-processing point of view. The reason for this is that the nature of the computations that underlie perception depends more upon the computational problems that have to be solved than upon the particular hardware in which their solutions are implemented. To phrase the matter another way, an algorithm is likely to be understood more readily by understanding the nature of the problem being solved than by examining the mechanisms (and the hardware) in which it is embodied" (MARR 1982, p27).

A simple thought experiment illustrates MARR's point. Imagine a giant machine of some unknown but definite function. Further imagine that this machine is constructed entirely of Tinker Toys. Each piece is made of wood, and is one of a small set of types (e.g., cylindrical with holes, or long and stick-like). What algorithms are instantiated in this machine? That is, what are the rules that guide its operation? The answers to these questions are relatively unconstrained by a physical examination of the machine or by a description of its specific movements or 'behaviors'. The set of possible rules guiding the operation of this machine is substantially reduced, however, if we first formulate a hypothesis about the problem the machine solves: It plays, and never loses at, tic–tac–toe (this machine does exist; DEWDNEY 1989). This piece of information now constrains the possible algorithms instantiated in the machine to such a degree that only a small number are viable. For example, algorithms such as, "Cooperate on the first move. Then defect if your partner defects, and cooperate if your partner cooperates," and "Flip pancakes after cooking for two minutes," are no longer worth consideration. These algorithms are technically possible given the physical medium involved but are unrelated to the machine's function and so represent 'blind alleys' of investigation. However, this machine may include a system for representing the possible configurations of X's and O's in a 3 by 3 environment, and may perhaps embody a set of strategic algorithms such as, "If two of your opponent's symbols are in adjacent squares, place your next symbol in the next successive square," and "If moving first, always place your symbol in the center square". These algorithms embody solutions to specific sub-tasks necessary to accomplish the larger goal—never losing at tic–tac–toe.[1]

MARR's (1982) computational approach revolutionized theories of visual processing, in particular, and cognitive science, in general. It provided a framework for understanding perceptual processes through a careful consideration of the demands of the problem. MARR's ideas, however, have not penetrated social psychological circles to the same degree. One possible reason is that MARR (1982) and others concerned primarily with perceptual processes have had it comparatively easy in applying a computational approach. The existence of a perceptual process is evident and need not be inferred. Furthermore, once a perceptual process is identified, a task analysis can proceed 'from the ground up'. MARR (1982) relied heavily on observation (what features are, and are not, detectable by people) and intuition (for example, to see a table, we must perceive its edges and its surfaces) to develop his computational theory of vision. Operations were identified as 'appropriate' based on intuitions about the relevant processes and relations between them. For example, MARR explains that the reason a cash register uses addition, rather than multiplication, is that "the rules that we *intuitively feel to be appropriate* for combining the individual prices in fact define the mathematical operation of addition" (1982, p22, emphasis added). And so the addition of prices would be part of any computational theory of cash registers. Thus, observation and intuition give the perception researcher an initial foothold from which to identify sub-processes, and the analysis can then proceed 'from the top down', with the computational theory providing constraints on possible algorithms (see Figure 1).

Developing computational theories in social domains is not as straightforward. Humans pursue friendships, form social hierarchies, and become romantically involved with others, for example. These social phenomena are accompanied by a baffling array of psychological processes, but even the existence of these processes (unlike most perceptual processes) is not always immediately evident. Furthermore, it is not always clear when a social agent is operating successfully, or even what an appropriate metric for 'success' is (Is success equivalent to subjective happiness? To the maximization of pleasure? To the minimization of pain?). Nor is it intuitively obvious what sub-problems must be solved by a social agent in order to be successful (What must we do to ascend successfully a social hierarchy?).

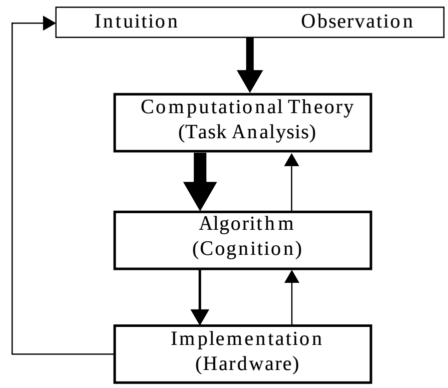

Figure 1: MARR's (1982) computational approach. Arrows represent the direction of inferences from one level to another. The thickness of the arrow indicates the relative importance of the associated inference process to MARR's approach.

