Towards a Computational Model of Creative Societies using Curious Design Agents

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Abstract. This paper present a novel approach to modelling creative societies using curious design agents. The importance of modelling the social aspects of creativity are first presented and a novel agent-based approach is developed. Curious design agents are introduced as an appropriate model of individuals in a creative society. Some of the advantages of using curious design agents to model creative societies are discussed. Results from some initial investigations into self-organisation within creative societies using the model are given. This paper concludes by discussing some related work and exploring possible directions for future work.

1 Introduction

Creativity is often described as the ability to produce work that is both novel and appropriate [1] and researchers generally acknowledge that creativity must be defined differently at the level of the individual and the level of society [2, 3] but the relationship between individual and social creativity is complex.

An individual may determine that their work is creative independently of the judgement of others, but for it to be generally recognised as a creative work, other members of the society must agree that it is significantly novel and appropriate for a particular domain. In addition, an individual's determination of what is creative is informed by their experiences that are in turn based in the social and cultural environment within which they are situated. Consequently, we can say that creativity, at whatever level it is determined, is ascribed through a dynamic process of interactions between an individual, their society and the domains within which they work. This dynamic process of interactions is nicely captured by Csikszentmihalyi's systems view of creativity [4], illustrated in Figure 1.

In Csikszentmihalyi's view, creativity can only be discussed in terms of the creative system that extends beyond any particular individual and includes the socio-cultural context within which the individual works. Csikszentmihalyi identified three important components of a creative system; firstly there is the person engaged in the creative work referred to as the *individual*, secondly there is a social component called the *field*, and thirdly there is a cultural component called the *domain*. Creativity can be characterised by the following cycle of interactions; an

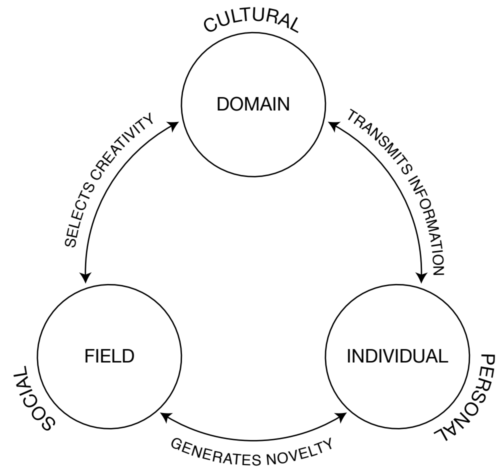


Fig. 1: Csikszentmihalyi's Systems View of Creativity

individual takes some knowledge from the domain and produces a work that is assessed by the field and if it is deemed to be creative the work, and any knowledge inherent in the work, is added to the domain.

The great majority of the research developing computational models of creativity has followed the lead of Newell et al. [5] and has focussed on developing computational models of creative processes such as divergent thinking, analogy making, and pattern recognition. Based the systems view of creativity, Csikszentmihalyi has questioned the validity of this approach [4], arguing that the these computational models cannot be said to model creativity without interaction with a field and its associated domain.

This paper presents a computational framework for studying the emergence of individual and social creativity within multi-agent systems based on the systems view of creativity. The goal of this research is to explore some of the interactive processes that occur within creative societies and how they might affect judgements of creativity.

2 A Framework for Modelling Creative Societies

The framework presented here provides an approach to developing models of social creativity based on Csikszentmihalyi's systems view. Previous work by Liu [6] recognised the need for a unified framework for modelling creativity. Liu's dual generate-and-test framework provided a synthesis of the personal and sociocultural views of creativity in a single model. Liu proposed that existing computational models of personal creativity complemented computational models of social creativity by providing details about the inner workings of the creative individual missing from the models of the larger creative system. Liu proposed the dual generate-and-test model of creativity as a synthesis of Simon et al's generate-and-test model of creative thinking [5] and Csikszentmihalyi's systems view.

The dual generate-and-test model of creativity encapsulates two generate-and-test loops: one at the level of the individual and the other at the level of society. The generate-and-test loop at the individual level, illustrated in Figure 2(a), provides a model of creative thinking, incorporating problem finding, solution generation and creativity evaluation. The socio-cultural generate-and-test loop models the interactions among the elements of Csikszentmihalyi's systems view of creativity, as illustrated in Figure 2(b). In particular, it captures the role that the field plays as a social creativity test; ensuring that artefacts that enter into the domain are considered creative by more that just its creator. The combined dual generate-and-test model of creativity is illustrated in Figure 2(c).

