Social Change: Exploring Design Influence

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Abstract. This paper explores some aspects of group divergence based on principles of design disciplines and social dissemination. Extensions to an elementary model are used to explore the fundamental relation between divergence and social influence mechanisms previously employed to explain group convergence. The possible role of a change agent is investigated supporting the notion that there is no need to invoke any extraordinary mechanism other than convergence to trigger social change.

1 Design Disciplines and Social Change

Social influence has been addressed in agent-based systems from a variety of viewpoints [1-8]. A predominant approach focuses on aspects related to convergence phenomena and the formation of social groups or communities. Design disciplines like architecture and industrial design benefit from findings related to the dissemination of values throughout a population of agents in the following ways. Inquiry on the formation of social groups illustrates the fundamental processes by which a particular value -a design artifact- may be adopted and transmitted by clients and the processes by which competing artifacts may bring together a group of adopters or a client base. These models also contribute to a basic understanding of the processes by which some artifacts dominate and prevail throughout extended periods contributing to the definition of an artifact's life-cycle, and the co-existence of alternative artifacts. In sum, elementary models of social influence have captured key issues that provide insights into essential group mechanisms and the emergence of shared values, which are of particular relevance to design studies.

On the other hand, design practitioners often aim to innovate and bring about social change, which could be intuitively seen as a process opposite to the spread of artifacts. That is, if designers are interested in expanding their user base by continuously increasing the number of individuals that adopt their design artifacts, the generation of an alternative artifact could be seen as to cause the reversal of the desired effect, i.e. the dissolution of a social group. This apparent contradiction can be inspected in a model of social influence based on a variety of theoretical views of social change [9]. In this paper we address some elementary aspects of social influence by which a dominant artifact may be replaced by an alternative artifact following the notion of *creative destruction* [10]: the recurring cycle that revolutionalizes a social structure from within, “repeatedly destroying an old one and creating a new one”.

The maintenance of diversity has been of interest in the agent simulation literature [11, 12]. However, not many models of social influence seem to explore the possible sources of diversity and their relation to convergence. Axelrod [1] suggests that a model of social influence needs to include *social drift* proposing this for future extensions and advancing explanations for why diversity may persist. In this paper we address design activity not as an explanation for the persistence of diversity but as a possible source of diversity and social change triggered by an individual [13].

The macro-micro link of social change is arguably one of the open questions in social studies [9] where agent-based simulations could extend the dominant individualistic approach to inspect circular causation [14]. Nonetheless, it seems relevant to discern what type of influence behavior is necessary to trigger social change in the first place. If Axelrod’s [1] model of social influence leads to group convergence, what other mechanism (if any) would be needed to transcend a converged equilibrium and trigger a collective change? To address this question, extensions to Axelrod’s model [1] are presented to include some aspects of divergence. Some limitations of cellular automata modeling are illustrated in this study and the need for a more comprehensive agent-based approach is elaborated.

2 Inspecting Convergence

Axelrod’s model of social influence [1] is a variant of the voter model or the stochastic *Ising* two-dimensional model [15]. These models capture properties of ergodic systems, i.e. those with a recurrent invariant measure to which convergence occurs for any initial distribution. In d-dimensional models where $d \geq 3$ random walks become transient and a probability 0 of total convergence is approached. Nonetheless, significant variants of these models such as where the state space is not compact are still important open questions [15]. Agent-based simulation offers a way to empirically experiment with these phenomena.

Culture in Axelrod’s model [1] is defined as the set of values shared by a population of individuals. Dissemination of culture is approached in a cellular automaton (CA) model of homogeneous agents in a two-dimensional space addressing how a community (i.e., a group of individuals with common values) forms according to the transmission of elements among its individual members. The model describes an individual’s culture in terms of a list of features or variables and for each feature a set of traits or values. Equivalent results are observed in our replication on a torus grid where sites on the edge interact with the neighboring site in the opposite edge of the grid. Agent interaction consists of agents checking for a shared trait with a random adjacent neighbor and picking a different trait, if any, to copy from the neighbor. The execution of this behavior description and the interaction of these simple agents within a shared space produce interesting phenomena. More formally the model is described as follows:

1. Let culture c at a site change as

2. select a random site s, a random neighbour of that site n, and a random feature f
3. let $G(s, n)$ be the set of features g such that $c(s, g) \neq c(n, g)$
4. if $c(s, f) = c(n, f)$ and G is not empty, then select a random feature g and set $c(s, g)$ to $c(n, g)$.