Intuition and observation provide little help. Our intuitions often are blind to the complexity of tasks that we perform well with little or no conscious effort (COSMIDES/TOOBY 1994). The apparent (phenomenological) ease with which we use language to convey and consume ideas, for example, masks the cognitive complexity that underlies even the simplest conversation about the weather (PINKER 1994; SPERBER/WILSON 1995).

To be effective in social domains, this intuition-dependent approach must be replaced with an approach that specifies the tasks and sub-tasks present in an information processing domain and that specifies (1) what it means for a social psychological process to be successful and (2) what specific problems an organism must solve to be successful in a particular social domain. Evolutionary psychological theory can provide social psychologists with a powerful set of tools for these purposes.

The Use of Evolutionary Theory within a Cognitive Approach

Recent advances in evolutionary psychology enable the application of a computational approach to social psychological domains. Computational modeling provides a framework for decomposing complex psychological phenomena into the specific information processing tasks required for the phenomena to occur in real-world circumstances. Evolutionary psychology can strengthen the computational approach and allow its application to social phenomena by supplanting the role of intuition in the process of generating computational theories, and by providing a theoretically grounded metric for deciding when psychological processes are operating successfully. Combining evolutionary psychological theory with a key component of the computational approach, a task analysis, can greatly reduce the chance of making conceptual errors when building theories of social cognitive processes.

Task analysis

A computational approach provides a heuristic for building viable theories of cognitive processes. The computational approach to the mind, in addition, is an epistemological statement: Mental processes are computational (i.e., they involve representations, operations, manipulation of symbols); the mind 'computes' (HOBBES 1974; PYLYSHYN 1984). It is useful, however, to distinguish the epistemology of computational theory from the procedural heuristic of task analysis in thinking about social cognitive processes.

Adopting a task analysis involves breaking a psychological process into the sub-tasks that must be solved for that process to occur. Adopting a task analysis does not require the belief that the mind computes anything in the formal sense (although this approach often will lead to that conclusion). Nor does it require formal computational (mathematical) models of social cognition, or a working computer simulation. In adopting a task analysis, one simply is disposed toward decomposing a proposed psychological process into its constituent parts by specifying the tasks that must be solved to reach the end state.

Using evolutionary theory

This approach involves one simple assumption: that any proposed set of cognitive processes must be evolvable. Because the cognitive architecture that underlies social cognition is a product of natural selection, it must be structured in such a way that is consistent with this causal history. Detailed models of the process of natural selection, including a specification of relevant selection pressures and ancestral environments, can provide a principled set of tools to begin specifying the cognitive tasks that are solved in a particular domain.

The first step in applying an evolutionarily informed computational approach is to identify the selective constraints on potential cognitive adaptations in a particular domain. Game theory models can be used profitably at this step. In the domain of cooperation, for example, the theories of kin selection (HAMILTON 1964) and reciprocal altruism (AXELROD 1984; COSMIDES/TOOBY 1992; TRIVERS 1971) provide models of some of the constraints any set of cognitive processes must have satisfied recurrently if they presently guide cooperative or altruistic behaviors (e.g., 'HAMILTON's rule'; HAMILTON 1963). These models suggest a series of sub-tasks that must be performed to meet these constraints. Using these models, we can generate hypotheses about the algorithms that guided cooperative behavior under ancestral conditions. For example, in cooperation and altruism, the uncertain nature of kinship (due to the possibility of cuckoldry) imposes a class of constraints that may have designed mechanisms for evaluating the uncertainty of relatedness (DALY/WILSON 1982; DEKAY 1995, 2000; EULER/WEITZEL 1996; see below).

