Computational Social Creativity

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Abstract

This paper reviews the development of computational models of creativity where social interactions are central. We refer to this area as 'computational social creativity'.

The context surrounding computational social creativity is described, including: the broader study of creativity, the computational modelling of other social phenomena, and computational models of individual creativity. Computational modelling has been applied to a number of areas of social creativity and has the potential to make a contribution to our understanding of creativity. A number of requirements for computational models of social creativity are common in artificial life and computational social science simulations.

Three key themes are identified: (1) computational social creativity research has a critical role to play in understanding creativity as a social phenomenon and advancing computational creativity by making clear epistemological contributions in ways that would be challenging for other approaches; (2) the methodologies developed in artificial life and computational social science carry over directly to computational social creativity; and, (3) the combination of computational social creativity with individual models of creativity present significant opportunities and pose interesting challenges

for the development of integrated models of creativity that have yet to be realised.

Keywords: social creativity, multi-agent modelling, computational social science, computational creativity.

1 Introduction

Artificial Life (ALife) has contributed to our understanding of biological processes in real life and in "life as it could be" [43], with particular emphasis on understanding emergent processes: those processes by which something new comes about through the interaction of existing elements. Computational Social Science (CSS) shares a common history with ALife and also treats mechanisms of emergence as central to its capacity to contribute to knowledge [17]. A third related field of multi-agent modelling directly concerned with the study of creativity can now be distinguished. It is at an earlier stage of development, with work often falling under the scope of ALife, CSS or Computational Creativity (CC) [48]. We refer to this field here as Computational Social Creativity (CSC). The goal of CSC is to contribute to the understanding of human creativity as a social phenomenon using multi-agent computational models, and consequently to contribute more generally to an understanding of creativity.

This article discusses this emerging field. We begin by describing the context surrounding CSC, in which we discuss its relationship to the wider study of creativity and to computational modelling, as well as the relationship between social and individual models of creative behaviour (Section 2). We then review areas in which computational models are applied to social creativity, including a "prehistory" of CSC (Section 3). We discuss the potential for CSC to make a contribution to the understanding of creativity (Section 4). Drawing on this review, we present a number of opportunities provided by a CSC approach, and lay out a set of requirements for computational models of social creativity, based on similar theoretical discussions in ALife and CSS.

2 Computational Modelling in the Study of Creativity

Research devoted to understanding creativity spans a wide range of disciplines from history to computational modelling. One of the most widely accepted definitions of creativity, particularly within computational creativity, is that it is an ability to produce outcomes that are both *novel* and *valuable* [6]. Both aspects are subjective; value depends on a use or context, and novelty requires a metric in which similarity is measured. In particular, novelty can be considered in terms of the violation of an observer's expectations, for which the term "emergence-relative-to-a-model" was introduced by Cariani [14] with reference to ALife. Creativity can also be seen as having a 'scope'. For example, Gardner [33] distinguishes between little-c (mundane) and big-C (eminent) creativity.

Many researchers concerned with creativity as a contribution to a collective body of knowledge (i.e., big-C) believe that creativity needs to be studied as the product of a multi-actor system [19, 35, 70, 50]. Even when the focus is on the psychology of the creative individual, evidence reveals the interdependency between individual and social process. Tardif and Sternberg [75] and Martindale et al.[51] found that the perception of creativity changes with exposure to examples of works. This research highlights how the social-cultural context informs the motivations, judgements and strategies of creative individuals.

Theoretical frameworks that attempt to take into account super-individual factors are often described as "systems theories", deriving from the view of societies as systems, potentially sharing properties with systems found in other domains. Vygotsky first proposed a systems theory of creativity emphasising the reciprocal relationship between creative individuals and their socio-cultural environment [78]. In Vygotsky's theory, creative individuals are both influenced by their personal understanding of their socio-cultural environment and through their actions cause changes in their environment [45].