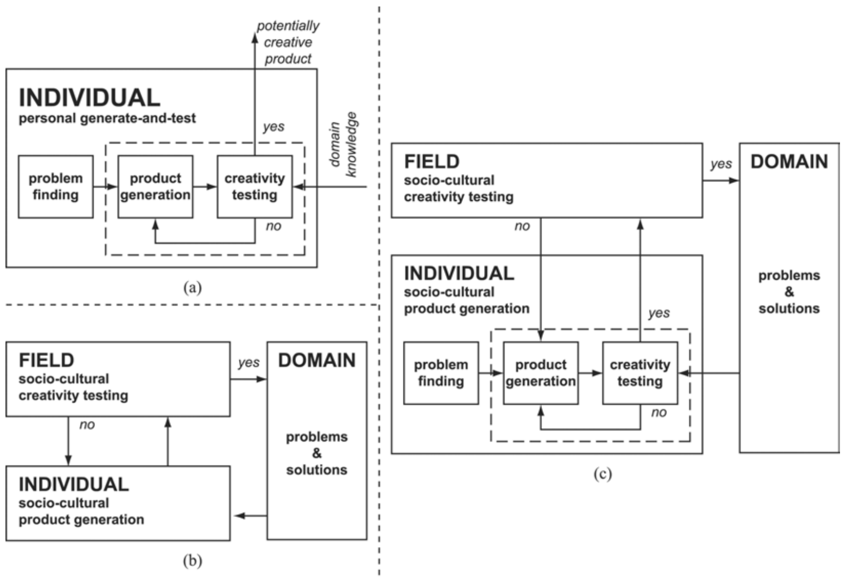
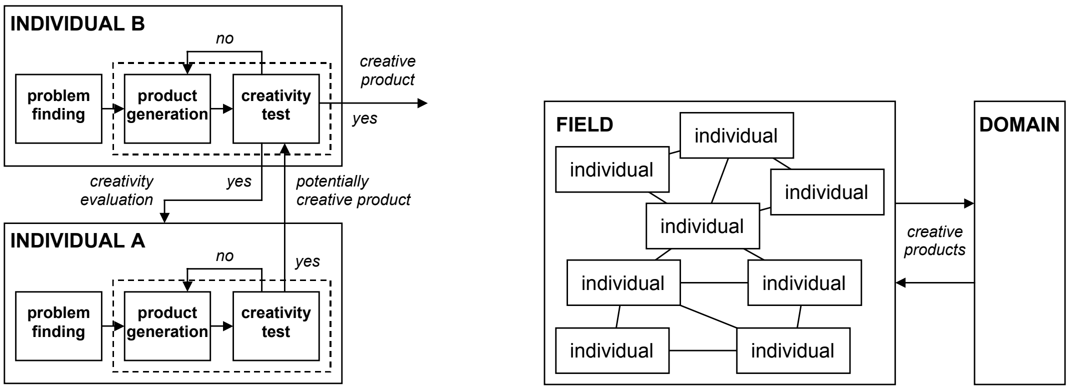


Fig. 2: Liu's Dual Generate-and-Test framework for building models of creative systems.

A literal implementation of Liu's model requires separate processes to model the individual and social creativity test. This can be a pragmatic approach to adding a model of social factors to existing models of individual creativity and it is a viable solution for modelling some aspects of creativity, as demonstrated by the computational model developed by Gabora to study the memetic spread of innovations through a simulated culture Gabora [7].

The framework presented here takes a different approach, instead of implementing the social creativity test as a monolithic function, it distributes the social creativity test across all the individuals that constitute the field. The social creativity test is modelled through the communication of artefacts and evaluations of their creativity between individuals. An illustration of two individuals communicating artefacts and evaluations is given in Figure 3(a).



(a) The communication of artefacts and evaluations between agents.

(b) A model of a creative system using agents.

Fig. 3: The framework for modelling creative societies using agents.