Studies of hunter–gatherer societies (HILL/HURTADO 1996), paleontological research (TRINKAUS/ZIMMERMAN 1982), and reverse engineering (reconstructing the past from examining currently existing adaptations; DENNETT 1995; PINKER 1997) aid in identifying the environmental features available for exploitation, and in identifying the conditions under which the proposed algorithms must have been operative. The end result is a set of proposed cognitive processes, which can (and could) solve the problem in question, given the constraints operative in the relevant ancestral environments (see Figure 2).

Grandparental Investment: An Example of an Evolutionary Approach to Social Cognition

DEKAY (1995, 2000) has applied an evolutionary–cognitive approach to cooperation by developing an analysis of the relevant evolvability constraints, performing a task analysis, and proposing previously undiscovered psychological processes

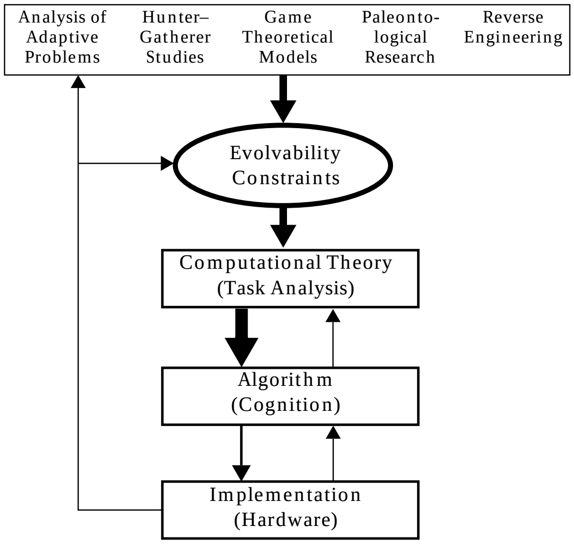

Figure 2: An evolutionary approach to social cognition. Arrows represent the direction of inferences from one level to another. The thickness of the arrow indicates the relative importance of the associated inference process to the evolutionary approach.

involved in kinship interactions. This work is presented as an example of the approach we advocate.

Evolvability constraints on cooperation and altruism

The first step in DEKAY's analysis was to recognize a universal evolvability constraint—that any set of processes, on average and over time, must have led to greater reproductive benefits than costs. This general constraint applies to the evolution of any mechanism, including those involved in cooperation and altruism, and subsumes both the processes of natural selection and sexual selection.

Step 2 in DEKAY's analysis was to express the initial constraint in Inclusive Fitness terms (HAMILTON 1963, 1964). That is, the reproductive costs and benefits specified in step 1 include not only the costs and benefits to the individuals directly involved in the cooperative interaction, but also the sum of the costs and benefits to all individuals affected by the cooperative interaction, times the degree of relatedness (r) between each individual affected and each directly participating individual. Degree of relatedness is defined as the probability that two individuals share some genetic unit (e.g., gene) due to common descent, or by direct generational genetic transmission. An individual's degree of relatedness with siblings, parents and children is 0.50; with grandparents it is 0.25; and with cousins it is 0.125.

Step 3 focused on the kinship aspect of these constraints. True relatedness is a function of kinship category membership (e.g., sibling, parent, half-sibling, grandparent), but also is a function of relational certainty (R), or the probability that two individuals are related, independent of their putative kinship status. Kinship is usually uncertain due to the possibility of cuckoldry severing the line of descent from one individual to another. This is the case for any two individuals related, at some point in their ancestry, through a common male. For example, two grandmothers can be differently uncertain about their relatedness to their grandchild. One grandmother, with a grandchild by her son, is certain that her son is her genetic kin, but is less than 100% certain that her son's child is actually his. The other grandmother, with a grandchild by her daughter, is 100% certain that her daughter is actually hers, and that her daughter's child is actually her daughter's. This is an important aspect of kinship and must be part of the evolvability constraints on kin-directed cooperation and altruism.

Step 4 in the analysis elaborated the constraint of R to recognize that R is a function of the product of the probability of cuckoldry in each generation separating two putatively related individuals. The result is a detailed set of constraints that any set of mechanisms involved in cooperation and altruism must have met, on average and over time, to have been favored by selection and to exist in their current form (see Table 2).