Csikszentmihalyi proposed a systems views of creativity [19], which he later developed into the Domain Individual Field Interaction (DIFI) theory of creativity [28]. The latter sets out to systematically describe the components and interactions involved in creativity: the domain is a repository of knowledge held by the culture; the individual brings about some transformation of the knowledge held in the domain; the field is a set of social institutions that selects the knowledge that is worth preserving. The DIFI model associates the common use of the term "creativity" to transformations of knowledge by individuals that when judged by the field are determined to have a significant impact on the domain, i.e., big-C creativity, but also recognises that the entire system is required for this creativity to occur. A number of other researchers have examined systems-theoretic formulations, such as Luhmann's [46] and more recently Iba's [39] autopoietic approaches.

Researchers also aspire to *achieve* creativity in different ways at both social and individual levels, from improving innovation in organisations to building artificial creative systems that produce music and art. Theories of organisational structure may propose how to maximise creativity at the social level. The goal of building artificial creative systems is the primary focus of CC research, to which we now turn.

2.1 Three Types of Model

Computational creativity is a relatively young field [13], situated within Artificial Intelligence (AI) and with links to the early studies of discovery systems within AI. According to the co-founders of the International Conference on Computational Creativity (ICCC), computational creativity "places a vocational emphasis on creativity and attempts to draw together the commonalities of what human observers are willing to call ‘creative’ behaviours” [13, pages 15–16]. We identify three core strands of modelling that contribute to CC research:

Computational models of abstract creativity: By taking a broad view of creativity as any process in which novel outcomes emerge, many systems other than individual human brains can be described as creative. For example, biological evolution has been described as a creative process [4], bringing novel living systems into the world. Simple computational models such as Conway’s ‘Game of Life’ can be said to exhibit emergence by producing behavioural properties that are not written into their rules, showing in principle how computers may be capable of processes leading to open-ended, or, at least, advanced levels of generative complexity. Open-ended generativity is one of Bedau’s open problems in ALife [3], and a number of results, e.g. [72], suggest that this is a potentially irresolvable issue. Thus despite having nothing to do with modelling human cognition, the ‘Game of Life’ might optimistically be defined as a “minimally creative” process. Some researchers have sought to extend such abstract ALife-based approaches within the field of CC [56, 54, 63, 55].

Accordingly, strands of CC are methodologically similar to ALife. These models are explored for the formal properties that they exhibit, such as degree of diversity, organisational complexity, or less formal qualitative properties. For example, the emergence of a new, qualitatively different, fighting strategy in a competitive coevolution model may be described as a creative event [71] from the perspective of an observer.

Computational models of cognitive processes: Cognitive aspects of creativity lie at the heart of the CC literature. What cognitive processes go into the creation of a valued artwork or a novel design by a human? Can we recreate these, or equivalent processes, in software? At first sight this area of modelling research resembles traditional cognitive modelling, such as models of perception, in which measurements of human behaviour are used to evaluate the accuracy of the model. A number of CC researchers build software systems that generate cultural artefacts such as visual artworks and music, with the intention that such outputs may be compared to human artworks in informative ways, e.g., [16, 76, 26, 44].

But the evaluation of models remains an empirically challenging issue. CC theorists have undertaken to formalise the epistemological contribution this work makes (e.g., [82, 60]), attempting to formulate a common methodology built around the creation of artefacts by machines, and their evaluation by humans. For this, the categorisation of creative acts, such as Boden's triad of combinatoric, exploratory and transformational creativity [5, 6] underlies the field's conceptual framework, supported by attempts to categorise the evaluation of creative outputs according to a number of criteria, either by humans or automated systems [62, 40, 49].

CC modelling in artistic contexts sometimes overlaps with forms of creative practice-based research, following the pioneering work of artist-programmers such as Harold Cohen [53]. Alternatively, the production of creative systems that involve collaborative input from both humans and computers can be viewed as applied design research focusing on the human user experience scenarios that emerge from working with such systems in practice [8]. This is increasingly being recognised in the practice of CC researchers as they look at how their computational models operate as artefacts in social interaction contexts.