The main results of this model revolve around the emergence of regions -sets of contiguous sites with identical culture. Namely, what determines region formation or convergence in this model includes the range of cultural values, the range of interactions, and the size of the space. For instance, with the Moore neighborhood (i.e. eight adjacent neighbors) the final configuration presents fewer stable regions than with the Von Neumann neighborhood showing that increased interaction channels cause further convergence. Zones, on the other hand, are defined in this model as sets of contiguous sites with compatible cultures where compatibility exists if at least one feature is shared. Increasing the number of sites in a population results in a lesser number of final stable regions because sites will have more time to integrate within a common zone. In other words, bordering regions that were incompatible will take longer to converge and this gives more time for a third culture to ‘break the ice’ and make interaction possible across otherwise incompatible boundaries. The longer a culture takes to dominate therefore, the higher the chances for boundaries to be dissolved.

As the number of traits decreases fewer regions survive since from the initial configuration most sites will share at least one value and thus there are only small chances of an individual being incompatible with the rest. From the outset the population consists of one large compatible zone. On the other hand, small feature spaces tend to hinder agent interaction since the chances of having a compatible adjacent neighbor decrease. In that case multiple alternative regions become locked-in rapidly. In essence, by adjusting the amount of cultural variants, the size of the population, or the interaction channels, it is possible to manipulate the range of final stable regions. Figure 1 shows five typical cases of populations of agents having 3 to 15 features with ten traits each, where culture diversity is plotted against iteration steps. These five cases show how variance in one parameter affects the convergence trend. Notice the ergodicity of the system, i.e. the equilibrium state to which the system converges for any initial distribution.

One central issue towards the inquiry of divergence phenomena is already visible in Figure 1 in relation to the emergence of new cultures during a system run. For instance, if agents have values with a format of five features each with ten possible traits, then two neighboring agents could have values of say 8-7-8-3-1 and 9-7-2-6-4. These agents share a trait (the second feature is 7) and are likely to interact. At the next event, the ensuing value could result in 9-7-8-3-1, thus potentially generating a new culture by a kind of crossover process. Under some circumstances, this divergence can be significant as illustrated in Figure 1 where a system run with a larger number of features presents a steeper divergence stage as part of the convergent trend. Observe that culture variety actually increases on time. Figure 2 shows a more dramatic case after a Monte Carlo simulation (20 system runs) of a population of 100 individuals with 10 features and 20 possible traits.

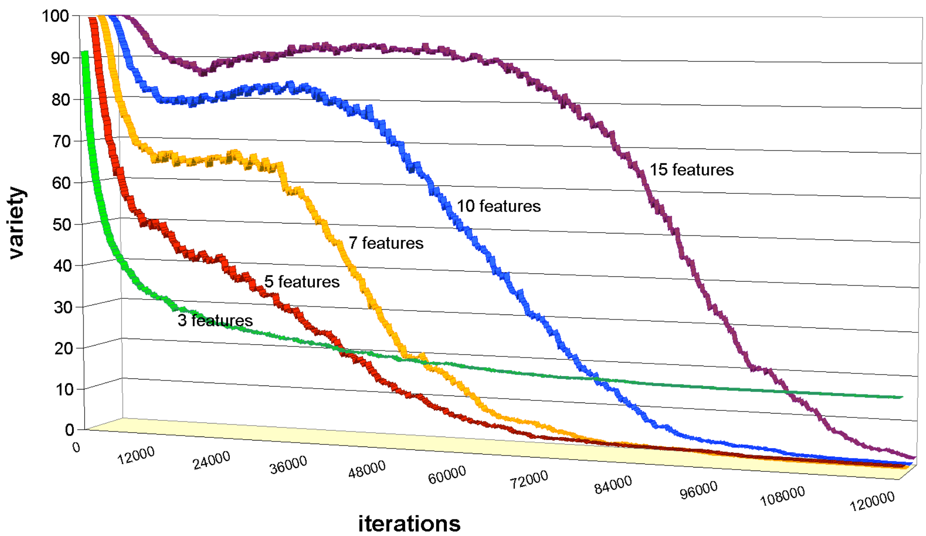


Fig. 1. Convergent trends of five typical populations with varying features (3 to 15) with ten traits each feature. As the feature space increases, divergence stages appear within the convergence trend (humps in variety over iteration steps). All cases consist of populations of 100 individuals run over 120,000 time steps.