Task analysis

The evolvability constraints identified by DEKAY allow a detailed task analysis of mechanisms involved in cooperation and altruism (see Table 3). For example, these mechanisms must include processes designed to identify and recognize putative kin, and processes designed to identify and deal appropriately with cheaters—individuals who accept the benefits of an interaction without incurring the costs (COSMIDES 1989; COSMIDES/TOOBY 1992). Also included in the sub-tasks involved in cooperation and altruism are some that previously have been overlooked. In addition to mechanisms designed to identify and recognize putative kin, cooperation and altruism directed towards kin must also involve processes designed to (1) evaluate relational certainty (R), (2) weigh putative relatedness by R, and (3) weigh cost/benefit evaluations appropriately.

$B_1 > C_1$ *Step 1*: For mechanisms involved in reciprocal and unidirectional 'altruism' the average reproductive benefits (B_1) must outweigh the average reproductive costs (C_1).
$\sum_{i=1}^{x} r_{(1,i)}B_i > \sum_{i=1}^{x} r_{(1,i)}C_i$ *Step 2*: The reproductive benefits and costs are equal to the sums of the reproductive benefits and costs for all individuals (i) affected by the interaction, times the degree of relatedness (r) between the individual directly participating in the interaction and each individual affected (inclusive fitness).
$r_{\mathrm{true}(1,i)} = r_{\mathrm{put}(1,i)}R_{(1,i)}$ *Step 3*: True relatedness (r_{true})is equal to putative relatedness (r_{put}) times 'relational certainty' (R).
$R_{(1,i)} = \prod_{j=0}^{y} [1 - p(\mathrm{cuck})_j]$ *Step 4*: Relational certainty is the product of one minus the probabilities of cuckoldry [$p(\mathrm{cuck})$] in each generation (j) separating two individuals.
$\sum_{i=1}^{x}\left[r_{\mathrm{put}(1,i)}\left(\prod_{j=0}^{y} 1 - p(\mathrm{cuck})_j\right)B_i\right] > \sum_{i=1}^{x}\left[r_{\mathrm{put}(1,i)}\left(\prod_{j=0}^{y} 1 - p(\mathrm{cuck})_j\right)C_i\right]$ *Result*: Detailed constraints on the evolution of cooperation and altruism. Any set of mechanisms must have, on average and over time, satisfied these constraints.

Table 2: An Analysis of the Evolvability Constraints on Cooperation and Altruism. Adapted from DEKAY (2000).

Cognitive processes involved in cooperation and altruism must include mechanisms that:	
1	Recognize different individuals
2	Identify kin and distinguish between individuals based on degree of relatedness (r)
3	Evaluate the 'relational certainty' of kin (DEKAY 2000)
4	Weigh degree of relatedness by relational certainty (DEKAY 1999)
5	Estimate the costs and benefits of an interaction to oneself and to others
6	Weigh the costs and benefits by degree of relatedness and relational certainty
7	Store information about past interactions
8	Detect and punish, or exclude, cheaters (COSMIDES/TOOBY 1992)

Table 3: Results of a Task-Analysis of Social Exchange. Adapted from COSMIDES/TOOBY (1992) and DEKAY (2000).

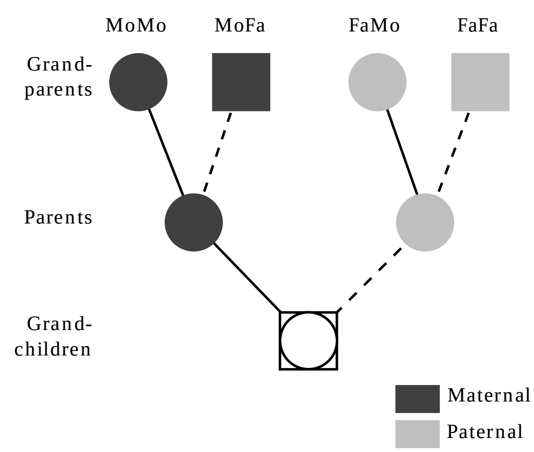

Figure 3: Relational certainty between grandparents, parents, and children/grandchildren. Dashed lines indicate uncertain connections due to the possibility of cuckoldry.