In the interaction illustrated in Figure 3(a), Agent A communicates an artefact that it considers to be creative, i.e. that passes its personal creativity test, to Agent B. Agent B evaluates the artefact according to its own personal creativity test and sends its evaluation back to Agent A. Each agent's evaluation of an artefact is affected by the traits of the individual, e.g. its preference for novelty, and its experiences, e.g. other artefacts it has evaluated.

Through the communication of evaluations, Agent B can affect the generation of future artefacts by Agent A by rewarding Agent A when it generates artefacts that Agent B considers to be creative. More subtly, Agent A can affect the personal creativity test of Agent B by exposing it to artefacts that Agent A considers to be creative, because the evaluation of creativity involves an evaluation of novelty, Agent A affects a change in Agent B's notion of creativity by reducing the novelty of the type of artefacts that it communicates. By exposing Agent B to artefacts that Agent A considers to be creative it can alter Agent B's evaluation of novelty and hence creativity.

To implement the social creativity test as a collective function of individual creativity tests a communication policy is needed. A simple communication policy would be for agents to communicate a product when their evaluation of that product is greater than some fixed threshold. To complete the implementation of the field as a collection of individuals, the individuals must be given the ability to interact with the domain according to some domain interaction policy. A simple domain interaction policy would follow the communication policy above and allow agents to add products of the generative process if the personal creativity evaluation is greater than a domain interaction threshold with the restriction that no individual is allowed to submit their own work to the domain. Thus, at least one other agent must find an individual's work creative before it is entered into the domain.

The individual, agent-centric, evaluations of creativity are key to the framework described here and permit the emergence of social definitions of creativity as the collective function of many individual evaluations. Without agent-centric evaluations of creativity, or at least interestingness, the collection of agents would simply represent parallel searches of the same design space. Curious design agents provide the necessary evaluations of creativity for this framework to be implemented.

2.1 Curious Design Agents

A curious design agent embodies a model of curiosity that uses a learning system called a novelty detector [8, 9]. A novelty detector can determine the novelty of a new input with respect to all of its previous inputs as a function of the errors generated when it attempts to classify the new input against one of its existing prototypes. Using a novelty detector, curious design agents are able to determine the novelty of new artefacts as they are produced. The novelty of each new work is measured as the distance between it and the nearest matching prototype, where the distance can be any measure of dissimilarity between a new work and an existing prototype, in the implementation that follows the distance is defined as the Euclidean distance between vectors representing a new work and the closest matching prototype.

The model of curiosity used by the curious design agents transforms the value of novelty determined by the novelty detector into a measure of interest by applying a "hedonic function". The hedonic functions used in the implementation are based on the Wundt Curve that Berlyne [10] used as a model for the typical reactions that animals and humans display in the presence of novel situations. A Wundt Curve for the determining the hedonic value, i.e. interest, from novelty is illustrated in Figure 4 as the combination of a reward function and a punishment function for discovering some novel work. Using a Wundt Curve to calculate interest, curious design agents favour works that are similar-yet-different to those that have been experienced before. By changing the value of novelty at which the hedonic function is at its maximum, the agents can differ in how similar a new work must be for it to be considered interesting and therefore potentially creative.

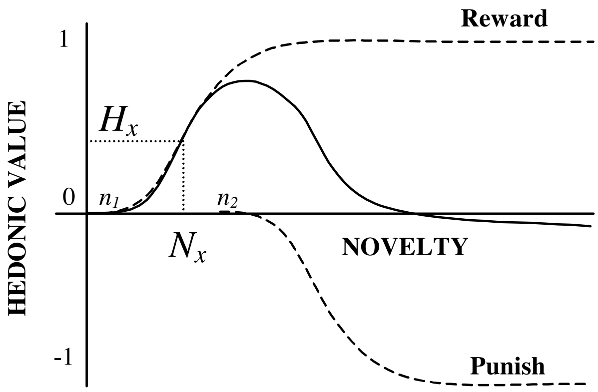


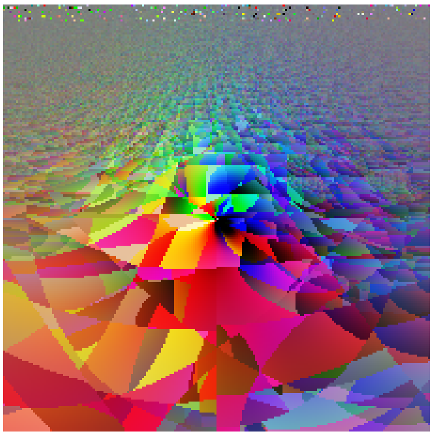
Fig. 4: The Wundt Curve.