Fig. 2. Monte Carlo simulation with 20 runs of a population of 100 sites with 10 features and 20 traits over a period of 120,000 iterations. Notice the divergence stage characteristic of the general convergence trend. New cultures are created as a product of site interaction.

Figure 2 illustrates an implicit and necessary divergent process within the existing convergent trend. As cultural diversity increases new value combinations appear and the less control that any single individual has over a dominant culture since agent interaction will collectively transform the culture. This is reminiscent of the fundamental principle that controlling how a set of values will be disseminated through a population is indeed difficult for an individual. Instead, once the value is released, it is subject to contingencies of social interaction [9, 18]. In design disciplines this could point towards the fact that a design artifact is commonly transformed by its adoption and use by members of a population. The designer is therefore in control of features discernible at the time of conception and much of design activity is in fact concerned with problems caused by previous design solutions.

Lastly, in regards to the possible role of change agents it is noticed that intuitively, the formation of dominant zones and regions accounts for the observation that “a majority culture is more likely to survive than a minority culture” and similarly that “a larger region is more likely to ‘eat’ a smaller region that the other way around” [1]. From this observation the role of designers in generating alternative artifacts to replace a dominant one would appear in principle highly unlikely if not impossible. Notwithstanding, design practitioners are indeed deemed as able to trigger social changes [13]. It is our aim here to explore what particular mechanisms are necessary to enable an individual to trigger a social change. How could it be possible for a minority - of initially only one differing individual - to spread an alternative value across a social group with a dominant culture? Figure 3 illustrates the intuition that a majority region tends to ‘eat’ the smaller region [1] conveying the idea that a small group would inevitably be absorbed by a larger cultural group -or remain isolated if incompatible.

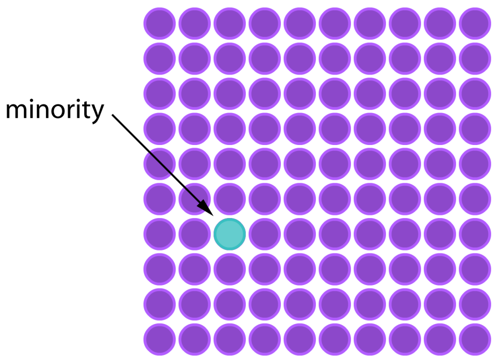


Fig. 3. Design activity is seen as a minority, of initially one individual, triggering a collective change, a notion apparently unaccounted for in a model of social influence that focuses on the formation of convergent structures. Minorities like the one shown in this figure are likely to disappear and be replaced by a dominant culture.

The next section presents extensions to the model where an alternative value is periodically introduced addressing the capability of an individual to transform its social group.

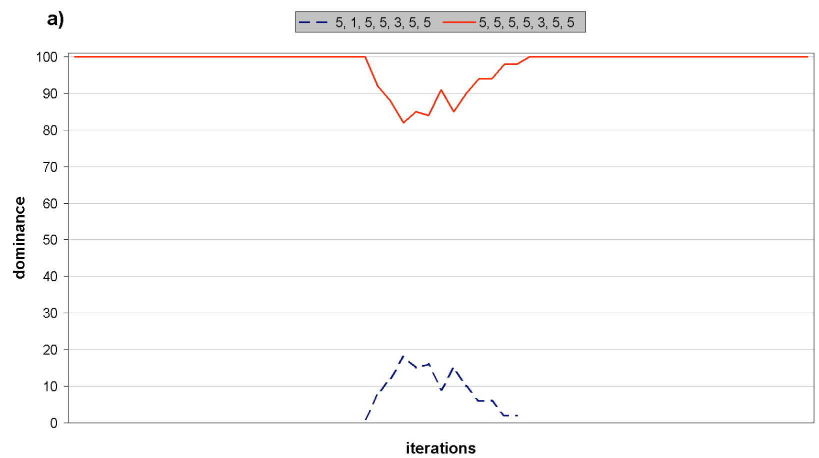
3 Exploring Divergence

This extension of the model proposes that faced with perceived routineness and uniformity, an individual may dissent. The aim is to observe the conditions under which such a dissenting individual may be able to trigger a group change that has an effect on the majority of the population causing the rest of the population to adopt the alternative value. The algorithm of social influence is the same as Axelrod's [1] except for the following procedure added to the model: if all adjacent neighbors have the same culture, and with a given a probability *Pn*, set a random feature to a random value, where the probability is an independent variable. More formally:

1. Let a site *s* introduce an alternative feature *f* in culture *c* as
2. select all adjacent neighbours n_n
3. let $G(s, n_n)$ be the set of features *g* such that $c(s,g) = c(n_n, g)$
4. with a probability *Pn*, select a random feature *g* and set $c(s, g)$ to $c(s, \square g)$.