Processes involved in kin-directed cooperation and altruism

If people have psychological processes designed to assess relational certainty, and if they use these assessments in their helping decisions, we should see predictable patterns in grandparental investment. All else equal, mother's mother (MoMo) should be the most investing because she has no uncertainty about her relationship to her daughter's child. Father's father (FaFa) should be the least investing because he is 'doubly uncertain'—uncertain about his relatedness to his own son, and uncertain about his son's relatedness to his grandchildren. Mother's father (MoFa) and father's mother (FaMo) should be intermediate in investment because each have one place in the line of

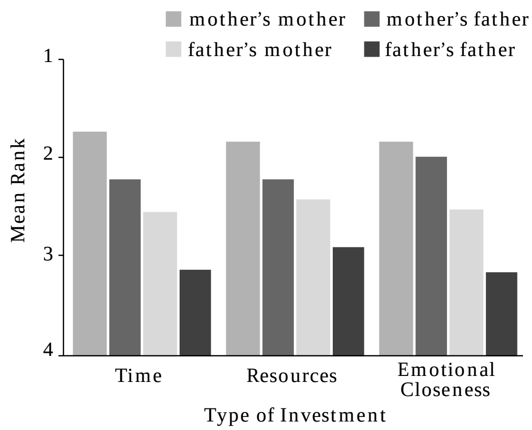

Figure 4: Mean rank of grandparents by grandchildren on the dimensions of 'emotional closeness', 'time spent', and 'resources (gifts, money, etc.)'. Lower ranks mean more investment (adapted from DEKAY 1999).

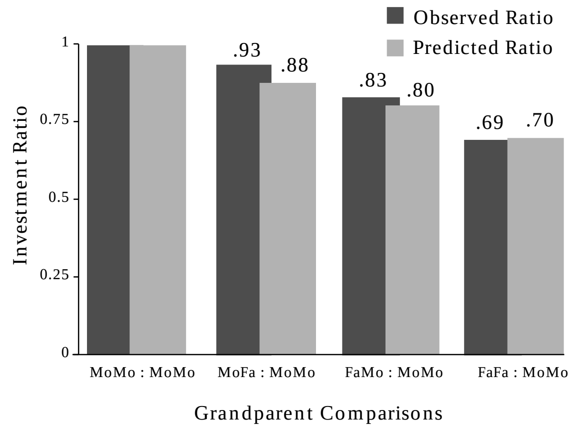

Figure 5: Predicted and observed ratios between Mother's Mother and other grandparents. Predictions are based on self-reported infidelity rates for female grandparent and parent cohorts (from LAUMANN et al. 1994).

descent between them and their grandchildren where cuckoldry could sever relatedness (see Figure 3).

If people use cues to infidelity in their assessments of relational uncertainty, and if they are reasonably accurate in these assessments, we can make additional predictions about grandparental investment patterns. If women's sexual infidelity is greater in the grandparental generation compared to the parental generation, FaMo should invest more than MoFa. This is because the uncertainty for MoFa lies in his own (grandparental) generation—he is uncertain about his relatedness to his own daughter. FaMo is less uncertain because her uncertainty lies in her son's generation. If women's sexual infidelity is greater in the parental generation compared to the grandparental generation, we should expect the opposite investment pattern (MoFa invests more than FaMo). If women's sexual infidelity is equal across generations, we should expect equal investment from MoFa and FaMo (see Figure 3).

In a recent study of the sexual attitudes and behaviors of a nationally representative sample (LAUMANN et al. 1994), 19.9% of women between 43 and 53 years old admitted to an extramarital affair. These women are the approximate age of the mothers of typical college students. In contrast, 12.4% of women 53 to 63 years old admitted to an extramarital affair. These women are the approximate age of the grandparents of a typical college sample. Therefore, among college-age subjects, we should expect the following general pattern of investment: MoMo > MoFa > Fa Mo > FaFa. Actual rankings by undergraduates of their grandparents' investment of time, resources, and emotional closeness confirm these predictions (DEKAY 2000; see also EULER/WEITZEL 1996, for supportive data from Germany; see Figure 4).