The autonomy of curious design agents for determining what is interesting, and therefore potentially creative, is the key to adapting Liu's dual generate-and-test model to the study of emergent notions of creativity. This approach substitutes the monolithic social test of creativity found in Liu's model with a distributed agreement that emerges from the communication of individuals.

3 Experiments and Results

This section describes some results with an implementation of the framework described above. In this implementation the domain consists of "genetic artworks" [11]. Genetic artworks are images that are produced by evaluating an evolved program, typically a Lisp expression, at each (x, y) co-ordinate over the plane of the image. An example of a genetic artwork is shown in Figure 5(a) together with the evolved Lisp expression that generated the image.

The curious design agents in this implementation use an interactive evolutionary art system based on the one developed by Witbrock and Reilly [12]. The images produced by the evolutionary system are converted into a vector that represents the contrast values of the pixels in the image. The vector is assessed using a novelty detector based on a self-organising map (SOM) [13] that provides a measure of each image's novelty whilst at the same time adapting the prototypes represented in the SOM to take into account the new images.



(a) Genetic Artwork

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(mod (iexp (mod (* (iexp (isin (* k x_iy_jx_ky))) (A1
(floor (iexp (conj golden))) (/ (/ x_iy (/ (exp (iexp
(/ x_iy (imax (iexp (rolL (iexp (* (conj golden) (normp
(exp (iexp (isin (/ j (* (floor x_iy_jx_ky) (+ i (conj
x_iy)))))))))))) (inv x_iy))))) (floor (exp (iexp (isin
(* k x_iy_jx_ky))))))) j))) (mod (iexp (conj golden))
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(iexp (/ x_iy (imax (iexp (rolL (iexp (* (conj golden)
(normp (exp (iexp (isin (/ j (* (floor x_iy_jx_ky) (+
i (conj x_iy)))))))))))) (inv x_iy))))) (iexp (exp (iexp
(isin (* k x_iy_jx_ky))))))))) j) (inv x_iy)) (/ golden
(/ (/ x_iy (/ (exp (iexp (/ x_iy (imax (iexp (rolL (iexp
(* (conj golden) (normp (exp (iexp (isin (/ j (* (floor
x_iy_jx_ky) (+ i (conj x_iy)))))))))))) (inv x_iy)))))
(iexp (exp (iexp (isin (* k x_iy_jx_ky)))))) j))))
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(b) Lisp Expression

Fig. 5: A genetic artwork and the Lisp expression that was evaluated at every (x, y) co-ordinate in the image to produce it where the x co-ordinates and y co-ordinates are in the range -1 to 1.

For the sake of simplicity, and to demonstrate the effects of different novelty evaluations on creative societies, all genetic artworks are assumed to be appropriate, i.e. any artworks that can be produced using the interactive evolutionary system are assumed to be acceptable instances of genetic artworks that can potentially be added to the domain.

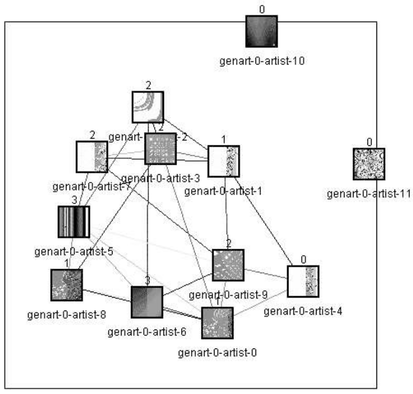
3.1 The Law of Novelty

In "The Clockwork Muse" [14] Martindale presented an extensive investigation into the role that individual novelty-seeking behaviour played in literature, music, visual arts and architecture. He concluded that the search for novelty exerts a significant force on the development of styles. Martindale illustrated the influence of the search for novelty by individuals in a thought experiment where he introduced "The Law of Novelty". The Law of Novelty forbids the repetition of word or deed and punishes offenders by ostracising them. Martindale argued that The Law of Novelty was merely a magnification of the reality in creative fields. Some of the consequences of the search for novelty are that individuals that do not innovate appropriately will be ignored in the long run and that the complexity of any one style will increase over time to support the increasing need for novelty.