Computational models of social creativity: Understanding the impact of social factors in human creativity is a large empirical research area grounded in disciplines such as organisation science and economics, and with practical goals such as improving creativity by structuring companies, collaborative teams or even cities effectively. The research includes predictive models of the relationship between contextual factors and creative outcomes, as in [15], where a predictive model is used to understand the indicated degree of creativity of actors based on their position within a social network. In the context of CC, researchers approach the same subject matter by looking at the qualitative outcomes of multi-agent models within which artefacts are produced and shared. Researchers developing computational models of social creativity seek to understand a wide number of patterns of behaviour related to creativity, such as trends in music, art and design fields, and the impact on the creative process of certain organisational structures. Examples of modelling creativity in the qualitative style associated with ALife research include [64, 34, 81, 58, 10, 74, 30].

Often working with simplified multi-agent systems, CSC research is not focused on the details of cognitive processes or the production of creative outputs. Instead, the discovery or demonstration of identifiable mechanisms to produce social phenomena associated with creativity forms the core contribution to knowledge.

Typically, computational models of creativity fall into one of the above approaches, but there is clearly potential for all three approaches to be combined.

3 A History and Prehistory of Computational Social Creativity

We turn to look in more detail at examples of models that can either be described as CSC or as a part of its 'prehistory'. These are organised according to the aspect of creativity being explored, and the methodology used in making a contribution to knowledge.

3.1 Emergence as a creative process

According to systems views of creativity, new outcomes depend not only on individual innovations but on super-individual processes: a network of interactions between people and things. Just as biological evolution can be creative with no cognitive processes involved, social processes can cause new structures to emerge without recourse to explicit processes of creative cognition [7]. An important area of modelling looks at the creative capacity existing at this super-individual level.

Amongst the computational models of social phenomena from the 60s and 70s that have since risen to canonical status, Schelling's [68] model of social segregation stands out for its simplicity. The spatial model showed the imposition of a weak bias in individual agents resulting in a marked effect at the macro-level. Schelling used a simple cellular grid model where each grid cell could be populated by one of two kinds of individual. Individuals have a moderate preference to be surrounded by individuals of the same kind as themselves, and are sequentially given the opportunity to relocate. The result is a clear self-organisation of individuals, from a random scattering to an alternating patchwork of regions. A simple rule at the individual level results in a novel structure at the macro-level. This bottom-up causality is familiar to ALife researchers.

Schelling's model is illustrative of the epistemological nature of CSS modelling for a number of reasons. Firstly, it has qualitative outcomes; the model is concerned with showing the relationship between individual behaviour and qualitative macroscopic effects. Secondly, although hypothesised as applying to real social dynamics, it is not *directly* focused on modelling real-world empirical data; the demonstration of the process is the main contribution to knowledge, not the modelling of the behaviour of a real world system. Indeed, a modelled phenomenon may not actually occur in the real world, but can still be known as a real phenomenon with theoretical value. Thirdly, the model is simple enough to understand and analyse, and general enough that it can become a laboratory for further experimental questions. For example, in Schellings case, one can perform analysis on the long-term behaviour of agents at the boundary between different regions; see [37] for a review of variation to Schellings original model.

Qualitative computer simulation modelling frames its contribution to knowledge by asking, Is it possible that macro-effect X is achieved by process Y? Such 'is possible' statements take the form of empirical discoveries in a computational research laboratory. Often known as *proofs of concept*, such studies have been compared to thought experiments in the natural sciences [22]. In CSS they are referred to as *generative* [17], describing the ultimate epistemological outcome, which is to support the understanding of a potential process by implementing it in a model and showing how it works. Classic examples of agent-based models from ALife include Hinton and Nowlan's demonstration of the Baldwin Effect [38], Axelrod's demonstration of the emergence of cooperation through kin-selection [2] and Sim's Evolved Virtual Creatures [71], often cited in CC and ALife literature alike.

Simple computational models, e.g., [2, 27], have confirmed the validity and impact of this approach. None of these works explicitly study creativity, but much research in both ALife and CSS provides knowledge, methods and inspiration for CSC, particularly in the context of emergence, where new systems and structures come into being as a result of interaction between multiple agents.