If people are accurate in their assessments of the probability of infidelity, we can also make point predictions about the relative investments of various grandparents. Using the figures from LAUMANN et al. (1994), we can calculate the expected ratio of investment, based on relational certainty, using mother's mother as the 'standard', because she is the only grandparent with no uncertainty. Relational certainty (R) is equal to one minus the product of the probability of cuckoldry in each generation separating two putative kin members. For MoFa, the single chance for cuckoldry exists in the grandparental generation. Since 12.4% of grandparent-aged women reported extramarital affairs, the approximate relational certainty (R) for MoFa is 0.88, and the expected ratio of investment between MoMo and MoFa is also 0.88. For FaMo, the single chance for cuckoldry exists in the parental generation. Since 19.9% of parent-aged women reported extramarital affairs, the approximate R for FaMo is 0.80, and the expected ratio between the investments of MoMo and FaMo is 0.80. For FaFa, there are two chances of cuckoldry, in both the parental and grandparental generations, and so R for FaFa is the product of those two probabilities, or approximately 0.70, and the expected ratio of investment between MoMo and FaFa is also 0.70. Actual reports by undergraduates of grandparental investment (rated on a 7-point scale) closely match these predicted ratios (DEKAY 2000; see Figure 5).

Summary

DEKAY's work on grandparental investment illustrates the advantages of using a top-down, task-analytic approach guided by evolutionary theory. The resulting task analysis revealed previously ignored processes that are necessary for cooperation and altruism between related individuals. This example represents only a first step in uncovering social cognitive processes using an evolutionary approach. Further decomposition of this domain into more specific sub-tasks will reveal additional layers of cognitive complexity. Cost/benefit evaluations, for example, are central to cooperation between strangers and between relatives (COSMIDES/TOOBY 1992; DEKAY 1995), but the specific processes underlying these evaluations are unknown. These examples also are not without controversy (see, for example, SPERBER/CARA/GIROTTO 1995). An evolutionary approach is one strategy for generating viable hypotheses about cognitive domains, not a guarantee that the resulting hypotheses will prevail over alternatives. A computational theory limits, but still underdetermines, the algorithm level of analysis and empirical research must decide between alternative accounts of the same phenomena.

The process of combining evolutionary and cognitive approaches promises to strengthen both evolutionary psychological work and social cognitive work. Each approach has limitations that can be avoided through the use of task analysis within an evolutionary framework. We discuss some of these limitations below.

Evolution without 'Cognition'

A common criticism of evolutionary approaches to social phenomena is that they are post hoc, or are simply stories that are untestable. Although this criticism is often misinformed, evolutionary psychologists can avoid certain pitfalls by using evolutionary theory within the top-down system described above. Often, these pitfalls occur because general evolutionary principles are applied directly to behavior, and bypass the psychological, or cognitive, level of analysis.

Process versus product

A common problem with evolutionary approaches to social phenomena is that they conflate evolutionary processes with evolutionary outcomes, or adaptations. This occurs when there is insufficient attention paid to the task demands of a domain. For example, 'HAMILTON's rule' states that natural selection favors designs for helping genetically related others if, on average and over time, the benefits to the helpee, times the degree of relatedness between the helper and helpee, are greater than the costs to the helper (HAMILTON 1963, 1964).

HAMILTON's rule represents a description of one aspect of the evolutionary process (or the conditions under which selection might operate), but is not itself a model of psychological mechanisms. There is no reason, based upon HAMILTON's rule alone, to expect that people have processes that compute the inequality 'on-line' during social interactions. Nor is there reason to expect that people's behavior in any specific instance will conform to the rule. To do so would be to jump erroneously from a description of the process of natural selection to features of organisms. Rather, HAMILTON's rule is best conceptualized as an evolvability constraint on the evolution of mechanisms involved in cooperation between related individuals. It sets conditions that processes within the domain must satisfy to be evolvable. There are unlimited ways to satisfy the condition, and computing HAMILTON's rule in each situation and using the outcome in behavioral decisions is only one of these possibilities. HAMILTON's rule, when combined with information about the past ecology and social structure of a species, can provide the foundation for a task analysis of the processes involved in kin-directed altruism. For example, DEKAY's work on grandparental investment patterns used this approach (see above).