The following experiments were designed to study the effects of the search for novelty in creative societies modelled as curious agents that have hedonic functions with different preferred novelty values. The preferred novelty of each agent is expressed as a value N that indicates the amount of novelty associated with peak interest in the agent's hedonic function. In this implementation, N ranges from 0 to 32; this is equal to the range of the potential classification error generated by the novelty detectors used.

Agent ID	Preferred Novelty (N)	Attributed Creativity
0	11	5.43
1	11	4.49
2	11	4.50
3	11	3.60
4	11	4.48
5	11	1.82
6	11	6.32
7	11	8.93
8	11	10.72
9	11	5.39
10	3	0.00
11	19	0.00

(a) The attributed creativity between agents.



(b) Screenshot of the running simulation.

Fig. 6: The Law of Novelty simulated within a single field of agents with different preferences for novelty.

In the first experiment a group of 12 agents were created. Ten of the agents, agents 0–9, shared the same hedonic function, i.e. the same preference for novelty (N=11). Two of the agents were given quite different novelty preferences. One, agent 10, was given a preference for low amounts of novelty (N=3) and the other, agent 11, was given a preference for high amounts of novelty (N=19).

Figure 6(b) is a screenshot of the running simulation; the squares represent agents, the images in each square shows the currently selected genetic artwork for that agent, the number above each genetic artwork shows its attributed creativity, and the lines between agents indicate the communication of rewarded works between pairs of agents. Figure 6(b) shows how the network of communication links developed between agents that communicate artworks and evaluations on a regular basis excludes the two agents with different hedonic functions.

The results of the simulation are presented in Figure 6(a). The results indicate that the agents with the same preference for novelty to be somewhat creative according to their peers, with an average attributed creativity of 5.57. However, neither agent 10, with a preference for low amounts of novelty, nor agent 11, with a preference for high degrees of novelty, received any credit for their artworks. Consequently none of the artworks produced by these agents were saved in the domain for future generations. When these agents expired nothing remained in the system of their efforts.

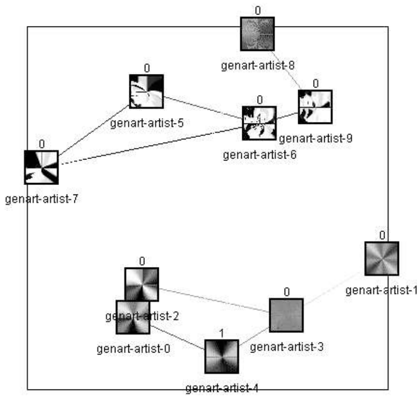
The results of this experiment appear to show the emergence of the Law of Novelty in models of creativity societies that have agents with different preferences for novelty. One explanation for this may be that agents with a lower novelty preference tend to innovate at a slower rate than those with a higher hedonic preference and while an agent must produce novelty to be considered creative, it must do so at a pace that matches its audience. There is no advantage in producing many highly novel artefacts if the audience cannot appreciate them.

3.2 The Formation of Cliques

In this second experiment, the behaviour of groups of agents with different hedonic functions is investigated. To do this a group of 10 agents was created, half of them had a hedonic function that favoured novelty close to N=6 and the other five agents favoured novelty values close to N=15. Figure 7(a) shows the payments of creativity credit between the agents in recognition of interesting artworks sent by the agents.

Receiver \ Sender	0	1	2	3	4	5	6	7	8	9
0		2	8	1	2					
1										
2	2	1		1	3					
3	4	5	2		5					
4	2	3	3	2						
5					1		6	1	3	5
6						3		4	5	1
7						3	5		1	4
8						4	3	2		4
9						1	4	4	4	

(a) A matrix of the number of positive creative evaluations sent between agents.



(b) A screenshot of a simulation showing two non-communicating cliques.

Fig. 7: The formation of cliques between agents with different hedonic functions.

Two areas of frequent communication can be seen in the matrix of payment messages shown in Figure 7(a). The agents with the same hedonic function frequently send credit for interesting artworks amongst themselves but rarely send them to agents with a different hedonic function. There are a large number of credit messages between agents 0–4 and agents 5–9, but only one payment between the two groups – agent 4 credits agent 5 for a single interesting artwork.

