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Information, Entanglement, and Emergent Social Norms: Searching for 'Normal'

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Abstract: Social norms are often regarded as informal rules or strategies. Previously, we have proposed that norms are better understood as information. Social norms represent a behavioral adaptation that identifies and curates the information required to create and maintain a predictable environment. Here, we further demonstrate that social norms act as the leading edge of individual and collective search and optimization processes. These processes provide efficient and effective evolutionary mechanisms for constant adjustment and adaptation to an environment. We show that social norms constitute the forefront of our ability to ingest and process information, and are responsible for the conditions under which social and collective cognition are possible. This new model of social information processing provides not only insight into how humans adapt and evolve to diverse environments, but also provides concrete definitions of human sociality and its distinctions from that of other social animals. Our social constructs and behaviors are not separate from the physical world we inhabit, but are instead the primary means by which we exist within it.

Keywords: social norms; information; collective behavior; cultural evolution; social learning; social cognition; social allostasis

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1. Introduction

Social norms are neither informal rules nor strategies. Social norms are how we identify when rules or strategies are *needed*. They are beliefs about the information derived from a complex search across physical and social environments by members of a community. These beliefs represent dominant solutions to optimizing individual and collective fitness within a given landscape of socially mediated information. The fitness of social groups and their members, within that landscape, depends on entangled processes of individual and social cognition to efficiently identify dominant solutions. This naturally occurring system emerges as a dynamic and responsive mechanism regulating social and cultural practices to meet biological needs.

We propose this system of social information processing is a progressive scaling of lower-level behavioral responses to natural evolutionary imperatives. Social organisms have evolved these behavioral adaptations in response to principles of least action and parsimony towards efficient strategies of survival. Social norms evolved as a behavioral adaptation to balance the needs of maintaining a low-surprisal social environment with promoting collective information gain. The resulting complex behaviors are fundamentally based on the basic needs of organizing and classifying information. More significantly, this adaptation has allowed us to act and react quickly, with minimal cognitive effort, despite the enormous density of information required to successfully navigate both physical and social environments.

There is an extensive literature on social norms across many fields, but operationalization of the core terms and concepts vary widely across applications and academic research domains [1–5]. Traditionally, norms have been described as unwritten social rules or strategies

that guide or govern behavior and social interactions (e.g., [6–11]). Beyond that generalization, however, there remains little consensus as to why and how they operate within society.

A social norm is one of the most fundamental concepts in all the social and behavioral sciences, and yet just how norms emerge and how they affect behavior remain substantially open questions [4,12–17]. In truth, there is surprisingly little agreement as to what social norms are or their role in mediating individual and collective behavior or practices (e.g., [1–3,13,18]).

In our previous work [4], we conducted an interdisciplinary review of numerous conceptual frameworks surrounding *social norms*. We examined recent systematic literature reviews and leading theories across the social and behavioral sciences, such as social and evolutionary psychology, cognitive and neuro-sciences, sociology and behavioral economics, and cultural and evolutionary anthropology, to identify the current status of research and open questions surrounding social norms. Although each approach's theoretical constructs provided various descriptive characterizations for social norms, all acknowledged that substantially open questions and contradictions remain unaddressed.

We proposed that these questions are largely resolved by reconsidering social norms as part of a process of deriving socially curated information. We argued that norms embody the coalescence of collective information within a social network. Social norms and normative institutions would, therefore, be the natural consequence of a set of underlying processes of social information search and curation. Furthermore, we suggested that the social processes and institutions that promote norms are formed out of the need for long-term preservation (i.e., curation) of information on socially essential domains of interactions.

This information-centered approach has reframed the concept of norms, their origins, and their influences based on the premise that norms constitute an effective infrastructure for curation of collective information. In this paper, we extend that conceptual model, demonstrating *how* information acts as the common source from which norms, normativity, institutions, and other associated social concepts are derived. We illustrate how norms facilitate efficient information processing from individual agents to larger communities (Figure 1). Specifically, we show how social norms—and the underlying processes that establish norms—are prerequisites for a functional environment where repeated social interactions are feasible.

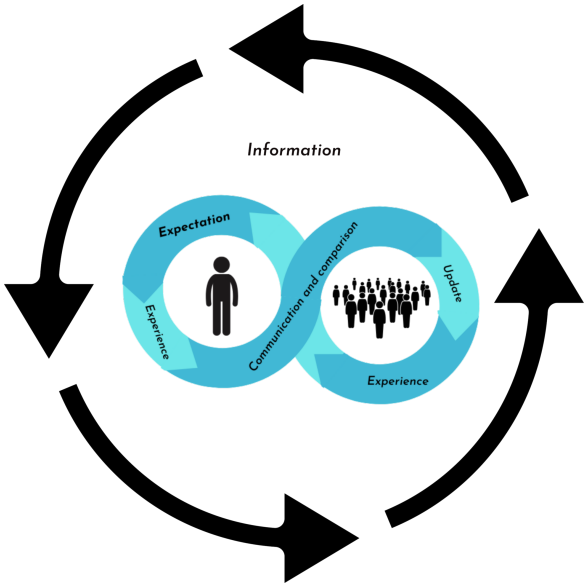


Figure 1. Social norms emerge from the sharing and rectification of individual experiences, which promotes both individual and group adaptation to the information in their environment.

In order to present this system of information norms, the following sections provide contexts and open questions from existing social norms research. This is followed by a brief review of our previous work, with the objective of exposing all the "moving parts" in that conceptual framework. Although we believe that all aspects of social behavior are fundamentally grounded in the same general processes of information filtering and sharing at scale, here, we present more specific abstractions for the relationships that exist between and among these scaled events—i.e., between individuals, communities, institutions, and population.

2. Open Questions in Social Norms Research

There has been a recent growth of interest in practical applications for socially or behaviorally informed methods and technologies. Ideas such as behavioral economics (e.g., [19,20]), socio-technical systems [21,22], artificial intelligence [23–25], game theory [26,27], and other similarly abstract fields of study have transitioned from academic discussions to corporate and political strategies. Advances in information technology, data acquisition and processing as well as growing computational resources have prompted rapid developments in behavioral science.

Yet, for all their potential, we have also witnessed some spectacular failures in understanding and utilizing those advances. Social media seemingly dominates public discourse, providing platforms from which carefully crafted messages are served to narrowly targeted commercial, personal, or political interests. Massive amounts of social and behavioral data are feeding various algorithmic recommendation and decision support systems guiding everything from consumer choices to public policies and business strategies.

Machine learning applications in healthcare, finance, and law enforcement have been criticized for reinforcing or exacerbating existing biases [28–30]. Experiments with human-like artificial intelligence and human–computer interfaces have often produced nonsensical or antisocial outputs [31,32]. Behavioral interventions (i.e., "nudges") intended to promote prosocial actions or persuade consumers and voters often result in inconsistent or counter-productive outcomes [33,34]. Moreover, social media and personalized content delivery, driven by attention and recommendation algorithms, have fostered and amplified extensive misinformation networks that undermine civil discourse and prosocial behavior [35,36].

These applications of social data rely on a complex interplay of assumptions, formalization, and operationalization of social concepts. Failures often arise at the intersection between theoretical assumptions and the unique behavioral patterns of individuals and groups. Any model that assumes social behaviors and responses, whether individually or collectively, will inevitably confront one of the most persistent and elusive concepts in the social and behavioral sciences—they will run headlong into social norms.

2.1. Where Do Social Norms Come From?

Current research on social norms and collective action favors the perspective of individual acquisition of, or compliance with, norms in an existing social environment (e.g., [3,9,12,37–42]). The intersection between norms and social cognition framed under these approaches is defined by the individual's cognitive processing of perceived rules of conduct in contrast to the intentions, expectations, mental states, and/or strategic choices of others.