Sociobiology and fitness maximization

Sociobiologists view social behaviors as adaptively patterned: Organisms currently behave in such a way as to maximize their inclusive fitness, or their relative genetic contribution to future generations (ALEXANDER 1979). According to this perspective, behavioral patterns vary across ecological and social contexts because particular behaviors have different fitness consequences in different contexts, and organisms are able to assess these fitness consequences and adjust their behavior in order to maximize fitness outcomes. Behavior is viewed as highly flexible, shifting in response to shifting fitness consequences.

Sociobiology has been criticized on several grounds (BUSS 1991, 1995; SYMONS 1989; TOOBY/COSMIDES 1990). A key problem of sociobiology is that it (often implicitly) proposes an impossible psychology. For an organism to adjust its behavior to maximize its inclusive fitness, it must have cognitive processes designed to evaluate its current fitness trajectory, decide if that trajectory could be improved, associate behaviors with increases or decreases in fitness, and predict the fitness outcomes associated with changes in behavior. Fitness consequences, however, are temporally distal to the organism. Fitness is not observable by the organism because it is determined in hindsight, based on the reproductive outcomes of an individual's children's children's… *ad infinitum*. It also is not clear how the organism might decide what to do, assuming it could determine that its current fitness trajectory was not maximally positive. The problem space is not sufficiently narrow to restrict potential solutions much beyond random trial–and–error, not a generally effective method for living (and dying!) things.

To solve the general problem specified by sociobiology—that of evaluating a current fitness trajectory and adjusting behavior to maximize that trajectory—a cognizing agent must solve sub-tasks that cannot be solved within real-world constraints. A model that proposes a set of cognitive processes that functions to evaluate on-line fitness and adjust behavior accordingly is not a viable model.

Standard Social Science

Standard social science (SSS) is a broad label for a heterogeneous endeavor. A full characterization of SSS is beyond the scope of this article, and is provided elsewhere (TOOBY/COSMIDES 1992; WILSON 1998). Common to variants of SSS is the assumption that the mind is initially content-free—a blank slate upon which experience writes, or a general-purpose computer, with 'culture', 'socialization', or 'learning' writing the programs. According to SSS models, social cognition and consequent behaviors are a function of general learning processes that have accumulated patterned cognitive contents (such as schemas and scripts, association strengths, or social roles), and have conditioned patterned behavioral responses, over the life of an individual. This view permeates current social science theory and research, although it often remains implicit (SYMONS 1989; TOOBY/COSMIDES 1992; WILSON 1998).

Organisms alter their behavior partly as a result of experience. The assumption that the mind is largely content-free, however, encourages the belief that a true causal process is being invoked by references to general, content-free concepts like 'culture' or 'learning'. An examination of the cognitive requirements for even the 'simplest' forms of learning (i.e., classical and operant conditioning) reveals a great deal of complexity (GALLISTEL 1990). Simple, general accounts of social phenomena fail partly because they underspecify the complexity of social cognition. The predominance of behaviorism, for example, crumbled under the weight of evidence demonstrating that its general principles, such as equipotentiality, could not account for the complexity of observations (GARCIA/ERVIN/KOELLING 1966; GARCIA/KOELLING 1966).[2]

Advantages of an Evolutionary Cognitive Approach

The rigorous application of an evolutionary approach to social cognition provides benefits that address some of the conceptual weaknesses present in other approaches. We elaborate these benefits below.