One way of estimating the ratio of change within a population from a design viewpoint is in the proportion of designers to the rest of society. Consider the recent U.S. Decennial Census of 2000 where the Standard Occupational Classification shows that 0.177% of the population of the United States works in the creative design professions (SOC codes 27-1021 to 27-1027). The extension to the model is thus set with a stochastic condition that enables a change probability *Pn* of 0.177%.

In a typical system run initial conditions are seen to play a minor role with this change rate since the population initially follows the convergence trend illustrated in Figure 1. In contrast, noticeably higher change rates prevent the formation of zones and regions since values repeatedly change before they can be spread across the population. A restriction is introduced by which agents aim to replace a value when they perceive that all their adjacent neighbors have the same value, i.e. local routineness. In this case we focus on the change rate specified above because it allows the whole population to form a single dominant culture where the impact of an alternative value is easier to inspect. Figure 4 shows a set of episodes in a control case where the dominant culture (continuous line) (i.e. adopted by all individuals in a population of one-hundred) faces the introduction and sometimes increasing spread of an alternative culture (dotted line) with varying outcomes over extended time periods.



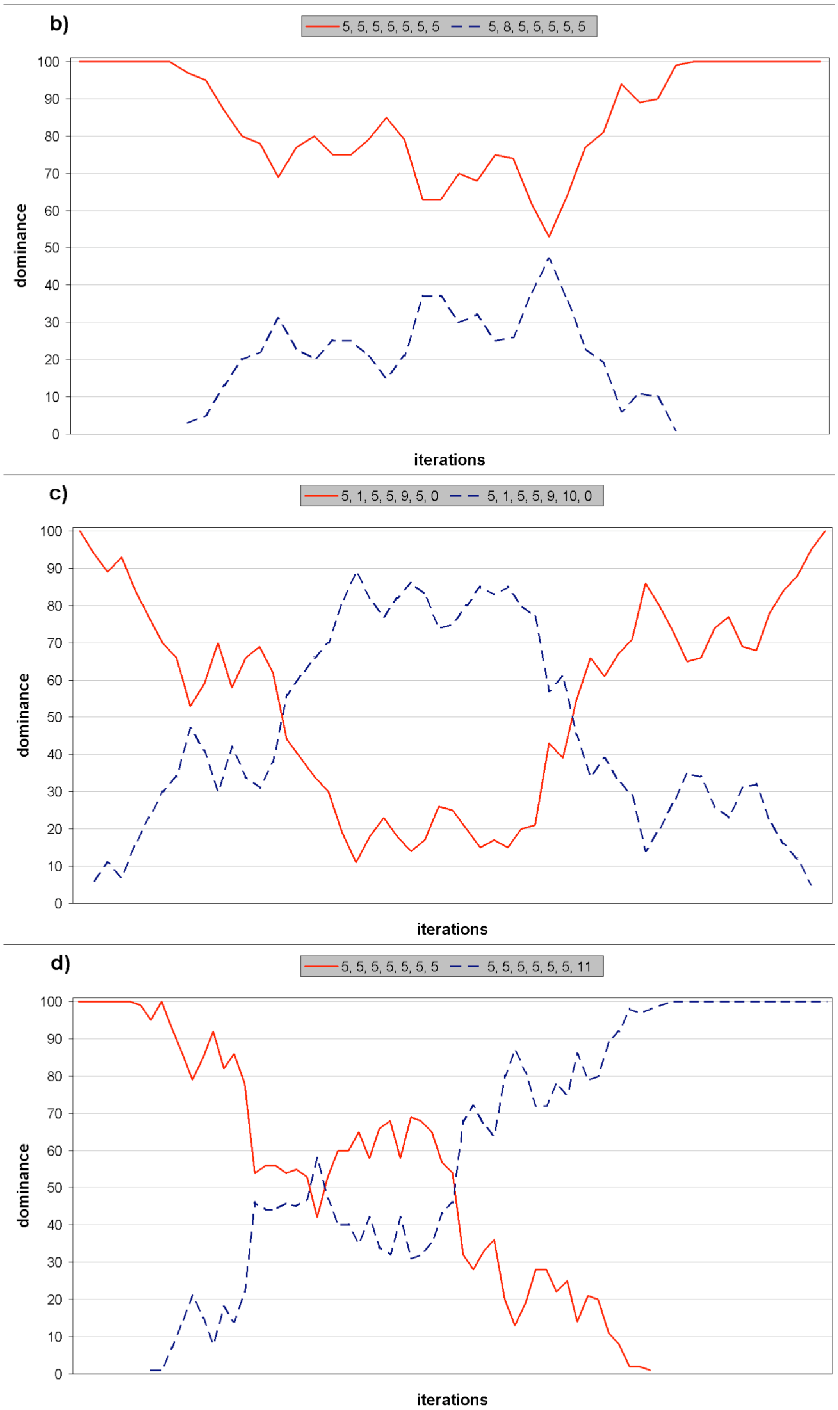


Fig. 4. Episodes where a dominant culture (continuous line) is challenged by the emergence of

an alternative culture (dotted line) with varying consequences. Case a) shows a nascent value that is spread to a maximum of 18 individuals before it decreases and disappears. A mirror effect in the dominant culture is seen as individuals exchange adopted values. Case b) is an episode where the competing cultures reach around fifty percent of the population, after which the dominant culture returns to total dominance. Case c) shows the dominant culture decreasing until only eleven sites share the value only to come back to dominance after a number of time steps. Lastly, in case d) the dominant culture is replaced by an alternative value that is spread across the population.

After the population converges in a stable region of total dominance, change episodes occur periodically over extended periods of time. This is at first counter-intuitive since dominant cultures were assumed to 'inevitably' take over marginal compatible cultures. In fact, such explanation appeared obvious before this extension when it was concluded that longer interaction times facilitate the dominance of a single culture. In some of the cases shown in Figure 4 the prevailing culture (shown with a continuous line) reverts to