These perceived rules (i.e., norms) are themselves a product of a learned social context or environment. Such approaches are often concerned with the identification of specific norms and associated practices within a particular domain of research. They focus on characterizing the psychology or strategic rationality involved in specific types of social interactions, leaving the origins and instantiation of the associated norms largely unresolved.

Presently, "rule"-based framing is often applied to predictive modeling or designing interventions for collective behaviors for social, political, or economic outcomes (e.g., [43–48]). Game theory has been the primary tool used to assess these normative environments (e.g., [37,49–51]), albeit not without its detractors (see [52,53]). Their operationalization

of norms prioritizes pragmatic measures for describing the beliefs and/or behaviors of individuals and groups under specific normative constraints (e.g., [17,50,54]). Since these are outcome-oriented research objectives, the underlying origins of normative rules or feasible strategies is considered tangential.

Without addressing the origin of rules and strategies, let alone the initialization of a normative social environment itself, the explanatory power of such models is limited [5,13,55]. These practice-oriented approaches arguably limit the ability to generalize the overall phenomena. Particularisms of specific scenarios or normative expressions of specific behaviors are not comparable or easily abstracted. Although there are several competing views on the emergence and maintenance of social norms under these models (see review and synthesis by [3,5,55]), there is little consensus as to the underlying mechanisms. The causally necessary and sufficient criteria for the instantiation and stabilization of social norms are still regarded as open questions.

2.2. What Is the Evolutionary Function of Social Norms?

Another prominent line of social norms research focuses on their emergence through the evolution of either human or animal sociality (e.g., [45,56–62]). These approaches address the phenomenon by exploring the adaptive advantages of specific social strategies (e.g., cooperation, altruism, and collective utility). The underlying premise is that cultural and behavioral traits are group-level adaptations following from the natural processes of Darwinian selection. Under this view, social strategies (i.e., norms) are derived from the particular contexts of those adaptations.

Evolutionary models are concerned with identifying the adaptive advantage of cooperative sociality, and tend to focus on higher-order social functions or traits [45,56,58,63]. These models assess the overall fitness and stability of broad social strategies as a generative interaction between collective agency and environment (e.g., [51,58,64–67]). Under these models, definitions for social norms tend towards what *should* be done (i.e., prescription) and what *should not* be done (i.e., proscription) by individual community members [63,68].

In essence, evolutionary approaches restrict the operational definition of social norms to what are typically considered *injunctive* norms (i.e., rather than as *descriptive*). Specifically, evolutionary approaches prioritize the observed regulatory role of norms to promote adaptive fitness by reinforcing collectively beneficial patterns of behavior (e.g., [69–72]). The roles of beliefs and expectations are typically viewed as psychological mechanisms or justifications for regulation and enforcement of compliance with those behaviors.

This more restrictive operational definition of social norms allows the adoption of causal and explanatory mechanisms from evolutionary biology. It does so, however, by excluding consideration of cognitive and psychological aspects of social behavior [73–75]. The particularism of specific cultures or systems of normative institutions are, therefore, deemed products of the circumstances under which those regulatory norms are formed [64,76].

Although there are observable patterns in the historical trajectories of group behaviors [64,77–79], explanations for those patterns are subject to debate [56,68,80–83]. When social norms and institutions are considered under evolutionary models, they are described as group-level traits or strategies (e.g., [67,82,84]). How such traits relate to cooperative behaviors—i.e., their emergence, maintenance, and influence—remain unresolved.

2.3. How Are Social Norms Learned?

The evolutionary basis of cultural behaviors and traits can be traced to Darwin's original theories [68,85]. Early theories of cultural evolution, however, held no means to reconcile biological inheritance (i.e., reproduction and genetics) with transmission of behavioral adaptations (e.g., enculturation or learned behaviors). A relic of the Spencerian view of evolution [68,86,87], social or behavioral adaptations were primarily viewed as epiphenomena to biological or genetic fitness (e.g., the "selfish gene" [88]). They did not provide an adequate rationale for why individuals would sacrifice fitness for the benefit of others.

There has since been a marked shift in the understanding of cultural evolution away from theories based on genetically heritable traits. Newer research explores the effects of the interactions between genes and culture [85,87,89]. This turn from genetic or sociobiological explanations of human behavior (e.g., [90–94]) has reinvigorated the interest of social scientists in cultural evolution (e.g., [95–97]). This newer framework avoids controversial aspects of cultural evolution [68,87], and has opened new avenues of empirical research.

These approaches to evolution view culture as behavioral adaptations to a given environment (i.e., an "extra-somatic means" of adaptation [98,99]). Evolution is viewed as interactions *between* biological and behavioral mechanisms. Dual inheritance or co-evolutionary approaches focus on the dynamics of social transmission for successful traits or strategies within and across generations (e.g., [87,89,100,101]). These models explore the mechanics of how different diffusion and learning strategies can produce coherent and stable effects within a population and across generations [102,103].

Broadly, *social* learning is contrasted against *asocial* or individual learning [103,104]. In asocial learning, individuals rely on their own experiences, trial and error, or exposure to environmental stimuli to acquire information. Conversely, social learning refers to the ways individuals acquire knowledge and skills through observing, interacting with, and learning from others. Learning strategies will be necessarily constrained by prior individual knowledge, individual capacities, social resources, and economy of cognitive effort.

Asocial learning can lead to innovation, but is cognitively and energetically intensive and has an elevated risk of unpredictability or failure [102,105–107]. Social learning, which entails a base level of requisite skills and information assumed from others' knowledge, bears less cost or risk but is susceptible to the "free rider" problem and Rogers' Paradox [108–110][1]. Some level of asocial learning remains essential to generating alternatives and enhancing efficiency through the acquisition of novel information. How and when individuals and groups prioritize different learning strategies remains a subject of active research.

Less attention has been paid to the social and cognitive mechanisms of adaptively beneficial *information* propagated through social learning mechanisms [103,104,112]. The models address the mechanisms of cultural transmission, but not what information is being transmitted or how it is selected.

2.4. How Do Norms Relate to Behavior?

The influence of Bayesian[2] models on theories of cognition, learning, and decision processes partially stems from collaboration between cognitive and computer sciences (e.g., [117–122]). These approaches model cognitive search and decision processes after a combination of empirical Bayesian estimation and information theory. They broadly propose a neurological basis for cognition regarding pattern detection, learning, decision-making, or stimulus response that parallels Bayesian search processes. Such models have been shown to be useful heuristics for modeling aspects of human cognition and processing environmental information (see [113,114,120,122–125]).

Bayesian cognitive models propose that individuals form beliefs, as probabilistic mental representations of the world, through continuous comparisons between prior information and new observations. Cognitive models by Friston [126] and others (e.g., [118,127–129]) suggest that individual cognition may be modeled as a particular form of empirical Bayesian search and reinforcement learning. Predictive processing (e.g., [130–133]) further emphasizes the role of error minimization, wherein the brain continuously generates predictions about sensory input and adjusts its expectations.

The general premise is that "…biological agents resist a tendency to disorder and therefore minimize the entropy of their sensory states" ([134], p. 293). In this sense, "disorder" refers to the surprise (i.e., "entropy") due to improbable or unexpected sensory or experiential information according to an agent's prior expectation. These mathematical formalizations describe how agents optimize the reconciliation of information states between expectations of their physical environment and sensory inputs from that environment. This Bayesian inference optimization model is theoretically supported by simulation and

machine learning studies (e.g., [129,135,136]), but empirical confirmations for cognition are still generally lacking (see [117,137–139]).

The extension of these models towards collective or distributed cognition is less well studied [124,140–142]. Bayesian cognitive models do not explicitly reconcile individual learning with social interactions (e.g., [83,143–145], and others). Each agent only seeks to minimize the surprise of actions within its existing social environment. Individuals then may engage in social learning to align their own predictions with those of their social peers.

