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THE CREATIVE VALUE OF BAD IDEAS

A computational model of creative ideation

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Abstract. This paper analyses two ideation principles: idea accessibility and idea connectivity. Access refers to the likelihood to generate a particular idea or set of ideas for a given design task. Connectivity refers to the likelihood of one idea leading to other ideas. These principles are evaluated through a computational model. The results suggest new metrics to assess the value of new ideas. Evaluating new ideas by their accessibility and connectivity has the potential to transform current idea generation practice and research.

Keywords. Design creativity; ideation; computational creativity.

1. Introduction

Creative design ideation is the process of generating new ideas that are ultimately perceived to solve a problem or improve a situation. Novelty, utility and surprise are broadly considered as necessary conditions (Runco and Pritzker, 2011), but to generate inventive, valuable and surprising ideas is not easy. Many ideation methods focus on maximising the number of ideas, called ideational fluency. Most techniques specifically separate generation from evaluation (Osborn, 1963). This is captured by Linus Pauling's phrase: "The best way to get good ideas is to get lots of ideas". This paper examines alternative approaches to such *brute-force* approach to creative ideation. It focuses on intrinsic characterisations of the landscape of ideas generated. A computational model is presented to provide general insights for future research and practice.

Many formal studies of creative ideation measure the total number of ideas produced by individuals or teams, and the average quality of such ideas as judged by experts (Runco and Pritzker, 2011). Some researchers have suggested that creativity research ought to study processes that maximize the quality of one or a very small number of great ideas. A result of one single breakthrough idea and half a dozen low quality ideas is preferable to a dozen of merely decent ideas (Girotra et al., 2010). In ideation research the latter would be judged as more creative as it produces both more ideas and a higher average score. Quality variance of a set of new ideas may be a more accurate and meaningful creative index (Gero and Gomez, 2009).

This paper considers two ideation principles: idea accessibility and idea connectivity, and explores their relevance through a computational model. Access refers to the likelihood to generate a particular idea or set of ideas for a given design task. This is customarily determined when repeatedly running a creative design task in similar conditions: participants tend to generate ideas following a skewed probability distribution. High accessibility indicates commonplace ideas, whilst low accessibility denotes original ideas. Conformity metrics (Genco et al., 2012) and design fixation (Gero, 2011) further provide support for idea accessibility.

Idea connectivity refers to the likelihood of one idea leading to other ideas. This is a more abstract construct based on a structural view of the idea space (i.e., fitness landscapes or network linkages). Priming effects further provide support for idea connectivity (Friedman et al., 2003). The model discussed here supports idea accessibility and idea connectivity as cross-domain heuristics that can guide idea generation independent from the design task or domain at hand.

Exploration and exploitation are ideation strategies specified in this model: the former uses random search while the latter derives rules from recent solutions in order to guide the search (Lazer and Friedman, 2007). In creativity, the structure of an idea space emerges from exploitation, i.e., rules generalised from recent solutions become source concepts leading to further solutions. This has been described in the literature as chains, streams or trains of thought. The topology of the idea space in this model can be shaped by inferred evaluation functions of interest. Ideation strategies to combine exploration and exploitation in a computational model can be predefined by the researcher, or monitoring methods can be incorporated; for example, as a function of the rate of new ideas within a recent time period.

We distinguish ideas according to their potential to generate new ideas. As a result, bad ideas (according to task performance) have the potential to become instrumental in the generation of creative ideas.

2. Computational Models of Creativity

The systemic character of creativity can be observed by the range of disciplines concerned with its study: neural, psychological, cognitive, social, linguistic, historical and management research programs (Runco and Pritzker, 2011). Computational creativity has the potential to capture the emergence of creativity from interactions at multiple levels (Sosa and Gero, 2013). Two main approaches have been adopted in computational creativity: firstly, systems that seek to model creative processes or seek to generate creative products. Generative models include those based on or inspired by human creativity, and those that aim to artificially produce solutions considered as creative by a panel of judges, audiences or critics.