dominance and in others it is replaced by the alternative value (shown with a dotted line). In Figure 4, case a) shows a nascent value that is spread to a maximum of 18 individuals before it decreases and disappears. A mirror effect in the dominant culture is seen as individuals exchange adopted values. Case b) is an episode where the competing cultures reach around fifty percent of the population, after which the dominant culture returns to total dominance. Case c) shows the dominant culture decreasing until only eleven sites share the value only to come back to dominance after a number of time steps. Lastly, in case d) the dominant culture is replaced by an alternative value that is spread across the population.

At first, it appears counter-intuitive that the same mechanism that enables a social group to reach consensus and form a cohesive collective unit would support dissolution of the group and reformation around a new value. However, it is precisely the tendency to stabilize a shared culture that occasionally facilitates the spread of an alternative value even when this is initially assumed only by one single individual. In this way divergence may actually consist of a kind-of-convergence that produces collective change. In these system runs a number of alternative values are introduced but most attempts to overtake a dominant culture are unsuccessful.

Models of social learning [16] suggest that imitation benefits a population only when coupled with some amount of individual change. Divergence or innovation may thus not be regarded as an extraordinary, opposite, or separate factor of social convergence or imitation [17]. Instead, it appears as an essential component inherent to the system in a fundamental way [10]. However, most research on the diffusion of innovations is characterized by the pro-innovation bias [18]: the assumption that a new solution ought to be spread and adopted by some or all members of a social system. This bias restricts inquiry to after-the-fact data gathering, impedes access to the study of unsuccessful solutions independently of their intrinsic value, and limits access to rejection mechanisms, discontinuance, and re-invention that may occur during evaluation and diffusion stages. This suggests that although potentially illustrative, a majority of cases like the first three in Figure 3 have largely remained outside the literature reporting on such studies. In all, this model captures an elementary notion of co-dependence between convergent and divergent structures. Perhaps the strength of this model is that it shows in a very simple way that an individual needs not invoke any extraordinary mechanism to transform its social group [9]. The same basic mechanism of social influence that initiates a social group appears sufficient to produce the recurrent occurrence of social change.