The cognitive mechanisms for coordinating social actions and collective practices remain open questions. Accounts of collective cognition (e.g., [146–149]) describe a system of cognitive conditioning for responses and expectations. Individuals minimize prediction errors regarding the external world and the behavior and mental states of others. Much like the behavioral or psychological approaches described above, cognitive approaches primarily focus on individual processes rather than socially embedded information networks.

Current accounts of collective cognition (e.g., [136,146,150,151]) largely presuppose an existing social environment—i.e., one replete with established social practices, norms, and conventions. This largely avoids the role social agents play in the production of that social environment. These models focus on individual-level processes that may not adequately capture the social and cultural dimensions of collective human cognition. Furthermore, these individual-focused models of cognitive processes do not yet address the dynamics of competing individual and collective priorities.

3. Searching for "Normal"

All of these open questions, and the various conceptual frameworks that have addressed them, presume that social norms act as informal rules or strategies that guide or constrain individual choices and actions (e.g., [9,37,38,152]). That presumption has consistently proven problematic due to one unavoidable and unequivocal observation:

People do not always follow the rules.

There is substantial empirical evidence that subjects frequently contradict or violate their own self-reported norms (e.g, [33,153–155]). Some studies show that people will often violate optimal or equilibrium strategies if information about rules and expected rewards are provided beforehand (e.g., [156,157]). Other research suggests that people may be more sensitive about norm violations by others than they are to their own compliance [157–160].

If people regularly fail to follow rules or optimal strategies, then how do we explain their utility? Rationally, a socially normative rule—self-reported *as* a rule—should be applicable regardless of a prior expectation of enforcement. Similarly, a purportedly optimal strategy should be preferred regardless of prior knowledge. Knowledge of a rule or strategy is necessary *but not sufficient* to affect behavior. This begs the question—what are social norms actually contributing to subsequent behavior?

Those questions become moot if we focus instead on the role of the information *from which* rules or strategies are derived. Social norms give the appearance of being rules or strategies because they represent how that information is identified. They are, as we stated at the outset, how social beings identify when rules may be needed and what strategies might be beneficial. In other words, norms are supplying information that is conditioned on *prior* information or beliefs—i.e., an interaction between the situational information and prior experience. That interaction culminates in a specific *posterior* expectation and consequent choice or action.

Our central argument (see [4]) proposes that social norms and institutions constitute behavioral adaptations that identify and curate socially acquired information. The purpose of this adaptation is to efficiently balance minimization of within-group surprisal and the acquisition of collective information.

3.1. Intuitions on Norms, Belief, and Information

Humans are, generally speaking, creatures of habit. By this, we mean that many of our regular activities are conducted with minimal conscious thought or cognitive effort. For most

of the scenarios and interactions we encounter, we know within a reasonable range of certainty what to expect and what is expected of us. These routine practices, however, are actually comprised of countless small decisions and an enormous amount of information.

There is rarely a need to devote attention to them, though, except in as much as it becomes necessary to accommodate changes in our surroundings. Even then, these adjustments warrant little thought or effort. Similarly, we navigate various communities comprised of family, acquaintances, or strangers and for each we subtly adapt our expectations and our practices. Without conscious effort or awareness, we continuously modify our behavior to any given situation—understood, expected, and *normal*.

Conversely, we recognize immediately when something or someone around us does *not* seem or act as expected. Whether there is a change in our environment, anomalous behavior by someone or something in our surroundings, or a situation that we have not previously encountered, we easily identify that something is not as expected. We detect nuances in speech or behavior, even though we might not be able to articulate what we are identifying or why, and intuitively know that something is out of the ordinary—that it is not normal. We do not need to think about the things we expect. It either is or is not consistent with our expectations.

We have, through our experiences and received knowledge, formed beliefs about what to expect under normal circumstances. Those expectations allow us to act or react with minimal cognitive exertion. Only situations introducing or requiring a significant amount of novel information necessitate conscious effort. This parsimony of information and cognitive efficiency enables us to navigate the complex information landscape of our environment without having to constantly reevaluate our surroundings.

3.2. Information, Social Norms, and Evolution

Evolutionary approaches have typically viewed the adaptive advantage of sociality, including collective behaviors such as social norms, from the standpoint of fitness (e.g., [56,64,80,82]). An individual's success is enhanced due to cooperation with others, and, therefore, we benefit from adherence to norms that promote or support such collective behaviors. In essence, for social animals, individual success depends on overall population fitness by sharing both resources and risks [67,68,82,84].

We propose that the adaptive advantage of sociality, and specifically, the collective curation of information through social norms, is more strongly related to mitigation of uncertainty [4]. Uncertainty imposes a substantial cognitive load, so there is a distinct adaptive advantage to maintaining a low-surprise environment. Reducing those energetic costs increases both individual and collective fitness. We preferentially select behaviors that promote *predictability* as well as efficacy.

As we have previously argued [4], social norms are the way we create and maintain that predictability. They are how we sort and normalize experiences with those of our communities to acquire information needed to adapt to our environment. This is how we collectively form preferred and effective beliefs and practices. If the evolutionary advantage of information is the reduction of uncertainty between individuals and their environment (i.e., as described in [123,161]), then the individual and collective fitness of sociality depend on minimizing the collective energy required to reduce uncertainty within that environment.

This makes, to our view, a far more compelling argument regarding the source, nature, and functioning of social norms and normative institutions as behavioral adaptations. A system for capturing and retaining validated information is essential for maintaining an optimal and stable information environment. The minimization of surprise is equally beneficial within the social environment as it is to the physical environment. Social norms serve as cognitive and behavioral adaptations for determining and retaining the information needed to do so.

3.3. Mitigating Uncertainty in the Social Environment

What we perceive as "normal" is behavior that is unsurprising. We can easily anticipate what to do because things generally align with our prior expectations. Little cognitive effort is required to assess or validate the situation or to puzzle through a wide array of possible alternatives. We act or react based on prior expectations, needing minimal novel or situational information.

As an example, consider the rationale behind seemingly arbitrary social norms or normative rules, such as driving on a specific side of the road. In the United States, we drive in the right-hand lane while other parts of the world have selected to drive in the left. There are socially normative and legally enforced rules in place, but there is nothing innately advantageous to choosing one side or the other. The norm and rule exist solely to make the behavior of drivers more predictable.

We conditionally violate that rule for passing other vehicles or avoiding obstacles, but generally follow the rule. Why? Not exclusively due to fear of social or legal consequences, but because experience tells us that unpredictable driving is risky and induces mental stress. Without predictability, driving would be a terrifying experience.

It is entrenched in most social norms literature, however, that compliance with these rules stems from fear of sanction or punishment [2,60,70,72,158]. If so, an individual would be in a perpetual state of strategic maneuvering within a tangled web of applicable norms and rules. Living in such a state of constant vigilance would impose an unreasonably high-stress social environment. It is more reasonable, and certainly more efficient, to maintain a predictable social environment and only direct effort toward identifying and adapting to anomalies.

Establishing a reasonable set of shared expectations becomes imperative for feasible and stable sociality. Arguably, navigating the social environment can be precarious due to its reliance on unobservable elements—i.e., the mental states, intentions, and motivations of other social agents. Without cognitive mechanisms to anticipate the likelihood of those unseen states, the social environment would be an intractable field of unknowns. Consequently, rules and strategies emerge from normalized domains of information and expectations.

The function of social norms, therefore, lies in identifying domains of information and what uncertainties need to be mitigated. In this context, social norms are coordinating mechanisms to sort experiences into particular domains of information (see also [4,18,162–164]). That coordination manifests as rules or strategies to minimize uncertainty within those domains. The process of determining manageable information against reasonable expectations drives the origin and operation of social norms. Social norms, and associated social phenomena, can then be viewed as a collective endeavor to optimize overall predictability in the social environment.

Social norms tell us where we need rules and when those rules need to be enforced.