The second and lesser explored approach to computational creativity consists of systems that seek to inform and inspire by enabling the systematic study of principles, factors, scenarios and interactions that assist in developing an understanding of what creativity is (Maher, 2012; Indurkhya, 2012). The systematic study of these systems helps to clarify and question assumptions, reveal insights, test hypotheses and in general help our thinking about creativity and potentially inspire innovative research and practice.

Systems built to yield products considered as creative by human judges irrespective of the generative processes, adopt a “strong” view of artificial creativity. Systems built to simulate generative and evaluative factors of creative products irrespective of the external validation of the products’ creativeness, adopt a “weak” view (Searle, 1980). This measure of strength is a continuous range, rather than a discrete categorisation.

Stronger approaches address questions such as “Can computers ever be creative?”, while weaker approaches consider questions such as “Can computation help us understand creativity?”. These approaches complement each other. Models that aim to help us understand creativity principles inform and are informed by models that aim to mimic and transcend human creativity. The contributions of all types of computational creativity can equally inform other research traditions, for instance by framing new hypotheses, testing the consistency and implications of assumptions, and proposing new experimental settings. In-vivo and in-vitro methods can complement and be complemented by in-silico studies of creativity (Wiltschnig and Onarheim, 2010).

A semantic network study relates the creativity score of design ideas to the structure of the thinking space (Yamamoto et al., 2009). In that study, a thinking space is represented as a network with nodes as the concepts evoked in concept generation and links as their semantic relationships as defined by a lexical database. The findings include a correlation between the evaluated originality of ideas and two features of the thinking space: mean degree or number of links and network density. A related early neural model of idea generation represents concepts in associative hierarchies where semantic entities interact in the presence of external cues (Marupaka et al., 2012). Such models based on functional neurocognitive networks explicitly represent creative ideation as "a function of how knowledge is organised". That certain thinking patterns can lead to creative ideas is a promising finding when concepts are represented by words, and provides guidance for our model of design ideation.

A complementary modelling approach has explored the connection between the creativity score of ideas and the structure of the social networks of individuals (Björk and Magnusson, 2009). They indicate a direct relationship between network connectivity and the quality of creative ideas. Similarly, Baer (2010) reports a personality dimension (openness to experience) as a moderator of the link between creativity and social network features including size, strength and diversity.

A comprehensive computational study of creative ideation could potentially combine the models described before in a tripartite system of neural networks, social networks, and idea networks. To this end, the idea-agent-social context (IAS) framework of computational creativity provides a modelling platform that includes design ideas (I), thinking mechanisms of individual agents (A), and the social context (S) (Sosa et al., 2009).

Recessive genes in genetic algorithms are building blocks in poor performing solutions that can later recombine to produce high performing solutions. The following section presents a simple computational simulation model of creative ideation. This is followed by preliminary results and a discussion of future work.

3. Modelling Ideation

The computational model of ideation described here is formulated based on the idea-agent-social context (IAS) framework (Sosa et al., 2009). In this paper we present and discuss the creative task model at the idea level (I) and leave aside individual cognitive agency (A) and the social context (S). The task used in our model can be described as a simple visual challenge as follows: "Use *g* geometries of *s* sides as the initial elements to generate as many different compositions (*g's'*) of more than *g* geometries of equal or more *s* sides". Graphically, Figure 1 depicts an example of 2 initial geometries of 3 sides (*2g3s*) that overlap to generate 3 new geometries of 3, 4 and 6 sides. Following a shape algebra notation (Stiny, 2008), a sample composition of shapes A and B includes all addition and subtraction operators, namely:

$$(g_1, g_2) \rightarrow (g_1 - g_2, g_1 + g_2, g_2 - g_1) \quad (1)$$

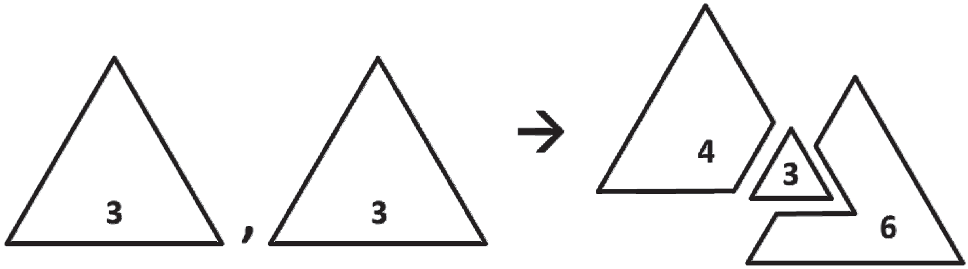

Figure 1. Two three-sided geometries (2g3s) generate three geometries of 4, 3 and 6 sides.

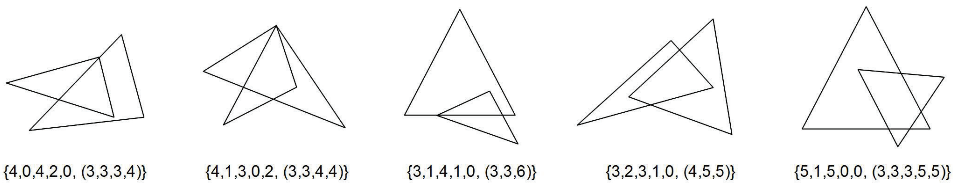

Figure 2. Five sample compositions from an initial set 2g3s and their notations.

In order to capture geometrical and topological relationships in this task, the following notation is used to represent shape compositions: $\{\Sigma g', i, o, l, v, (s'_1 \ldots s'_n)\}$ where: g' = final geometries, i = points located inside the area of an initial geometry, o = points located outside the area of an initial geometry, l = points located within a line of an initial geometry, and v = points located within a vertex of an initial geometry; $(s'_1 \ldots s'_n)$ is a subset of size $\Sigma g'$ that indicates the number of sides for every final geometry g'. Figure 2 depicts sample final compositions and their notations.

This visual divergence task is straightforward to represent computationally and demonstrates some elementary aspects of the ill-structured and open-ended character of design problems (Goel, 1995). It supports emergence since new shape semantics are not explicitly represented at input time (Gero and Jun, 1998; Gross, 2001). Finally, the task supports re-interpretation and learning since the final solutions can be used as input geometries or the goals can evolve over time to satisfy target geometrical or topological target features as the result of individual agency (A) or social conditions (S) (Sosa et al., 2009).

Exploration in this model of idea generation consists of defining random points in a given coordinate space from which initial shapes are built. Resulting candidate combinations are validated by criteria such as the presence of line intersections that cause shape emergence, and number of resulting shapes equal or greater than number of initial shapes. We hypothesise that some human subjects adopt exploration at least as an initial strategy for this type of visual tasks, however this paper only represents the ideation task and not the cognitive mechanisms of ideation. The following sample cases illustrate the range of ideational fluency (mean number of ideas) in exploration: *2g3s*: 10^3 steps = 7.23 solutions; *2g3s*: 10^4 steps = 9.38; *2g3s*: 10^5 steps = 15.35; *3g3s*: 10^4 steps = 134.22 solutions. Cases are normalised over 100 simulations.

There are no intrinsic evaluation criteria in this task beyond divergence, i.e., maximising number and variance of solutions. Further evaluation functions that capture domain-specific processes can be incorporated. For example, researchers may select specific geometrical or topological relationships, or visual semantic denotations. A characteristic of creative tasks is that such evaluation functions are likely to change over time (Goel, 1995). This model captures the notion that bad ideas at time t_i may become even worse at time t_{i+1}, and they may turn into good –even great– ideas at t_{i+n} as a result of the co-evolutionary nature of design problems and solutions (Maher and Poon, 1996). These changes of target features can originate from any IAS dimension: perceptual differences or preference drift in the agent architecture (A), evolving consumer patterns or influence channels (S), technological evolution (I), etc (Gero and Kannengiesser, 2009).