3.1.1 Modelling properties of social creative systems

Besides individual creative acts, a greater understanding of art, music, fashion and other cultural phenomena as creative domains can be achieved by modelling their high-level dynamics. Our understanding of creative cognition can be used in models of these high-level dynamics. Equally, an understanding of these dynamics may contribute to our ability to model creative cognition by providing more detailed requirements for how creative behaviour should play out.

Drawing on the systems view of creativity introduced by Csikszentmihalyi [20], Saunders and Gero [65, 66] implemented a computational model of social creativity using 'curious design agents' able to both generate novel artefacts and evaluate the novelty of artefacts generated by other agents. In this model, individuals produce novel artefacts and send those they determine to be significantly novel to other agents in the field for further evaluation. If a receiving agent determines that the work of a sender is novel according to its own model, based on experience, it can provide a positive reinforcement signal to the sender and add the work to the domain of exemplars for the field to draw upon. Simulations of this model demonstrate the emergence of a number of social structures familiar from human creative societies, e.g., the emergence of 'cliques', where a clique is defined as a subgroup of agents that reward the work of other individuals within the group, while ignoring the artefacts produced by other agents in the field.

Saunders and Grace [67] combined computational models of the evolution of language (e.g. [73]) with computational models of social creativity to propose a distributed model of creative domains that are more than repositories of previously generated artefacts. In this model, a creative domain is represented by both artefacts and descriptions of those artefacts distributed across the agent population. In this model, agents engage in 'language games' to develop commonly held descriptions for properties of things in the world across a population. Consequently, each agent in this artificial society maintains its own mapping from features of an artefact in order to reconstruct descriptions on demand. The distributed representation of domain descriptions permits the study of interactions between domains, as agents are free to leave or enter social groups and consequently transfer domain knowledge through their movement.

In an innovative approach, which indicates the future potential of integrating generative systems with real human evaluation, MacCallum et al [47] have used a generative music system, in which the music can be evolved over the net by the positive or negative responses of multiple users, to study the resulting evolutionary trends in the population.

3.1.2 The emergence of creative domains

Finally, creative domains themselves have distinct origins and histories which can be explored through modelling. An understanding of the nature of specific domains may reveal irreducible differences between them that challenge the notion that creative activity is identical in all domains.

The study of the evolutionary origins of language is a domain in which computer simulation models have had significant impact. Here, specific evolution of language theories compete using evidence from psychology, archaeology, social science and linguistics. In a series of computational experiments (e.g. [41, 42]), Kirby and Hurford showed that a process of non-fitness-based iterated learning was sufficient to explain various properties of complex language structure such as compositionality and syntax. Steels [73] has similarly shown the emergence of shared vocabularies of meaning grounded in the world through iterated multi-agent bouts of communication which he calls "Language Games", after Wittgenstein. Such results, analogous to the emergence of syntax in language, provide new ideas for understanding and modelling create processes, and demonstrate a new application area for the principle of self-organisation. For example, Miranda, Kirby and Todd [58] adapted language models, such as those discussed above, to a musical context.

Other researchers have looked at the biological evolution of human cognitive abilities in search of the origins of general creative capacities and domain-specific behaviours, such as musical or visual aesthetic preferences. Gabora has built several models of an evolutionary cultural system using similar iterated learning dynamics (e.g., [31]) and with di Paola [32] has attempted to produce models that inform us about the evolutionary psychology of human creative abilities, in line with a number of theories stemming from evolutionary psychology such as the work of Donald [23]. Werner and Todd [81] consider sexual selection as a generator of diversity and study models of the evolution of complexity in birdsong, hinting that the theory may also apply to human music; a view developed by Miller [57]. Their model focuses on abstract properties such as diversity in the population and its rate of change, and seeks mechanisms associated with sexual selection that would promote these features.