4. Balancing Risk Against Innovation

Maintaining predictability within a dynamically changing environment cannot rely on just consolidating prior information and expectations. Adapting to unknown or unforeseen circumstances necessitates identifying appropriate *new* information [165–167]. Environmental factors continuously shape behavior and adaptation, requiring the assimilation of new information with prior knowledge to anticipate and respond to evolving conditions. This interaction between predictable risk mitigation under known conditions with adaptive innovation in uncertain situations requires a delicate balance.

Finding this balance involves devising an optimal strategy despite conflicting criteria. High-surprise environments are rich in novel information, whereas low-surprise environments yield little new information[3]. To maintain a dynamic equilibrium between predictability and innovation requires continual optimization of tradeoffs between the two (e.g., a multi-objective or Pareto optimization [169–171])[4]. Futhermore, any solutions to this

optimization problem need to be both collectively and individually feasible and efficient across the community or population.

Norms operate at the intersection between individuals and their communities, reconciling the information needed to find optimal solutions. We view social norms as a mechanism for identifying, aligning, and refining information (see [4]). Social norms embody provisional information that forms the leading edge of selection for social evolution and learning. Subsequently, the utility or fitness of this information is evaluated against the repeated experiences of all members of the population.

Given the natural variations in individual experiences and abilities (e.g., [172]) and the diversity of contexts [173–176], each assessment of these norms yields distinct evaluations and expectations based on the provisional information. Individual evaluations are then transmitted back through the same social network, reintegrating updated information and contributing to the adaptive refinement of collective norms. Successes and failures as well as the specific environmental conditions and situational contexts all serve to refine the current information exchanged. This cyclical and recursive process of evaluation, assimilation, and retransmission of information functions as an evolutionary search to identify an optimal set of potential solutions within complex and dynamic environments.

4.1. Optimality in a Social Environment

Our model posits that social norms function as a social and behavioral adaptation that identifies and retains information. Specifically, it captures the information needed to regulate the effort and energetic costs of balancing risk avoidance with innovation in dynamic environments. Norms provide a basis for evaluation and measure (i.e., prior belief) in assessing the state of current information to address prevailing environmental conditions. Social identification and categorization of experiences against established expectations specifies the information resources available to address situational needs [4].

This remarkable dynamic adaptation of a system's internal regulation to ensure relative stability amidst changing conditions exhibits distinct parallels with established biological and evolutionary mechanisms. The concept of *allostasis*, or "stability through change" [177,178], describes a system maintaining an optimally stable state within a dynamic environment. In this context, an optimal state refers to a regulatory regime characterized by maximal parsimony and efficiency in anticipating and mitigating environmental stressors. A closely associated notion, *allostatic load* (see [178–180]), pertains to the energetic and systemic costs incurred, as well as the cumulative requirements of adaptive responses to stressful environmental conditions (e.g., *allostatic accommodations*, see [181]).

The notion of *social* allostasis [173,182,183] extends the psychological and physiological implications of adaptive regulation by integrating individual regulation and adaptation within social networks. Social allostasis is rooted in Social Baseline Theory [184–186], which asserts that human cognition evolved to expect "the presence of social conspecifics—and that the brain and body tend to operate more efficiently when social conspecifics are in fact available" ([183], p. 470). Cumulative allostatic load is, therefore, a characteristic shared by both individuals and their socially affiliated networks. The fundamental premise of Social Baseline Theory is that humans evolved an interdependent social network to facilitate adaptation to a wide variety of environmental conditions, rather than adapting to a specific ecological niche [184,185].

Effectively, our brains have evolved to rely on a "baseline" state of social proximity to a collective of external cognitive resources for maximum adaptive efficiency. This is achieved by distributing the energetic costs of risk mitigation and by sharing the cognitive and physical load of engaging with or adapting to the environment [184–186]. Social allostasis extends the risk distribution and load sharing effects of this social baseline in terms of the cumulative effects of stress regulation [173,182,183].

A growing body of empirical studies (e.g., [176,182,183,186] demonstrates the link between social affiliations and physical and psychological well-being, stress resilience, and cognitive functioning. As described above, both social baseline theory and social

allostasis promote the role of social networks and their adaptive regulation of individual and collective fitness. Implicit in these frameworks is the idea that social information facilitates both individual regulation and collective coordination of psychological and physiological states. This information provides not only parameters for individual allostatic regulation but also the mutual or reciprocal requirements from the network.

4.2. Costs of Social Learning with Collective and Social Cognition

It would be naive to imagine that individuals routinely discuss what "neuroendocrine responses" [178,183] are necessary for optimal allostatic regulation. We do not, generally speaking, consciously report detailed observations or specific experiences to our community. Instead, information moves by natural exchanges and social interactions. We constantly exchange information with those around us, communicating in numerous and subtle ways. Formally, however, the coordination and consequent allostatic regulation within a social network occurs through various processes of collective cognition, social cognition, and social learning. Information must undergo processes of communication, validation, and rectification with the prior knowledge of others within our communities.

Collective cognition involves aligning individual cognitive efforts towards common objectives of a community [7,187,188]. It enhances individual cognitive capacities by providing access to external cognitive resources (i.e., the accumulated stories and experiences of others) through social interactions. In contrast, *social cognition* refers to perceiving and interpreting the cognitive functions and mental states of others. This includes interpreting social cues, discerning intentions, and anticipating future interactions [189–191].

Theories of both collective and social cognition involve the exchange and interplay of information within a social context, respectively, from the group and individual perspectives. Together, social and collective cognition outline the processes necessary for cooperative or collaborative behaviors, including those necessary for social learning. Socially compatible beliefs among individuals and collective intentionality towards group objectives are both needed to translate mental representations between group members. The collective transfer and alignment of information between individuals requires the shared contexts of social and collective cognition.

Social cognition necessitates translating others' mental representations into an individual's pre-existing network of beliefs. Collective cognition requires that mental representations among individuals have already undergone translation and rectification to address inconsistencies in shared information. Group intentionality in collective cognition requires efficient information transfer and messaging between collaborating individuals to coordinate collective actions. Coordination emerges from the commonalities[5] between mental representations of the environment exchanged during our social interactions.

These interactions lead to the development of shared mental representations, coordination of beliefs and expectations, and rectification of behavioral practices within groups. This influences the preferential selection of social learning strategies and outcomes [192,193]. The interactions between individual and group mental processes inform expected utility in the heuristic balancing [194,195] of allostatic load, risk mitigation, efficiency, and information gain. Efficient transfer and translation of information are crucial to socially embedded cognition and action [196–198].

Social learning relies on the full suite of what Heyes [199] describes as "cognitive gadgets" to arrive at contextually optimal strategies, which, in turn, require sufficient information on expected utility [104,192,200,201]. This adaptation influences the selection of a specific social learning strategy—e.g., asocial learning, emulation, or observational learning—by identifying whether existing categories of prior information are sufficient. Social norms are comprised of collectively validated prior information, providing a baseline for comparing costs and risks associated with different learning strategies. The inherent information categories structuring those norms enable individuals to gauge the relative situational risk and effort associated with specific approaches.

5. The Dynamics of Social Information Norms

Our central focus throughout the preceding discussions is information—its acquisition, validation, sharing, learning, refinement, utilization, and retention. In our previous work [4], we demonstrated that social norms represent the emergence of socially mediated information across specific domains of individual and collective experiences. Our present objective is to integrate these various conceptual models to show how environmental and experiential information is identified, transformed, and maintained through the aggregation of individual and collective processes.

Sociality, as an evolutionary adaptation, extends the physical and cognitive resources of individuals by enabling collective and cooperative strategies [104,202,203]. One of the primary benefits of this cooperative behavior is the capacity to distribute the considerable energetic burden of processing new environmental information. The adaptation of cooperative sociality entails a process of distributed search and validation across a landscape of information derived from the physical and social environments. This process provides the means to discover solutions for engaging with the environment among potential equilibria of predictability and efficacy. These solutions, in turn, shape the dynamic processes of group cognition and learning, and therefore, the learning strategies best suited to rectify or verify information individually.