The result of putting collections of agents with different hedonic functions in the same group appears to be the formation of cliques: groups of agents that communicate credit frequently amongst themselves but rarely acknowledge the creativity of agents outside the clique. As a consequence of the lack of communication between the groups the style of artworks produced by the two cliques also remains distinct.

Figure 7(b) is a screenshot of the running simulation that has formed two cliques. To help visualise the emergent cliques, the distances between agents are shortened for agents that communicate frequently. The different styles of the two groups can also be seen, with agents 0–4 producing smooth radial images and agents 5–9 producing fractured images with clearly defined edges.

The results of this experiment show that when a population of agents contains subgroups with different hedonic functions, the agents in those subgroups form cliques. The agents within a clique communicate credit frequently amongst themselves but rarely to outsiders. The stability of these cliques depends upon how similar the individuals in different subgroups are and how often the agents in one subgroup are exposed to the artworks of another subgroup. Further research is needed to determine whether other factors that can affect judgements of interestingness can similarly affect the social structure.

Communication between cliques is rare but it is an important aspect of creative social behaviour. Communication between cliques occurs when two individuals in the different cliques explore design subspaces that are perceptually similar. Each of the individuals is then able to appreciate the other's work because they have constructed appropriate perceptual categories. The transfer of artworks from a source to a destination clique will introduce new variables into the creative processes of the destination clique, the two cliques can then explore in different directions, just as two individuals do when they share artworks. Cliques can therefore act as "super-artists", exploring a design space as a collective and communicating interesting artworks between cliques.

3.3 Domains of Complexity

To investigate the relationship between the search for novelty and the complexity of the resulting artworks an experiment was conducted to compare agents with different preferences for novelty. To measure the complexity of the images the fractal dimension of selected images was calculated using the box counting method [15]. For any two-dimensional image, a measure of its fractal dimension will produce a value between 0.0 and 2.0, depending on how much of the space is filled in the image at different levels of detail.

To investigate the relationship between the preferred degree of novelty and the fractal dimension of the resulting images, two types of agents were used. One type preferred novelty values of N=18 and the other type favoured novelty values of

N=11. Three agents of each type were allowed to explore the space of genetic artworks for 50 time steps. Figure 8 shows how the complexity of the images produced by the two groups of agents quickly diverge and then remain at a constant level. For the group with the higher preference for novelty, the results appear to confirm Martindales hypothesis that the search for novelty promotes increased complexity over time [14], at least up to some limited level of complexity.

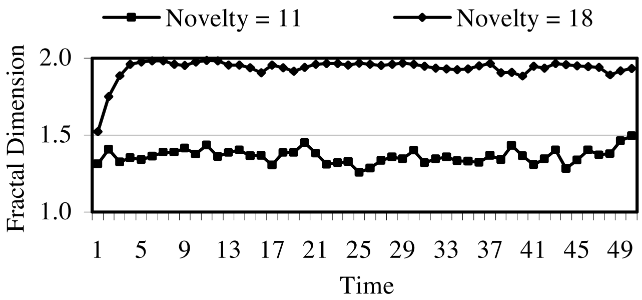


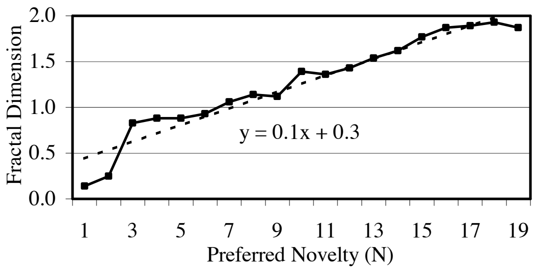
Fig. 8: The complexity of genetic artworks produced by two groups of agents with different preferences for novelty.

To investigate the relationship between a field's preference for novelty and the complexity of the artefacts produced by its members, 19 test groups were created consisting of 3 agents in each group. In each group the agents favoured the same novelty value, across the 19 tests the groups favoured novelty values in the range $1 \leq N \leq 19$. Figure 9 shows that the relationship between the preferred value of novelty and the average fractal dimension of the resulting images is almost linear for the large proportion of values for preferred novelty. In other words, agents with a preference for greater novelty produce images with higher fractal dimensions.