Bown and Wiggins [10] also look at evolutionary mechanisms surrounding the evolution of human musical behaviour. In their case they focus on music as a cooperative system of social interaction rather than as a sexually selected system. They show that a potential pathway towards the adoption of musical interaction can occur through kin selection. Successful cooperative behaviours start with kin before branching out to wider groups. In their model, a tendency to reward others for musical stimulation evolves, even though this transfer of reward is not beneficial to the individuals paying it. Kin selection, where behaviours that are not beneficial to the individual nevertheless evolve because they are of benefit to sufficiently closely related kin, provides a possible mechanism by which this can happen. In a more recent model, Bown [9] investigates an alternative view in which abstract and non-functional cultural patterns of behaviour emerge autopoietically through competitive interaction.

4 Opportunities Within Computational Creativity

In this section we continue discussing how CSC can make important contributions to our understanding of creativity.

CSC avoids methodological issues to do with evaluation. CC has an easily stated 'grand challenge', which dates back to the dawn of AI [52]: build a system that can produce art/music/designs etc. that are as good as human creative works. But the evaluation of creative systems has been hard to reductively break down into measurable properties that would support incremental advances in system development. Demanding scientific exactitude of phrases above such as *as good as* (judgement) and *on its own* (autonomy) proves challenging. An argument is developed in [7] and [8] that a large part of the phenomenon of artistic creativity, classified as *generative* creativity, is missing when taking this approach.

Population models do not suffer from these issues, but rather allow us to systematically examine the meaning of these concepts, drawing successfully on the precision of working with closed computational abstractions, as researchers have successfully done in ALife. Rather than focus on the ambiguous evaluation of artificially created outputs by humans, it is the global properties of human creative domains that are modelled. The evaluation conducted within these closed models by agents can be treated as an objective phenomenon and the autonomy of agents can also be measured in relation to other elements within the system. This clarifies the application of terms such as 'autonomy' and 'quality' to elements of the model. Furthermore, the outputs of CSC correspond to objective social observations, the patterns of behaviour that form in an artistic domain, such as fads and cliques, or the relationship between the creative success of individuals and their position in a social network. In such cases the basic methodological principles are aligned with those of ALife and CSS. CSC thus complements CC by explicating super-individual creative processes, whilst CC typically attacks individual cognition.

An example study, albeit not a simulation model, is illustrative of the understanding of social creativity that may be possible using simulation modelling. Cattani and Feriani [15] study the creativity of both individuals and teams within the film industry using data from publicly available sources (mainly IMDB: `http://www.imdb.com/`). These sources provide information on a number of factors that go into into movie production, as well as factors associated with its reception. Cattani and Feriani's approach is novel in conducting a social network analysis of the community. Building on existing creativity theory, backed by intuition and anecdotal evidence, they consider the hypothesis that creativity is maximal for individuals or teams that find an optimal position within the social network between the centre and the periphery. This hypothesis points to a view of creativity in which those too close to the periphery are sub-optimally creative due to a lack of familiarity with practices of the genre, whereas those too close to the centre are sub-optimally creative because they are over-entrenched in tried and tested norms. It suggests that achieving optimal creativity requires avoiding being either too conservative or too esoteric. Since the measure of creativity is based on objective data, any discussion of whether this is *actually* creativity is unimportant in this context.

In this example, a link is established between an individual's situation within a social context and their effect on that social system's collective creativity, supporting the view that the value of creative products is not reducible to a cognitive capacity to produce value.

CSC offers an integrated understanding of creative domains, fields and in-

dividuals. As a consequence of the context just described, CSC provides a platform for understanding the motivations and modes of evaluation that underlie creativity in different domains of activity. Again we use the example of the origins of human musical behaviour; a subject that Darwin speculated upon [21], that had a resurgence of interest beginning towards the end of the 20th Century [79] following advances in human music perception studies and in the understanding of animal vocal communication. Music has clear differences from language, and has been described as inherently ambiguous [18]. Yet it provokes strong reactions from people, and is entrenched in all human societies. A number of theorists have speculated about the possibility of a common origin for music and language, which has subsequently branched into two distinct functional communication systems, one focused on information transmission and the other focused on mechanisms of social interaction broadly associated with cohesion [12]. But music has social properties that suggest candidate functions very distinct from language [36].