Dominant solutions[6]—i.e., those that reliably minimize individual or collective allostatic load and/or improve efficiencies without degrading effectiveness—propagate through the network of individual and community affiliations. The dual processes of collective cognition and social learning serve to reinforce these dominant solutions as patterns of belief, supported and further tested and rectified by the experiences of group members. Potentially dominant solutions, and what we eventually recognize as social norms, begin to coalesce within communities[7]. Essentially, beliefs and expectations surrounding these solutions become "normalized" across the community's constituents, resulting in emergent social norms.

A critical advantage of this behavioral adaptation, in contrast to more rudimentary stimulus-response or rote learning mechanisms, is in its capacity to detect and retain broad-scale patterns as well as to categorize those patterns into informational domains [204–206]. This socially distributed search and rectification, in combination with the categorical curation of information (see [4]), allows the accumulation and synthetic generation of knowledge. The ability to recognize categorical domains of information serves as a prerequisite for abstraction and heuristics [207–209].

Comparison of recognized categories, vetted and shaped by all community members, is critical to gathering further information. Categories allow extrapolation of related information from limited or episodic events and observations. In other words, categories embody a domain of known or knowable information and delineate the boundaries of what is unknown. This capability enables the community to project into scenarios with unfamiliar or imperfect information by establishing a foundation for comparisons between analogous domains.

We view this system of social information capture as consisting of entangled interactions between individual and group processes with their physical and social environments. These interactions occur within what we are referring to as an *information landscape* that represents the effective "space" of a socially distributed search for feasible information, actions, or solutions. Social norms emerge as communities identify potentially optimal solutions within this search space, and converge to the establishment of normative expectations if those provisional solutions prove dominant. It would be premature to articulate a formal or algorithmic model, but the following abstractions for these processes suggest the feasibility of such a model to generate testable hypotheses.

5.1. Information and the Environment

Information, as opposed to data, refers to the organization of observations (i.e., sensory input) into meaningful categories to provide context and relevance. The reconciliation of individual and collective patterns of experience and expectation transforms interactions

with environment into information. Consequently, what we will call the *information landscape*[8] comprises the total information-bearing environment inhabited by social agents and the mediated patterns of expectations derived from it by the collective. This landscape represents the "space" where the adaptive fitness of actions, strategies, and behavioral adaptations is evaluated.

The information landscape is analogous to the biological concept of an evolutionary fitness landscape (e.g., [211–213]). Unlike the coevolution of genes or traits in biology, an information landscape represents the mutual information realized between an environment and mental representations of it. Social actors coevolve their mental representations to collectively identify optimal positions within the landscape, representing potential Pareto local optima [170,214,215]. This coevolutionary process of socially mediated information underpins a collaborative search across the information landscape, through which the collective identifies feasible and potentially optimal information from which social norms are determined.

The physical environment exists independently of the sentient agents within it, while the social environment arises from the interactions among these agents. The physical environment refers to the external reality where agents exist. In contrast, the social environment encompasses the network of individual connections and communities that emerge from the intention to engage with other agents. This environment is sustained by interactions within the social network and is characterized by agents' perceptions, experiences, and the beliefs and expectations derived from them.

Complete and objective information about the physical environment is unattainable, though. Individuals can only sample data from the physical environment through sensory interactions, forming patterns of experience that shape expectations for future interactions. This sampling process generates experiential data that individuals use to form and test mental representations of both the physical and social worlds. Agents' understanding of these experiential data—i.e., their mental representation of their environment—is a product of the combination of experience, belief, and expectation.

Our engagement with the environment is always mediated by the interplay between patterns of experience and expectations (see Figure 2). With the physical environment, this mediation stems from the meaningful categorization of individual sensory events. For the social environment, it arises from the collective assimilation and reconciliation of meaning with these categories. Consequently, the information landscape is necessarily conditioned on the socially mediated constraints and limitations inherent to the collective mental representations of the environment.

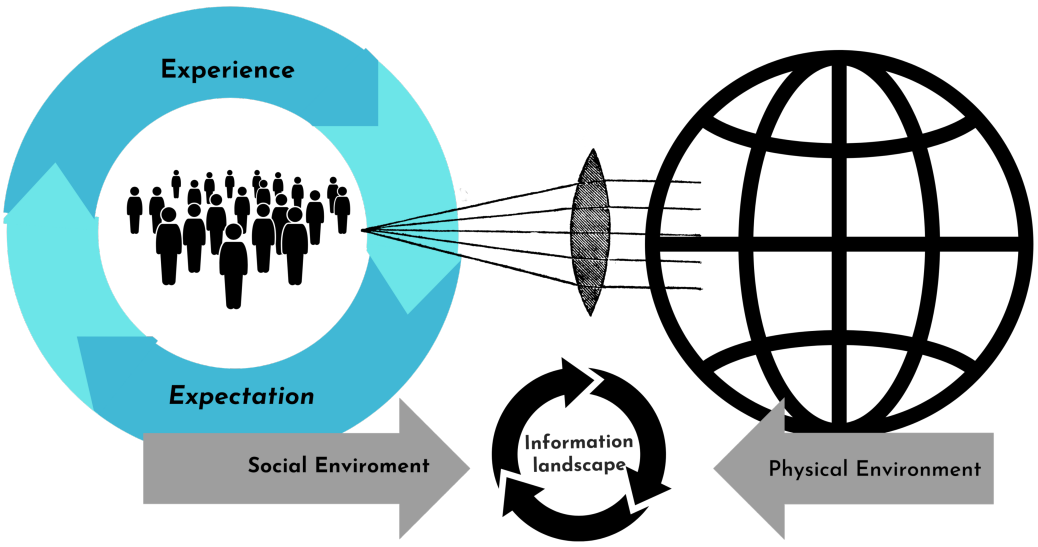


Figure 2. Our interactions with the world are mediated by our experiences, expectations, and perceptions of physical and social environments, which together entail an information landscape to which we adapt.

5.2. Search and Social Coordination

Navigating this information landscape means searching across the "topology" formed by the information it represents—i.e., the physical and social setting that exists around the community. The contours of that abstract topology reflect a hypothetical "value" of optimality or fitness for various combinations among multiple competing criteria and objectives, such as those described in the preceding discussions. Social agents, individually and collectively, operate within and search across that landscape to find the most successful combination of those traits.

In formal, mathematical terms this could be considered (and potentially modeled) as an abstract type of multi-objective search and optimization problem. The objectives of that optimization are the various criteria for promoting individual and group fitness—acquiring new information, obtaining expected outcomes from actions, regulating energetic requirements, and minimizing both risk and allostatic load. Each social agent independently seeks optimization within this landscape, and interactions between agents facilitate the identification of collectively optimal solutions within communities (Figure 3). Collaborative interactions and social learning would serve to distribute information about those possible solutions.

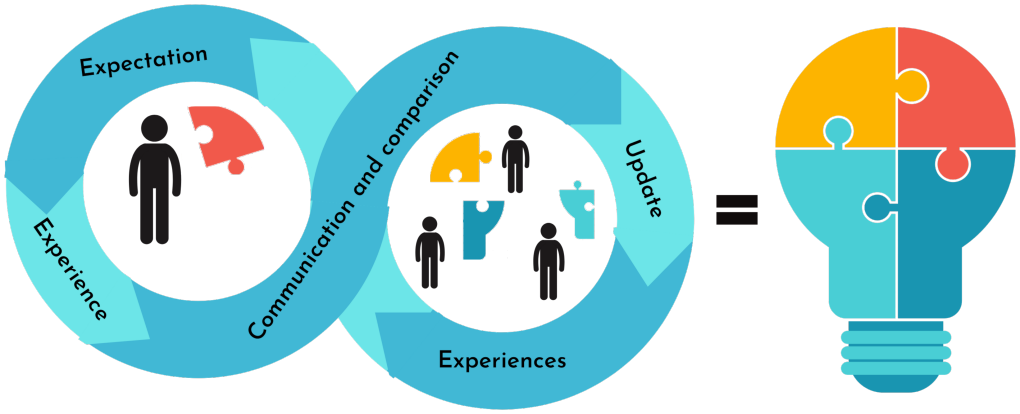


Figure 3. Individuals conduct autonomous searches across the information landscape, sampling potential solutions. The community aggregates these samples, updating expectations for subsequent searches until collectively optimal solutions are found.