Accessibility in this model is given by the mean frequency of solutions found in exploration over repeated cases. Since one of the main goals in creative ideation is to reveal uncommon yet useful ideas, in this model, ideas of low accessibility that still satisfy the task's goal can be considered as preferred over ideas that are commonly found across simulation runs. The accessibility distribution in idea spaces, r, can be characterised by $r = d_b/d_t$, where d_b represents the mean accessibility of the bottom decile and d_t stands for the mean accessibility of the top decile. When $r = 1.0$, the idea space has a uniform accessibility distribution, whilst as r approaches 0, variance increases indicating that a few 'gems' are found in a 'dense haystack'.

Exploitation in this model consists of a guided search informed by rules inferred from experience. Since time is a constraint in creative ideation, case *2g3s* in 10^4 iterations is considered in this paper. This particular choice of settings is not significant here –we plan to validate this model against human performance in this type of tasks in the future. The assumption behind exploitation as a complement to exploration is that agents are likely to develop generative heuristics as they progress in the task.

Design concepts in this model stand for generalised rules drawn from previous solutions that are used to guide the search. The rate of exploration/exploitation, defined as e, is the ratio of the total simulation steps that are spent in exploration/exploitation strategies. An e value of 25/75 means that in 25% of the simulation exploration is active, while the remaining 75% is spent in exploitation. In case *2g3s* in 10^4 iterations, $e = 25/75$ generates an increase of over 90% in ideational fluency over exploration-only runs (Sosa and Gero, 2012). Although the numerical values obtained from such cases are not transferable beyond this model, in principle the significant advantage of such combinations of explore/exploit processes could imply that creative tasks (ill-structured, open ended, NP complete) are highly sensitive to ideation management strategies such as facilitation and priming.

Idea connectivity is modelled here by tracing how design concepts lead to new solutions during exploitation. Connectivity variance appears to be an important measure; in particular, what task conditions generate either solutions that lead to many solutions or solutions that are "dead ends".

4. Results: Ideas of Low Accessibility and High Connectivity

The first outcome analysed here refers to the settings of our model that influence accessibility results. Task conditions such as the size of the coordinate space influence accessibility distributions in exploration since some solutions become unreachable or less likely as a function of grid size. Likewise, accessibility distributions vary as a function of the initial settings –for example, in *2g4s*, the probability of shared vertex is significantly higher than in *2g3s*. The first principle of ideation that can be observed in this model is that the representation and the initial conditions of the task determine what can be considered the *potential creativity* of a task. The choice of representation has been shown to influence the type and degree of creativity, for example when designers choose either to sketch or to build models of their early ideas (Acuña and Sosa, 2010). More research is necessary to better understand the impact of problem formulation in creativity.

Secondly, the exploration/exploitation rate, *e*, determines accessibility distributions in this model. With *e* ranges of high ideational fluency such as $e = 25/75$, accessibility distributions are also the highest. As the numerator increases in *e*, the accessibility distribution, *r*, increases until a point where longer exploration periods bring about high redundancy. Such diminishing returns effects are explained by the observation that in cases where exploration is active for long periods, every idea generated has a low probability of being new. This grounds the effectiveness of *e* values such as 25/75 in this model: such combinations generate the highest number of total ideas because they yield higher idea variances upon which exploitation builds on novel ideas. We conclude that high productivity in exploitation requires a sufficiently large idea base that is also as diverse as possible. Combinatorial or derivative processes in ideation are more efficient when they act upon a highly diverse population of initial ideas. Future creativity research could reveal the impact of anticipating and delaying concept variation during an idea generation session.

