



USING AI TO EVALUATE CREATIVE DESIGNS

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Abstract. Many have offered criteria for judging a design as creative. Among these criteria have been *novelty*, *value*, and *surprise*. We offer a unique perspective and synthesis of these three criteria with the goal of giving agents – be they artificial, human, or collectives thereof – a common model to judge the creativity of their own designs and the designs of others, and ultimately to inform computational modelling of creative design. We illustrate an AI approach to judging creativity using an example of sustainable design -- the Bloom laptop.

Keywords: *evaluating creativity, novelty, value, surprise, clustering, sustainable design*

1. Introduction

There is increasing interest in computational systems that model creative processes and generate creative designs, yet we still rely on humans to evaluate whether a specific design is creative. In parallel there is increasing interest in computational systems that encourage and enhance human creativity; these latter systems make no claims about whether the computer is being creative, but do make claims that the human/computer pairing is more creative than the human alone.

As the boundary between human creativity and computer creativity blurs, we are interested in evaluating creativity that makes no assumptions about whether the creative entity is a person, a computer, or a (potentially large) collective intelligence of human and computational entities. We desire a “Turing Test” for creativity that is not biased by the form of the entity that is doing the creating. Ultimately, such tests will imbue artificial agents with an ability to assess their own designs, informing computational models of creative reasoning. Such tests will also inform the design of cognitive assistants that are effective collaborators with humans in sophisticated socially intelligent computational systems.

This paper takes steps towards assessing creativity by considering formalizations of three criteria for creativity that are often referenced in the literature, though not always together and often by different names; these are *novelty*, *value* and *surprise*. We believe that our treatment of these criteria goes beyond earlier treatments, in part because we synthesize across them, suggesting and formalizing relationships between the three. Our paper begins with a survey of relevant creativity research;

followed by targeted surveys of novelty, value and surprise; formalizations of each of the three in terms of distance measures; and illustrate these measures with laptop designs, to include the Bloom laptop. We end with the relevance of machine learning for assessing creativity and to other future work.

2. Creativity research

When describing and evaluating creative processes and products, there is a “conceptual space” (Boden, 2003) of possibilities that structures, constrains and otherwise biases thought. Boden (2003) describes combination, exploration, and transformation as ways in which the conceptual space is traversed when generating a creative design: *combination* finds novel ways of combining ideas within the conceptual space; *exploration* finds parts of the space that were not discovered previously; and *transformation* extends the space to include novel ideas. Much work on creative thought has focused on processes of individuals (Mumford, Mobley, Uhlman, Reiter-Palmon, and Doares, 1991). Recently there has been interest in understanding individual and team cognition in creative processes, and the role of shared mental models (Reiter-Palmon et al 2008). From a computational creativity perspective, Gero (2000) presents combination, transformation, analogy, emergence, and first principles as processes for generating creative designs. Maher et al (1995) presents a framework to characterize different computational processes in terms of transformation and exploration and describes a zone of creativity to evaluate their potential for generating creative designs. Brown and Chandrasekaran (1989) distinguish routine, innovative, and creative design in terms of existing knowledge of decompositions and plans for generating the design. A similar distinction between routine, innovative and creative design is made in Goel (1997) and Gero (1994), showing how creative designs result in a new, often expanded conceptual space.

Often, we cannot observe the creative process directly. Rather, people often judge the design (or artefact, product, idea, etc) that results from a process instead of judging the process directly. Judgements of designs can serve as a “Turing Test” of the underlying process that produced the design. Though a Turing Test approach is imperfect, we continue in this tradition, and speak of “creative designs.”