Moreover, it has been argued that the formation of shared values generates a notion of *normality* [19] that facilitates collective work, communication, and judgment. Individuals may not be able to lean on culture if a higher rate of change is introduced in a population, i.e. everyone would need to learn independently and no collective structures of support would emerge. Clearly, further experimentation is needed to understand the conditions under which social influence may in fact generate group change.

One more aspect that can be inspected in this model deals with the interaction between more than two competing cultures. This is an interesting process but one that easily becomes hard to keep track of. Consider for instance Figure 5 where a cycle of group changes is shown in a control case.

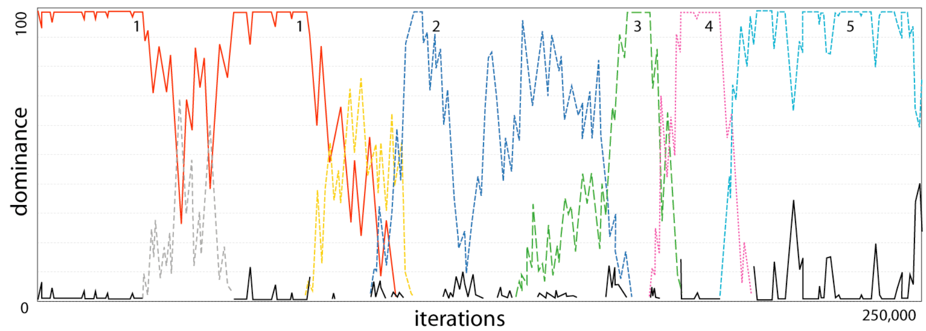


Fig. 5 A typical system run of a population of 100 individuals with alternative values being introduced with a 0.17% probability. Cycles of convergence and recurring replacement of cultures are observed. In this case five different values gain dominance at different times throughout a period of 250,000 iteration steps. Dominance is defined by the adoption of the value by the total number of individuals in a population. In cases 1 and 5 the dominant culture regains dominance a number of times. Notice in contrast the frequent appearance of unsuccessful values that disappear before being spread beyond a minority (lines at the bottom of graph).

In Figure 5 it is possible to observe cycles where a dominant culture is challenged by the appearance of alternative values, which often disappear after being shared only by a minority of individuals (solid lines at bottom of graph). This is reminiscent of the ration of successful innovations [18]. In this control case five different cultures become dominant during varying time lengths whilst around one hundred alternative values were introduced. The total system run consists of a population of 100 sites with initial conditions of total convergence and the data is recorded during 250,000 time steps.

Figure 6 illustrates the interaction between competing cultures in the period between time steps 75,000 to 107,500 of the same control case shown in Figure 4. In this episode a dominant culture is seen to decrease (line A) as a competing value is spread (line B). Around time step 95,000 a third value is introduced by a different site (line C) and in the boundary between the two alternative values a fourth *new* value appears and gains dominance (line D).

What is interesting in this control case is that the fourth value (line D) is not strictly 'new' but is a consequence of social influence: a combination of traits introduced by the two alternative values (lines B and C). In other words, the 'novelty' of the fourth value (line D) is not introduced by the specified behavior but is an emergent result from combining traits through the normal dissemination mechanism. Later, this mediated value becomes dominant. The reason may not be immediately apparent. Arguably, the fourth value (line D) becomes dominant because it capitalizes on the spread of the other values and since the original mechanism of social influence supports the dissemination of different traits (i.e. check for shared trait, copy different trait) the new value reconciles competing alternatives and benefits from their diffusion. This can be called *opportunistic innovation* and may be a significant component in the diffusion of innovations, in particular concerning the unexpected consequences of innovations [18].