Thirdly, the *fertility* of new ideas can be established by the accessibility of the ideas to which they are connected. On the one hand, some solutions of low-accessibility end up leading to solutions of high-accessibility. Such rare yet redundant ideas can be understood as a “difficult way to reach easy ideas”. However, other low-accessibility solutions do lead to new solutions of low accessibility too. These are very valuable in ideation as they represent “uncommon ideas that yield other uncommon ideas”. For example, if in our model two inter-connected ideas require each an average of 4,500 steps to be reached, an ideation agent would only require 4,500+1 steps to reach both, as opposed to 9,000 steps if they had to be reached independently. Fertile ideas need not be of low accessibility, some high accessibility ideas (commonplace) can be connected to low accessibility ideas. These represent the holy grail of ideation: “easy shortcuts to reach rare ideas”. Creativity research has yet to address the formation of chains or trains of ideas. Understanding how new ideas lead to further ideas either by ‘piggy-backing’ or ‘leap-frogging’ could yield facilitation heuristics and tools to improve collaborative ideation.

Finally, some bad ideas can be very valuable for creative ideation. In our model this is the case of low-score or even invalid solutions which nonetheless lead to valuable and uncommon solutions via a small variation. For example, solution {2,1,3,2,0 (3,6)} depicted in Figure 3a would receive a very low creativity score if the task’s goal was to find 3 or more final geometries, or if the goal was to find shapes of 5 sides. Nonetheless, solution {2,1,3,2,0 (3,6)} leads directly to solution {4,1,3,2,0 (3,3,4,5)} depicted in Figure 3b through a variation in the location of a single point. The resulting solution has a very low accessibility score (0.06%) in our model, yet it would receive a very high creativity score under the aforementioned criteria since it contains 4 final geometries, one of which has 5 sides. In these conditions, solution {2,1,3,2,0 (3,6)} is a clear example of the creative value of bad ideas.

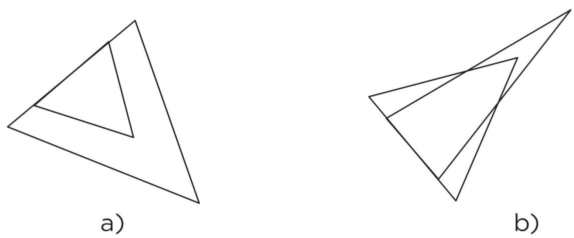

Figure 3. a) solution {3,1,3,2,0 (3,4,4)} and b) solution {4,1,3,2,0 (3,3,4,5)}.

5. Discussion

The modelling effort presented in this paper suggests an insightful addition to Linus Pauling's phrase: "The best way to get good ideas is to get lots of ideas" – with the addendum: "And the best way to get lots of ideas is to first generate a few that are as different as possible and then strategically build on them". This work shows the need for research in facilitation techniques that monitor idea accessibility (or any similar variance metric). The estimated accessibility distribution of the idea space can be used to balance exploration and exploitation in ideation. The estimated connectivity of solutions can be used to inform the exploitation strategies.

We are currently using this idea generation model to build multi-agent simulation models that include individual agency and social factors using the IAS framework of creativity (Sosa et al., 2009). With accessibility and connectivity mapped in a range of cases, we plan to implement ideation agents capable of self-regulating their exploration and exploitation processes. We also plan to seed the system with a few solutions of low accessibility in order to increase the generation of creative solutions. Further, we plan to validate this ideation model using human performance benchmarks to characterise the more realistic settings in our model. In such experiments, we plan to prime human subjects with fertile ideas to test whether they generate solutions of higher variance and quality.

This work aims to inform and inspire ideation researchers and practitioners. A new generation of creativity techniques could be derived from this type of work. For example, the model presented in this paper suggests that new metrics of ideation are necessary to assess the value of new ideas based on their potential to trigger more ideas, beyond their perceived value according to the task goals.

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