Most descriptions of creative designs, including dictionary definitions, include novelty as an essential characteristic. However, psychologists, computer scientists, and engineering designers suggest creativity goes beyond novelty. Csikszentmihalyi and Wolfe (2000) define creativity as an idea or product that is original, valued, and implemented. Amabile (1996) claims an outcome or result is interpreted as creative if it is both novel and appropriate. Runco (2007) summarizes several researchers who claim that creativity results in something new and useful, and others who claim creativity is more than that. Boden (2003) claims that novelty and value are the essential criteria and those other aspects, such as surprise, are kinds of novelty or value. Wiggins (2006) defines novelty and value as different factors of creativity, yet often uses value to indicate all valuable aspects of a creative product. Cropley and Cropley (2005) propose four broad properties of products that characterize their creativity: effectiveness, novelty, elegance, and genesis. Besemer and O'Quin (1987) define a Creative Product Semantic Scale of products along three dimensions: novelty (the product is original, surprising and germinal), resolution (the product is valuable, logical, useful, and understandable), and elaboration and synthesis (the product is organic, elegant, complex, and well-crafted). Horn and Salvendy (2006) report on consumer perception of creativity along three dimensions: affect (our emotional response to the product), importance, and novelty. Goldenberg and Mazursky (2002) report that creativity in products includes "original, of value, novel, interesting,

elegant, unique, surprising." From the engineering design perspective, Oman and Tumer (2009) combine novelty and quality to evaluate engineering designs. Shah, Smith, and Vargas-Hernandez (2003) associate creative design with ideation and develop criteria for novelty, variety, quality, and quantity of ideas.

Amabile (1982) summarizes the social psychology literature on the assessment of creativity: while most definitions of creativity refer to novelty, appropriateness, and surprise, current creativity tests or assessment techniques are not closely linked to these criteria. She further argues that "There is no clear, explicit statement of the criteria that conceptually underlie the assessment procedures." In response to an inability to establish criteria for evaluating creativity that is acceptable to all domains, Amabile (1982, 1996) introduced a Consensual Assessment Technique in which creativity is assessed by a group of judges that are knowledgeable of the field. Since then, several scales for assisting human evaluators have been developed, such as Besemer and O'Quin's (1999) Creative Product Semantic Scale; Reis and Renzulli's (1991) Student Product Assessment Form; and Cropley et al's (2011) Creative Solution Diagnosis Scale.

In sum, the two most-widely endorsed factors in the literature that contribute to creative designs are novelty and value. Surprise is articulated much less often, but we nonetheless believe it is an important factor, different from but related to both novelty and value. While these factors have been discussed to varying extents, and have informed the development of computational systems to generate designs that were then judged by humans to be creative, we know of no work that quantifies these factors so that an artificial agent can use them collectively to assess creativity.

3. AI models of novelty and surprise

Computational models of novelty and surprise have been developed for various purposes in AI and these models inform our understanding of these concepts for evaluating creative design. A clustering approach based on Self-Organizing Maps (Kohonen, 1993) is the basis for a real-time novelty detector for mobile robots (Marsland et al. 2000), using Stanley's model of habituation (1976). Habituation and recovery imbues a novelty filter with the ability to forget, which for design, allows novel designs that have been seen in the past to be considered again as potentially creative using a new value system. Saunders and Gero (2001) drew on the work of Berlyne (1996) and Marsland et al (2000) to develop computational models of curiosity based on novelty, using sigmoid functions to represent positive reward for the discovery of novel stimuli and negative reward for the discovery of *highly* novel stimuli. Negative rewards reflect that designs that are too different are not considered creative, perhaps because they were perceived as violating constraints or norms that help establish the value of a new design. This suggests that a creative design should be sufficiently different to be considered novel, but similar enough to be "in the ballpark".