Along with art and language, music is one of the core application areas for exploring CC questions, yet the evaluation of musical artefacts produced by artificial systems continues to be poorly understood. CSC provides a platform to experimentally investigate hypothesised conditions surrounding the nature of creative domains and can help answer questions such as; How would a better understanding of music's social psychology and demographics alter the way we think about evaluation in music?

We can also be clearer about distinguishing between the more ambiguous concept of creativity and the more quantifiable concept of creative success, as illustrated in the example above [15]. Creative success has a contextual component – being in the right place at the right time – for example, getting the right training or getting a *first break*, which establishes a feedback of investment, stimulating further success. However, an even more trivial way in which context can play a role is through "value creation", where creators actually have influence over others' evaluation. If there is coupling between being able to influence the taste of others and being rewarded by those individuals then it is theoretically possible that random individuals producing random creative outputs could rise to be successful. In the extreme, creative success could be randomly distributed, with differential access to knowledge or skills not necessary to establish differential success, as discussed in [9].

To our knowledge such aspects of creativity have not been directly explored through CSC models, although they have equivalents in biological models, such as in the principle of runaway sexual selection [29], and runaway cultural processes such as those modelled by Boyd and Richerson [11]. However, there are two related areas of modelling that can directly inform creativity studies and may make suitable starting points for specific creativity models. One is social network or small world network studies, such as [80], in which some individuals become beacons of influence, driven by feedback processes from random initial perturbations. The other is in models of status and dominance in species, such as those looking at Dunbar's 'social brain hypothesis' [24].

CSC enables a structured, refineable approach to creativity. Frequently, CC's main subcategories follow the domain-specific application areas to which the research is applied, e.g. music, art, language-based creativity etc. Consequently, CC has tended to be relatively domain-specific, with little shared experimental practice. A potential problem is that the field progresses along these domain-specific lines. In the worst case, researchers have their own isolated systems and spend little time reproducing or adapting the systems of others. However, the CC community is currently promoting the development of web services (e.g., [77]) as practical research platforms to allow computational models of creative processes to be combined. Similarly, CSC offers an abstract laboratory to investigate the nature of the creative process in a social setting. This abstraction, and the focus on qualitative modelling, allows for sharing, refinement and an incremental approach, providing a common platform for investigating generally applicable techniques for modelling creativity at different stages and scales.

5 What are the requirements of CSC models?

In this section we discuss four properties that are essential (the first two) or desirable (the last two) for models in CSC. The requirement to demonstrate a mechanism is, we feel, critical to producing valuable research contributions in this field, echoing similar calls in ALife and CSS. We are particularly interested in a focus on a mechanism-based methodology for research in CSC.

5.1 Models must demonstrate a mechanism

ALife and CSS share an approach to modelling which is qualitative and is focused on the discovery of mechanisms. At the core in both cases is the notion of *emergence*. Conte et al. [17] ground the epistemological foundations of qualitative CSS modelling in its *generative* nature: a model is constructed using ideas about how individuals behave, and is used to study the macroscopic effects of this behaviour as multiple agents interact. They describe 'agentification' as "the process of formalising a social theory as an agent-based model" (p. 333). This process can be used to test theories of the origins of macroscopic effects by discovering or demonstrating the efficacy of mechanisms relating individual and macroscopic forms. In both CSS and ALife, where individual behaviour includes adaptation, this can also include the effect of feedback from macroscopic properties leading to changes in individual behaviour. For example, following Simon's principle of bounded rationality [69], Conte et al. [17] explain how social complexity can result from adaptation to changing environments. Where such a feedback effect is observed in a multi-agent system, generative modelling is well-suited to the task, since one can simply run the proposed underlying process and see where it leads.