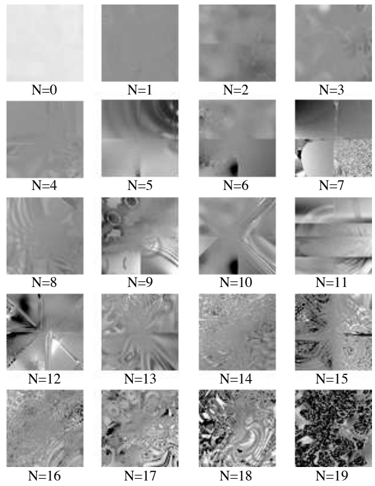
How can we explain this relationship between the preferred novelty of an agent and the fractal dimension of the resulting images? One explanation is that the curious exploration of the space of genetic artworks drives the agents towards subspaces that have an appropriate amount of local variability to continually satisfy the need for novelty. Consequently, agents that prefer novel forms will tend towards areas of the design space that produce more complex images, as there is a great deal more variability between complex images than between simple ones.

4 Discussion

Curious agents have been developed by a number of other researchers. Schmidhüber created curious agents that competed against each other to determine what was



(a) A comparison of the average fractal dimension against a range of peak hedonic values.



(b) A small gallery of genetic artworks evolved by the curious design agents.

Fig. 9: The relationship between preferred novelty and the complexity of the genetic artworks evolved by the curious agents with different preferences for novelty $0 \leq N \leq 19$.

interesting [16]. Marsland et al [17] produced curious robots that explored environments for novelty as a way of generating maps of the space. Interest in intrinsically motivated agents, like curious agents, is increasing as researchers discover the benefits of self-motivated learning in both modelling and applications [18, 19].

Other computational models based on Csikszentmihalyi's system view of creativity have also been developed [20] that demonstrate the important role that authority figures, or gatekeepers, play in creative fields. The contribution of the framework presented here is the bringing together of curious agents and the creative systems to support an approach to computationally modelling creative societies at multiple levels.

The work presented here is still in its early stages of development and there are many ways that it can be extended to improve the models or investigate other features of creative societies. Future work using this framework will aim to extend the experimental possibilities at both the individual and social levels of creativity. Three possible directions for future work are:

Integrating Evaluations of Appropriateness One of the obvious limitations of the work presented here is the lack of an explicit test for the appropriateness of artefacts. To apply the computational model of more significant domains, future work will integrate domain-specific knowledge so that the test for creativity can include a test for appropriateness within a domain.

Integrating Alternative Models of Creative Processes The curious design agents presented in this paper use an evolutionary design tool to explore a design space. Integrating alternative models of creative processes including analogy-making [21] could provide a useful framework for evaluating the effectiveness of such creative processes within a social and cultural context.

Modelling Individuals with Intrinsic Motivations other than Curiosity Curiosity is not the only intrinsic motivation for creative individuals, although it is one of the most persistent [14]. Other motivations for exploring a design space can be computationally modelled in design agents, e.g. competency [19].

Modelling Large Creative Societies The ability to simulate larger creative societies will permit the study of the spread of innovations and styles. It may also facilitate the emergence of new fields as cliques attain a critical size. Spatial and topological relationships will become more important issues in large population models.

Modelling Non-Homogenous Societies There are several other important players in creativity societies besides the producers of innovations including, e.g. consumers, distributors, critics, etc. Each has their own role to play in creative societies; consumers evaluate products, distributors distribute products widely, and critics distribute their evaluations widely. Convincing other people that you've had a creative idea is often harder than having the idea in the first place. In non-homogenous societies of agents, the selection of which agents to communicate with becomes an important strategy for agents seeking recognition as a creative individual.

Modelling More Complex Social Interactions Simulations of technological innovation in industry show that the consideration of the costs of innovation in decision-making can lead to complex behaviour [22]. Simulating similar costs in the design process may provide a better understanding of the economics of creative design in creative societies and the strategies needed to manage creativity with limited resources.

Modelling Domain-Specific Symbol Systems Domains in the real world contain much more than examples of previously produced artefacts. Creative domains often include symbol systems, e.g. languages, that are specific to the knowledge held in the domain. These symbol systems can present opportunities for domains to differentiate as they present barriers to the flow of information between domains.