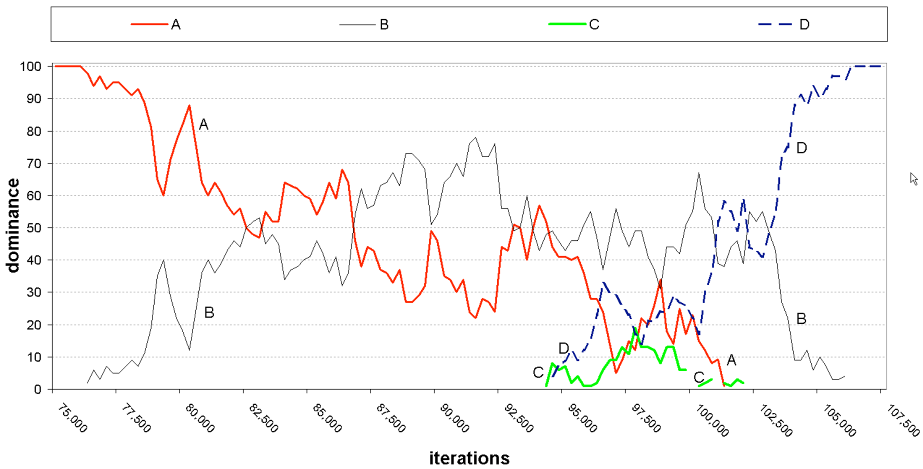


Fig. 6. A change episode is shown here where a dominant culture is challenged by two alternative values, after which a fourth new value, generated by the dissemination mechanisms, becomes dominant.

4 Discussion

Social convergence and divergence are trends commonly attributed not only to separate but to opposite mechanisms of interaction. In this paper we have presented an interpretation of an elementary model of social influence that illustrates a complementary role. These experiments allow the exploration of this interdependency which may be intuitively difficult to discern [1]. Whilst *mere* convergence may in fact generate value diversity (see Figure 2), extensions to this model have shown that the response of one differing individual to perceived routineness may be sufficient to trigger collective change through the same convergent mechanism that brings about group coherence. Therefore, the formation and transformation of communities may occur through a common process of social influence where the *status quo* is disturbed by the appearance of an alternative value around which the social group reassembles.

Design studies characterize designers as change agents of their society [13, 20]. The results presented here suggest that - in principle - it is indeed possible for an individual to trigger a social change and that in order to do this it is not necessary to invoke any special mechanism other than that used to account for group convergence and occasional individual disagreement. Although this is a simplified view of the dynamics involved in social change - particularly the agent/structure relation - it points towards a number of insights in relation to innovation and creativity issues in design.

Firstly, the eventual success of an individual that aims to change their society has been separated in this model from any explicit notion of *utility* suggesting that the merit of widely-spread values across a social group is not necessarily related to the particular attributes of that value. For instance, the dominant values in Figure 5 become so independently of their actual values. In design disciplines this may have important implications, including the partition between quality and creativity. Whilst it is possible to describe and measure the former within the internal characteristics of a design artifact, explanations of the latter need to include the relation of the artifact to the socio-environmental conditions within which it operates. Thus, the creativity of an artifact is not a stable property of itself but a temporal ascription that takes place in its interaction with other agency entities both at the individual and collective levels.

Secondly, the observed change cycles suggest that successful innovations (i.e. widely spread) may only take place sporadically irrespective of the number of attempts. If a population is to follow a convergence trend to give rise to cohesive groups then there would be a collective limit to the frequency of possible innovations. Inquiry into the factors that may determine the innovation rate of a social group is largely an open question for social science.

Thirdly, the results presented here similarly suggest that at the individual level designers and other creative practitioners may be restricted by a social ceiling of influence. That is, in order to become influential, a creative designer would depend upon a collective process by which others are indeed influenced. Persistence or persuasion may thus be an equally important personality trait to creativity as ‘imaginative thinking’. The implication that influential people or ideas are not necessarily the best but could have been in the right place at the right time [21] challenges the mainstream view of creativity. To any extent, socially-ascribed ‘creative people’ do shape their societies but are also product of social dynamics themselves. Whom we end up regarding as creative may or may not be more creative than others.

Perhaps the most significant aspect about this model of social influence in regards to the inquiry of design and innovation is its capacity to capture at such an abstract level change phenomena related to the mutually dependent phases of social convergence and divergence. As some of the points raised here suggest and the literature confirms [9, 10, 18, 19], numerous relevant findings and hypotheses could be explored in more complex agent-based models. Some of the aspects that are considered necessary to enable further experimentation include agent heterogeneity, learning abilities, and especially change of behavior in response to emergent conditions (circular causation) [14].

However, the advantage of simplification in cellular automata modeling carries with it serious limitations. In experimenting with convergent and divergent mechanisms, this framework has alluded to the fundamental relation between agent and social structure. It is within this interaction where a) influential agents arise and b) adequate social conditions arise. However, these interactions are concealed in the modeling approach and it may be necessary to modify the modeling assumptions in order to make this interaction explicit [20].

The implications of this model suggest that design studies may benefit from computational social models as much as the latter may profit from the idiosyncratic characteristics of design disciplines to study social change.

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