5.2 Models must be simple and reproducible

Reproducibility is a core principle in experimental science. In computer modelling, a trivial form of reproducibility can be obtained simply by sharing software, but the essence of reproducibility is that it should be applicable to the high-level claims being made, and results should therefore be reproducible from scratch by independent researchers.

Making simple models benefits this cause both for the communication of results and their validation by the original author, by minimising opacity and by minimising the gap between the models and the claims being made about the contribution of these models to knowledge.

Axelrod, a long-time proponent of the "Keep-It Simple, Stupid" (KISS) principle [1], helped to drive home the value of this approach in a series of models on the evolution of cooperation, that are both incredibly easy to follow and understand, but at the same time informative about processes applicable to high-level social phenomena.

Equally, there is the possibility that work carried out during the end of the 20th Century has gathered most of the 'low-hanging fruit', and that ALife and CSS now face diminishing returns from a commitment to simplicity. As Conte et al. indicate [17], as we move away from rationality as a model for human behaviour the individual agent behaviours are likely to become more complex, and it becomes harder to find solid ground that adheres to the KISS principle. For CSC this dilemma is prominent, as the behaviour it aims to study is high-level and highly complex. Although there may be arguments for stepping away from the KISS principle, such as [25], it remains a compelling position.

5.3 Models should preferably generate new hypotheses

"Fisher famously said that if we want to explain the prevalence of two-sex organisms, we should start by explaining what the biological world would be like if there were three sexes [94]" [17] (p.340). Both in ALife and CSS, the potential to explore hypothetical situations provides a powerful platform for discovery. Di Paolo et al. have accordingly referred to ALife models as "opaque thought experiments" [22], which are like thought experiments in that they merely allow one to step through the consequences of certain assumptions, but which, unlike thought experiments, are beyond our ability to think through the necessary steps.

5.4 A strong CSC model would actually be creative and achieve the goal of CC

Proponents of 'strong ALife' view the field as having the capacity to make systems that are *actually* alive [59]. Digital ecosystems such as Ray's *Tierra* [61] have been argued to achieve this status. Much of the work that is found in ALife journals and conferences, however, is more clearly focused on modelling as a means of understanding systems. CSS has no claim to a strong form, being at the opposite end of the complexity spectrum from the kinds of artificial chemistries and single-cell organisms that have been described as complete artificial living systems. But 'strong CSC', where an artificial creative social system is actually creative, even if its individual agents are minimally cognitive, seems plausible.

6 Conclusion

This article has given a brief overview of computational social creativity. We have shown that CSC is already a lively area of research with roots common to ALife and CSS, but have also attempted to better define CSC as a unique field with independent concerns. As far as we are aware there has been no attempt so far to define this as a distinct field, and we believe it will still be some time before a sufficiently large body of work warrants independent conferences and journals on the subject. In the meantime we hope this overview can support discussions amongst the ALife and CC communities. Throughout the paper, three key themes have appeared.

Firstly, CSC is as essential to understanding (and hence incrementally developing) creativity as a phenomenon as are individual-agent systems. The contribution of CSC lies in being able to look objectively at phenomena such as creative autonomy and agency, and the evaluation of artefacts. CSC is able to contribute to an understanding of creativity in which social processes may be as significant as cognitive processes, and is able to contend with problems such as how a new creative domain appears. CSC is able to achieve clear and rigorous contributions to knowledge through detailed simulation experiments in ways that are hard to achieve with individual-agent systems whose output is typically evaluated by humans.

Secondly, ALife and CSS provide the methodological rigour that must be carried over to CSC. Epistemologically CSC is a close relative of these fields. A key notion is the idea of discovering mechanisms through simulation models, or what Conte et al. [17] refer to as *generative* models. Other important principles include simplicity, reproducibility and the generation of new hypotheses.

Finally, a powerful future area of research lies in the combination of individual and social models. Our analysis provides pointers for how this can work, but a methodological challenge lies in managing the complexity that arises when sophisticated and potentially idiosyncratic individual models are brought into the context of simple and easily reproducible multi-agent simulation models. Nevertheless, there is no good reason to believe that these methodological issues won't be overcome.

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