Although evolutionary search heuristics, such as genetic algorithms, might seem appropriate analogies for this type of search, we argue that typical genetic metaphors of combinatorial replication and mutation are unsuitable in this case. Instead, the system we have described parallels cooperative multi-agent reinforcement learning (e.g., [215–217]), particularly that involving Bayesian belief networks and multi-objective optimization. These heuristics represent a distinct class of evolutionary algorithms where information is actively exchanged among multiple agents during a collaborative search.

The core features of these algorithmic abstractions are feedback and reinforcement of the information between cooperating agents. In the environment represented by the information landscape, social agents engage in both exploration for new information and exploitation of existing knowledge to find and assess improvements. The aim is to enhance the efficacy or efficiency of a state or action within various domains or conditions of that environment [104,218–220]. Social agents search the information landscape to identify superior (i.e., dominant) and inferior (i.e., dominated) solutions compared to previous ones.

These respective gains and losses are then communicated and compared among social agents. All agents must also navigate feasibility constraints, balancing the gains provided by exploration or exploitation (see [194,219]) with the costs and risks associated with individual versus social learning strategies [105,108,221]. This adaptive search "policy"

information is communicated within the community to further identify preferred search strategies and inform subsequent searches.

Social interactions coordinate the cooperating agents' searches across the information landscape, and individual experiences (i.e., learning and updates) guide the community towards local optima [170,214,215]. In this way, the social baseline expectation of agents [183,185] simultaneously reduces individual costs associated with asocial learning and enhances collective search efficiency by providing prior information through social learning. These searches characterize the topology of the information landscape of the community, discovering potential sets of solutions to the larger optimization problem of balancing various objectives and criteria.

5.3. Entanglement and Collective Optimization

The cooperation of social agents coordinates the search and characterization of the overall information landscape, but the point of that search is to identify optimal (i.e., dominant) solutions to balancing the objectives and constraints. Solutions need to be feasible and optimal for group members and also applicable and beneficial to the community as a whole. Essentially, there is an additional layer of optimization occurring between meeting the optimal conditions for individuals and ensuring the average optimality for the collective.

While the overarching goal is to balance information retrieval and allostatic load across the community, individual agents must also balance their own efficiency, risk, and fitness. These processes unfold within a dynamic information landscape, creating complex internal and external interactions and co-dependent adaptations. The collaborative nature of the search means that individual search and cognition are not merely *embedded* within a social context [222,223]. Individual and collective cognition within the information landscape are *entangled* processes in the formal sense [224–226], and cannot be decoupled as separate processes.

Entanglement, between individuals and their communities, integrates an "inner loop" of individual optimization with an "outer loop" of collective optimization (Figure 4). This integration facilitates both the passage of information and distribution of resources between individuals and connected communities within the larger population. In this sense, collective cognition coordinates and aligns searches among community members while social cognition rectifies the search outcomes against the information acquired by others.

The individual optimization (i.e., the "inner loop") constitutes a form of reinforcement learning within the information landscape that represents an individual fitness strategy. That optimization is, however, informed by the environmental constraints and the community's energy and knowledge resources in addition to those of the individual. Therefore, the allostatic load (i.e., stress) assumed by an individual for optimization is partially conditioned on the current availability of collective information resources and the allostatic status of the community.

Conversely, the collective resources are derived from the information gains and allostatic states of the individuals that comprise the community. This "outer loop" of collective optimization, however, is not just the sum of individual inputs. The capacities and experiences of individuals are distinct, but each is contributing to the available resources and overall social environment of the others. The allocation of these resources across communities, and the total population, depends on its networked community structure. This structure reflects the specific forms of social network (see [223,227]) that govern the flow of information through the system of connections and affiliations.

The community's integration of individual information is transferred through the connected structure of those communities. In doing so, information related to the relative dominance of a set of solutions is further conditioned on the expectations derived from the experiences of others. The community does not collectively shift beliefs and strategies, but instead accrues a repertoire of potential "outer loop" optimization solutions. These solutions are vetted through the experiences of the community, which individuals can then draw upon to inform their own "inner loop" optimization strategies and expectations.

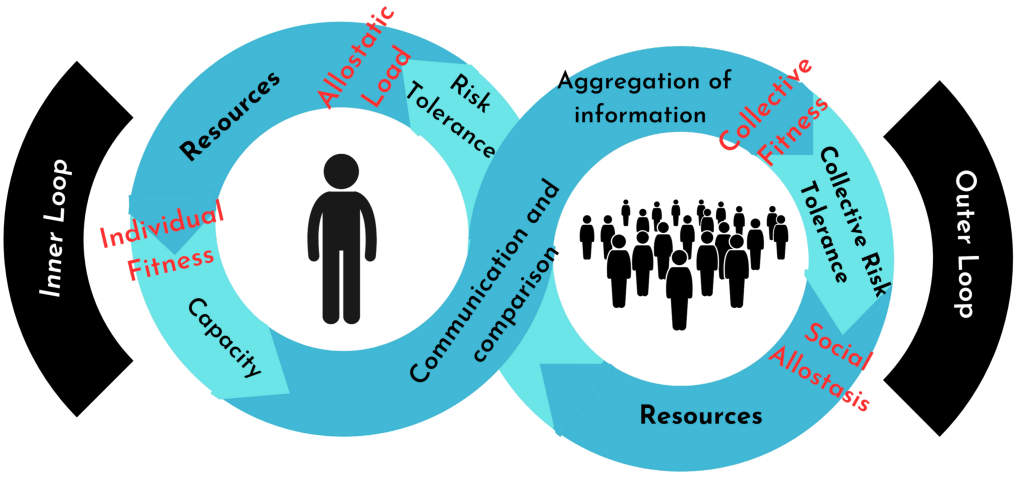


Figure 4. Individual ("inner") and collective ("outer") information "fitness" optimizations occur simultaneously, each continually modifying the constraints and available resources of the other.

This constant feedback and reinforcement, between individual social agents and communities, sorts and categorizes these experiential optimizations and solutions. The resulting coordination and alignment of categories of solutions within those communities entails a specific form of emergent structure, which Polani [228,229] defines as "observer-based" self-organization. Under this definition, the only structural requirements are an information channel between agents and some degree of uncertainty in the system[9]. The effect is analogous to murmuration (i.e., "flocking"), in which the autonomous actions of individual community members become coordinated within the landscape by clustered expectations.

Entanglement and self-organization between individual and collective processes means that, as individual solutions to the optimization criteria are discovered, the community's members will drift towards similar solutions within the information landscape. More dominant solutions to the optimization objectives and criteria will exert a greater influence on subsequent searches within that community. This self-reinforcement mechanism ensures common expectations and coordination of collective search criteria, resulting in communally validated solutions and alignment of community perceptions of the information landscape.

5.4. Emergence and Stabilization of Norms

Social norms initially arise within localized communities that are part of broader social networks. Individuals in these communities adopt viable solutions, which converge toward a local Pareto optimum specific to their contexts. While these local optima may be dominant within a particular community, they may not necessarily be optimal for other communities. The goal is for interconnected communities to identify globally optimal solutions, under the total system's constraints, among those local solutions. Numerous equally optimal solutions may exist, each reflecting various trade-offs among competing objectives and environmental constraints.

For a potential solution to become established as a social norm it must be generally feasible for the typical member of the community. In other words, a norm cannot depend solely on the unique capabilities or resources of remarkable individuals. For a social norm to be a norm, there must be both individual *and* collective expectations that it is a reasonably and predictably feasible. These solutions must fit within the capabilities and resources of the community, and guarantee predictable outcomes from those resources (Figure 5).