An evolutionary cognitive approach forces explicit examination of the nature of the mind and its component psychological mechanisms. Much social psychological and sociobiological theorizing proceeds without careful consideration of the assumptions made about the nature of the mind. Domain-general constructs such as 'fitness maximization', 'culture', and 'learning' often pass without a rigorous examination of the model of the mind they require (one that is equipotential and unstructured). An evolutionary cognitive approach, by contrast, forces an explicit description of the nature of the mind and demands that this description be empirically and theoretically scrutinized before research proceeds. Sociobiological and SSS notions of the mind are limited because they assume a relatively content-free, and hence impossible, architecture.

An evolutionary cognitive approach forces explicit examination of the adaptive tasks and subtasks required in a psychological domain. By considering the computational tasks associated with a psychological phenomenon, and by investigating only those solutions to the specified tasks that are possible in a real-world environment, one is prevented from disguising complexity with underspecified, global concepts such as 'socialization', 'culture', and 'learning'. In addition, new areas of inquiry emerge as the problem space is defined more clearly. GALLISTEL (1990) has applied such an approach to non-human learning and has documented numerous and complex information processing sub-tasks that are required for 'simple' learning processes (e.g., representations of the time, rate of event occurrence).

An evolutionary cognitive approach demands explicit consideration of the cognitive algorithms that underlie psychological phenomenon. In employing this approach, one is forced to describe the rules by which a psychological process operates. This results in a sustained focus on the most appropriate level of analysis for understanding cognition, and for describing cognitive adaptations.

An evolutionary cognitive approach prevents proposing simplistic notions of causality. Decomposing a psychological phenomenon into its component processes prevents one from being lulled into proposing or believing that the cognitive tasks performed by the mind are simple, as can happen when our intuitions overlook complex tasks that we experience as effortless. An evolutionary cognitive approach forces one to examine the cognitive complexity underlying global concepts like 'culture' and 'learning'. By failing to appreciate the complexity implied by these underspecified concepts, sociobiology and SSS models have failed to produce models of cognition that respect the complexity of the mind. Consequently, sociobiology and SSS models have stopped short of investigating the complex cognitive details of social phenomena.

An evolutionary cognitive approach prevents proposing impossible solutions to psychological problems. Because it forces a decomposition of larger information processing problems into smaller ones, an evolutionary cognitive approach can expose proposed solutions that are not viable given the information available in real-world environments. The evolutionary component of this approach demands a focus on ancestral environments, both for specifying the constraints that must be met for a task to be solved, and for evaluating whether the proposed algorithm could have accomplished its presumed task. Sociobiological analyses, for example, fail partly because these analyses propose an impossible psychology, as fitness consequences are too distal to be used by cognitive processes.

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Conclusion

Using an evolutionary cognitive approach is difficult because it requires interdisciplinary knowledge. It requires an understanding of psychology, anthropology, evolutionary biology, and cognitive science. It is increasingly clear, however, that psychological research can profit from such an interdisciplinary, integrated approach. This approach can help researchers avoid the pitfalls inherent in more traditional approaches and can help psychology to become integrated with the other life sciences.

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Notes

1 For a task as relatively simple as playing tic–tac–toe, with a limited number of possible states (board configurations), a simple 'look-up' table can suffice. Still, this look-up table simultaneously embodies a representation of possible board configurations as well as strategic algorithms, though they are simple and are equal in number to the possible board configurations themselves (e.g., if board configuration is X, then do Y). As the problem increases in complexity, however, the efficiency of a look-up table algorithm plummets, and algorithms are likely to profit from shortcuts or privileged hypotheses cutting through the exhaustive solution space.

2 Domain-general, content-free theories of social cognition also are problematic because, like sociobiology, they propose an impossible psychology. Any information-processing device must solve successfully the 'frame problem' (PYLYSHYN 1987; TOOBY/COSMIDES 1992). As a problem space increases (e.g., by the addition of dimensions to consider), the number of possible solutions to consider increases exponentially. Any information-processing device (including the human mind) must be able to limit the possibilities in order to operate successfully in real time. This means that the size of a problem space must be limited by imposing 'frames' (privileged hypotheses, domain-specific mechanisms). The domain-general procedures proposed by SSS fail to solve the frame problem and, therefore, constitute an impossible conception of human cognitive processes.

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