Modelling the Evolution of Domains Domains and the symbol systems they contain evolve over time through use by the field. Computational models of the evolution of language [23] may provide a useful technique for developing computational models of domain-specific languages that evolve over time.

The aim of this paper has been to present a framework for computationally modelling creative societies using curious design agents and to show some of the research opportunities that exist using models developed using this framework. By using curious design agents as models of individuals within creative fields, the framework provides a flexible basis for developing multi-agent systems that can be used to study the interaction between personal and social judgements of creativity.

References

[1] Sternberg, R.J., Lubart, T.I.: The concept of creativity: prospects and paradigms. In Sternberg, R.J., ed.: Handbook of Creativity. Cambridge University Press, Cambridge, UK (1999) 3–15

[2] Boden, M.A.: The Creative Mind: Myths and Mechanisms. Cardinal, London, UK (1990)

[3] Gardner, H.: Creating Minds: An Anatomy of Creativity Seen Through the Lives of Freud, Einstein, Picasso, Stravinsky, Eliot, Graham and Gandhi. Basic Books, New York, NY. (1993)

[4] Csikszentmihalyi, M.: Society, culture and person: a systems view of creativity. In Sternberg, R.J., ed.: The Nature of Creativity: Contemporary Psychological Perspectives. Cambridge University Press, Cambridge, UK (1988) 325–339

[5] Newell, A., Shaw, J.C., Simon, H.A.: The process of creative thinking. In Gruber, H., Terrell, G., Wertheimer, M., eds.: Contemporary Approaches to Creative Thinking. Atherton Press, New York, NY. (1962) 63—119

[6] Liu, Y.T.: Creativity or novelty? Design Studies **21** (2000) 261—276

[7] Gabora, L.: Meme and variations: A computer model of cultural evolution. In Nadel, L., Stein, D., eds.: 1993 Lectures in Complex Systems. Addison-Wesley, Reading (1995)

[8] Markou, M., Singh, S.: Novelty detection: A review, part i: Statistical approaches. Signal Processing **83** (2003) 2481–2497

[9] Markou, M., Singh, S.: Novelty detection: A review, part ii: Neural network based approaches. Signal Processing **83** (2003) 2499–2521

[10] Berlyne, D.E.: Conflict, Arousal and Curiosity. McGraw-Hill, New York, NY. (1960)

[11] Sims, K.: Artificial evolution for computer graphics. Computer Graphics **25** (1991) 319–328

[12] Witbrock, M., Reilly, S.N.: Evolving genetic art. In Bentley, P.J., ed.: Evolutionary Design by Computers. Morgan Kaufman, San Francisco, CA (1999) 251–259

[13] Kohonen, T.: Self-Organizing Maps. Springer–Verlag, Berlin (1995)

[14] Martindale, C.: The Clockwork Muse. Basic Books, New York, NY. (1990)

[15] Mandelbrot, B.B.: The Fractal Geometry of Nature. W. H. Freeman & Co., New York, NY. (1977)

[16] Schmidhuber, J.: Curious model-building control systems. In: Proceedings of the International Joint Conference on Neural Networks. Volume 2., Singapore, IEEE (1991) 1458–1463

[17] Marsland, S., Nehmzow, U., Shapiro, J.: Novelty detection for robot neotaxis. In: International Symposium On Neural Computation (NC'2000). (2000) 554—559

[18] Singh, S., Barto, A.G., Chentanez, N.: Intrinsically motivated reinforcement learning. In: Neural Information Processing 18. (2004)

[19] Merrick, K., Maher, M.L.: Motivated reinforcement learning for non-player characters in persistent computer game worlds. In: ACM SIGCHI International Conference on Advances in Computer Entertainment Technology, (ACE 2006), Los Angeles, USA (2006)

[20] Sosa, R., Gero, J.S.: A computational study of creativity in design: the role of society. AIEDAM (2005)

[21] Falkenhainer, B., Forbus, K.D., Gentner, D.: The structure-mapping engine: Algorithm and examples. Artificial Intelligence **41** (1989) 1–63

[22] Haag, G., Liedl, P.: Modelling and simulating innovation behaviour within micro-based correlated decision processes. Journal of Artificial Societies and Social Simulation **4** (2001)

[23] Steels, L.: A self-organizing spatial vocabulary. Artificial Life **2** (1995) 319–332