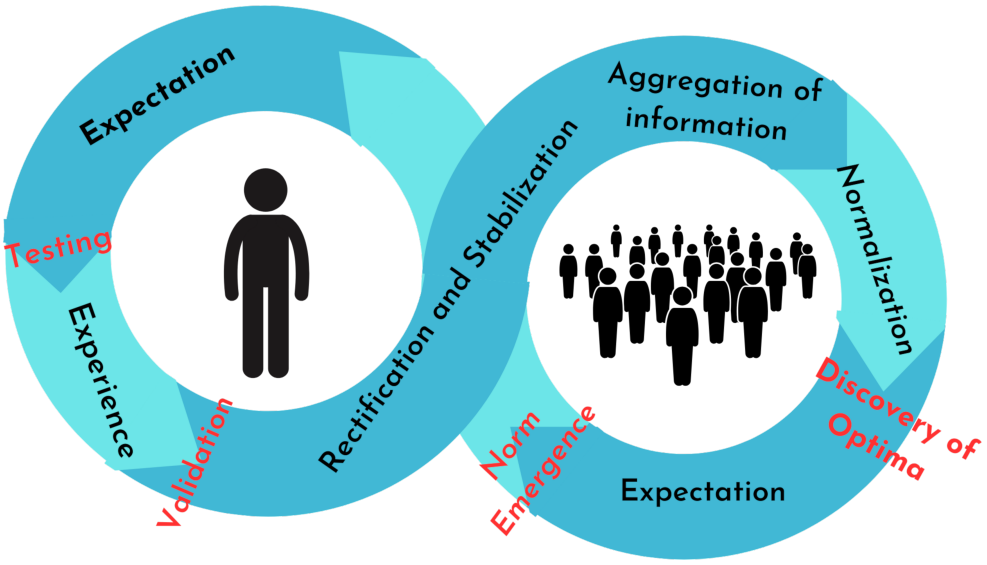


Figure 5. Norms emerge within communities as the collective aggregates and normalizes individually tested solutions. Once locally optimal solutions are found, they continue to be validated and refined against expectations and experiences within the community and the broader population.

As provisional solutions emerge as norms and spread through their social networks, interactions across connected communities foster iterative enhancements and mutual validations. This process enables individuals to adjust their expectations based on others' inputs. It also allows the community to evaluate these experiences and confirm the conditions under which the solutions remain optimal. Asocial learning introduces innovations, potentially leading to new solutions, and adaptive social learning validates and reinforces solutions that prove advantageous or dominant.

In this way, the boundary or frontier of dominant solutions for specific domains within the information landscape evolves towards a globally optimal state of allostasis for a community. This refined information circulates through social networks in recursive iterations of search, social learning, and experiential validation until these emerging norms converge toward a stable allostatic state. Social norms therefore indicate the emergence of a stable boundary of locally optimal solutions that satisfy both the information requirements and resource constraints for a community.

Such locally dominant solutions may not be *globally* dominant, though.[10] As information disseminates between connected communities, they are further evaluated against the pertinent requirements and constraints. A community's local norms may then be superseded by those from another community if it improves some aspect of the global optimization criteria without degrading others or incurring additional costs. This does not necessarily preclude the retention and efficacy of a community's locally optimal norms within its own context. Social norms reflecting a community's locally optimal criteria may persist within those communities, but only globally dominant solutions can propagate further through the total population.

5.5. Establishing "Normal"—Convergence of Normative Expectations

Any new social norm, along with the accompanying beliefs and expectations, becomes the prior expectation for future information searches within communities. In other words, successful social norms tend to converge towards normative expectations reflecting the baseline assumptions individuals hold about others' beliefs and expectations (Figure 6). Ideally, this iterative process of norm emergence and normative convergence progresses towards globally optimal solutions, representing a Pareto frontier between competing objectives [65,171]. Consequently, social norms evolve and converge into a normative framework of beliefs and expectations that serve as a baseline for community members. This

framework aims to minimize individual and collective allostatic load while maximizing predictability and effectiveness.

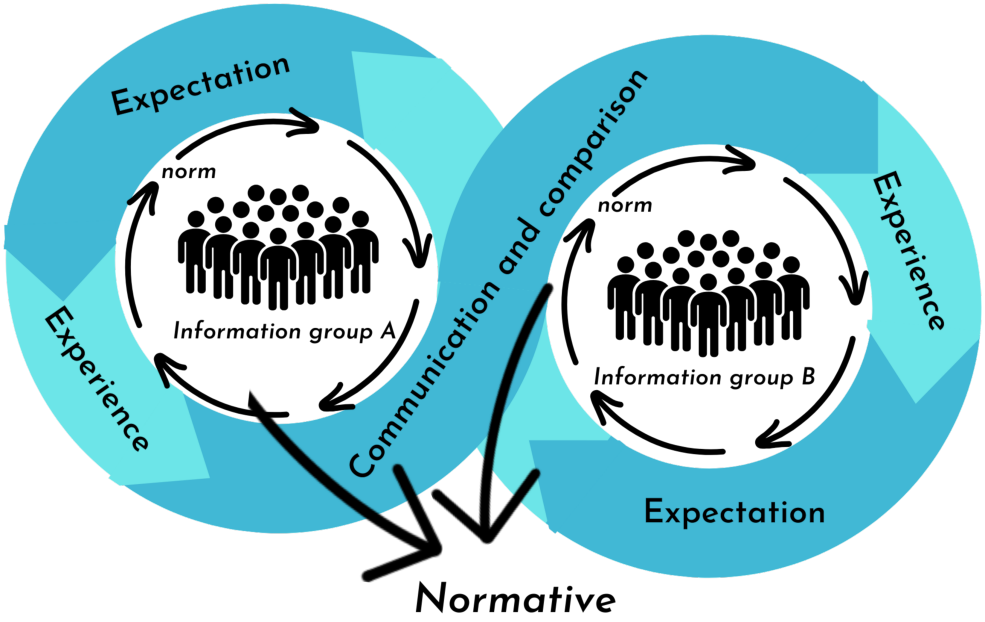


Figure 6. Norms that remain stable as they propagate throughout the population converge towards normative expectations that represent globally optimal solutions to maintaining beneficial social allostasis and adaptability.

The establishment of normative expectations within a community facilitates collective behaviors by coordinating social cognition for specific environmental conditions and behavioral responses. These beliefs and expectations entail the individual mental representations of both physical and social environments that constitute their combined information landscape. Social cognition depends on these representations to generate reasonable beliefs about the expectations of fellow community members.

Similarly, such normative expectations provide a shared basis for collective cognition, which relies on common knowledge and beliefs to coordinate group dynamics and problem-solving. Because normative expectations arise from the convergence of distributed search and validation processes across communities, they are more stable and resilient to new information than social norms. They represent the best approximation of a non-dominated Pareto frontier. These optimal solutions are derived from the community's repeated experiential sampling and the communication of that experiential information within and between communities.

Normative expectations guide the coordination of individual and collective behavior towards solutions that promote an optimal allostatic state for the community. While social norms reflect the dynamic search for optimal states, normative convergence reflects the retention of provisionally optimal states for community allostasis. Normative expectations remain stabilizing points of social coordination as long as the environmental conditions and constraints of the information landscape are maintained.

The set of solutions described by these normative expectations helps maintain coordination and allostasis. Solutions to the global optimization provide necessary and sufficient information to address systemic risks to the community, whether by mitigating uncertainties or by averting potential risks. Social norms that converge to normative expectations become preferred or a priori solutions that coordinate individual behaviors and provide an information structure for collective and cooperative actions.

6. Discussion

The model we have presented here not only addresses open questions surrounding social norms, but also resolves a more general and long-standing question within the social sciences—i.e., the perceived contradictions between autonomous agency and collective sociality, or (in evolutionary framing) individual versus group-level adaptive fitness of complex sociality. It illustrates the intrinsic entanglement of information, between both the physical and social environments and individual and group-level information processes, using abstractions that are already well-understood within multiple fields of study. This interdisciplinary synthesis provides a coherent conceptual foundation on which to frame practical applications for behavioral science and empirical research questions for the social sciences.

By re-examining social norms through the lenses of information and surprise, we demonstrate a fundamental simplicity beneath their seeming complexity. Social norms are behavioral adaptations that enable a social group to maintain an optimally low-surprise environment while simultaneously facilitating the discovery of new information that improves the group's overall fitness. The structure and purpose of these norms reflect critical, innately human evolutionary adaptations. Humans invest significant energy in acquiring, classifying, and validating new information. Consequently, norms have evolved to categorize and use social information efficiently.

This collective mechanism for maintaining a low-surprise environment ensures that our energetic and resource needs are met both individually and collectively. By promoting a stable and predictable environment, social norms minimize the energy required for routine activities and interactions, allowing resources to be redirected toward adaptive improvements. Additionally, the coordination achieved through mutual information represented by social norms ensures that the cumulative energy and resource demands of individuals do not exceed the collective's capacity. This energetic and allostatic balance through socially mediated information provides a significant evolutionary advantage in diverse environments.

Understanding the role of social norms in human behavior is another matter, and requires examining how individuals, communities, and cultures develop their distinct sets of norms for various social contexts. These norms depend on the specific accumulation of mutual information unique to each group. People may adhere to different norms depending on social contexts (e.g., friends, family, work, community, public, private) and navigate these contexts seamlessly. The defining characteristic is a coherent set of mutual information pertinent to each distinct context. The mutual information that norms represent consistently categorizes experiences and observations within a group's context, establishing parameters for individual actions and interactions within that particular setting.

Much like the ambiguity surrounding the term social norm, and perhaps partly *due* to that ambiguity, there has been no generally accepted definition for *culture*. In a way, these characteristic repertoires of group-specific beliefs, practices, and institutions almost seem to exist outside of the natural world. Truthfully, though, our experience of that external natural world is filtered through this suite of mental representations formed from our collective processing of information. A "tree" is just as much a mnemonic category of related information as it is a separate physical entity—it is everything we collectively do and do not know about "tree" as a category of thing, our beliefs and experiences of them, and their relationship to everything we broadly associate with trees.

We explore, identify, and classify information about our physical environment collectively as well as individually. Our mental representations of the natural world—and thus our understanding of it—are mediated through our collective social categorization of information. What we informally recognize as culture are these collective mental representations and particular categorization of information. This entanglement of collective information and sensory experiences constitutes an information landscape in which social actors explore and classify their environment. New experiences are described in terms of

pre-existing knowledge, whether by association or comparison, while collectively derived classifications provide context and shape perceptions.

The "resolution" of our understanding, both individually and socially, is determined by the categorical attributes we use to describe the information landscape. Similarly, our ability to infer from the known to the unknown is limited by these same categorical descriptors. Socially mediated information organizes our experiences into collectively recognizable domains, facilitating comparison within and between communities. At the same time, it sets the boundaries of what is known and unknown within the information landscape by defining the categorical domains through which we perceive and understand it. This collective reconciliation of experiences within identified domains coordinates community understanding of how to interact with and within the derived topology of information.

Cumulative knowledge generation within the total population results from this progressive and iterative reconciliation of information between individuals and communities. This regular and repeated comparison of individual information to that of the community allows the organic evolution of information within the population. Improvements to the collective mental representations of the physical environment, mediated through mental representations of the social environment and establishing the total information landscape, increase the overall population fitness. Individual contributions to collective information refine its boundaries and limitations, so the successes of one benefit the whole.

The implications of this are not merely academic. From climate change to sustainable practices, systemic inequality to disruptive technologies, or the increasing reliance on machine learning and artificial intelligence on our access to and utilization of resources and information—there is a growing interest in leveraging the tools of social and behavioral sciences to serve various interests. Increasingly, behavioral interventions are used in public policy and industry to "nudge" desired outcomes while social media has significantly altered the landscape of our social interactions and sources of information. These all raise serious ethical concerns about a potential flood of misinformation and growing influence of agenda-driven manipulation of social perceptions.

If, however, information is central to social adaptation as we have argued here then altering or manipulating social information—no matter how well intentioned—may have unpredictable and far-reaching consequences. The disciplinary ambiguities in our understanding and apprehension of the critical role of social norms and their relationship to normative institutions is no longer a purely academic matter for debate. Our model demonstrates how the healthy functioning of a population depends on its ability to naturally classify, curate, and adapt to the information in its environment.

In effect, we not only stand on the "shoulders of giants" but also on the landscape of information created by our communities as well as those that came before us. Perhaps more importantly, we are all part of an evolutionary structure of information that is *perpetually* being recreated through our ongoing social interactions. Here, as with our prior work, we show how this information is at the core of our social existence. Through the exchange of information, we augment ourselves and, in so doing, perpetuate the ongoing conditions of our collective success as a species. Social norms are not conventions that facilitate the coordination of social behavior but are instead the objective of that coordination and ultimately of sociality itself.

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Notes

[1] Rogers' Paradox [111] is a form of free-rider problem particular to evolution and social learning. Under certain circumstances social learning may lead to the retention of a maladaptive trait or behavior, thereby lowering the overall mean fitness of the population. This occurs when the environment is changing, but there are insufficient individual (or asocial) learners in the population to produce innovative solutions.

[2] Bayesian models of cognition suggest that the brain is a probabilistic inference machine, constantly making predictions and updating beliefs based on incoming sensory information. These theories posit that neural processes integrate prior knowledge with sensory data to form perceptions and guide behavior, emphasizing the brain's role in minimizing prediction errors (see [113–116]).

[3] Shannon [168] defined the concepts of *information* and *entropy* to quantify the uncertainty or surprise within a system. High-surprise environments contain a greater degree of unpredictability, meaning each new observation provides substantial information. Conversely, low-surprise environments are more predictable so new observations add little information.

[4] A multi-objective optimization is one in which there is more than one competing or conflicting attributes or criteria for the desired outcome. In such cases, there may be multiple equally optimal solutions representing specific trade-offs between those competing criteria. A Pareto optimization is a particular approach to solving these problems, stipulating that a solution is efficient or optimal if it improves the objective value of one or more criteria without worsening any other criteria.

[5] More precisely, coordination could be represented by the *convolution* of mental representations (in the mathematical sense of the interactions between functions), if modeled as probability or generative functions, to identify the degree of overlap between them.

[6] We are using the term "dominant" here in the sense of a multi-objective optimization problem such as Pareto optimization. A dominant solution refers to a solution that is superior to another solution in at least one objective and not inferior in any other objective. A solution that is not dominated by *any* other solution in the problem space is called a "non-dominated" or "Pareto optimal" solution [65,171].

[7] In the previous sections, we have been using the term *community* in the vernacular or sociological sense—i.e., a group of people who share common interests, values, norms, and often geographical location, and who interact with each other on a regular basis. In the following text, however, we are using the term in its more technical definition, formalized within social network analysis, to denote a subgroup or cluster of individuals within a larger network who are more densely connected to each other than to individuals outside of the group. These communities are often identified based on patterns of interactions or relationships among nodes (individuals or entities) in the network.

[8] We are using "information landscape" slightly outside of its contemporary common usage (i.e., the range and contexts of information sources). Here, we use the term to denote something between a formal *information topology* (in the mathematical sense, see [210]) and a *fitness landscape* (in the evolutionary biology sense, [211]).

[9] A system *without* uncertainty would be a wholly deterministic system, for which properties such as emergence or self-organization would be moot [229].

[10] Note that we are using *local* and *global* with respect to the system or network as a whole. In this particular context, local would refer to a community whereas global refers to the larger population of which that community is a part.

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