Horvitz et al (2005) develop a model of surprise for traffic forecasting. They generated probabilistic dependencies among variables, for example linking weather to traffic status. They assume a user model that states that when an event has less than 2% probability of occurring, it is marked as surprising. They use a temporal model of the data, grouping incidents into 15 minute intervals. Surprising events in the past are collected in a case library of surprises. Itti and Baldi (2004) describe a model of surprising features in image data using a priori and posterior probabilities. Given a user dependent model M of some data, there is a $P(M)$ describing the probability distribution. $P(M|D)$ is the probability distribution conditioned on data. Surprise is modeled as the distance d between the prior, $P(M)$, and posterior $P(M|D)$ probabilities. Ranasinghe and Shen (2008) develop a model of surprise as integral to developmental robots. In this model, surprise is used to set goals for learning in an

unknown environment. The world is modeled as a set of rules, where each rule has the form: Condition \rightarrow Action \rightarrow Predictions. A condition is modeled as: Feature \rightarrow Operator \rightarrow Value. For example, a condition can be feature1 > value1 where “greater than” is the operator. A prediction is modeled as: Feature \rightarrow Operator. For example, a prediction can be “feature1 >” where it is expected that feature1 will increase after the action is performed. Comparisons can detect the presence (%) or absence (~) of a feature, and the change in the size of a feature (<, <=, =, >=, >). If an observed feature does not match its predicted value, then the system recognizes surprise.

The models of surprise and novelty provide different approaches to recognizing creativity using clustering and distance, probability and expectations, and generalized rules based on previous experience. In the remainder of this paper we focus on clustering and distance, while acknowledging that other AI models may be part of a larger toolbox for evaluating creativity.

4. An AI approach to evaluating factors of creativity

A “Turing Test” for creativity presupposes that characteristics of a design tell us something about the process that created it. To develop such a test we elaborate on two principles: (1) creativity is a relative measure in a conceptual space of possible and existing designs and (2) novelty, value, and surprise capture distinct characteristics of creative design within that space. We illustrate these principles using the laptop domain, describing the conceptual space initially of Mac laptops only, and consider the addition of a new laptop to this set: The Bloom laptop (Figure 1), which was designed by mechanical engineering students at Stanford University and Aalto University (Bhobe et al, 2010). The laptop was designed for ease of recycling with design requirements including minimum number of parts and types of material, modular construction and disassembly, ease of disassembly, minimum disassembly time and has an unexpected value-adding feature of a removable keyboard during use.

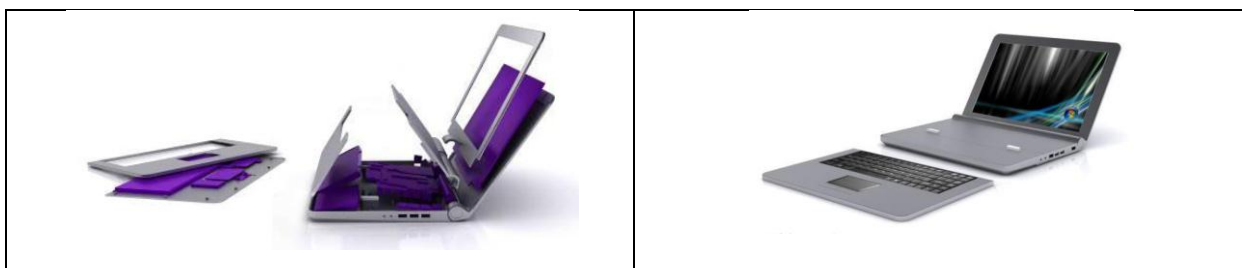


Figure 1. Bloom laptop modular design and removable keyboard; images from (Bhobe et al 2010); available under CC BY-SA licence (<http://creativecommons.org/licenses/by-sa/3.0/>)

4.1 Relative measures in a conceptual space

Novelty, value and surprise for a new design are measured in a conceptual space of existing and possible designs. We assume a representational schema in which a design is described by attribute-value pairs, though relational schemas are possible and often preferable. For measuring novelty and value, we suggest different aspects of the conceptual space: a description space for measuring novelty and a performance space for measuring value. For example, we characterize the description space of laptops as a set of attributes including Processor Speed (GHz), Height (in), Display size (in), Memory (GB), Storage (GB), HD Graphics Processor, Resolution-x (pixels), Resolution-y (pixels); and the value space to include Battery life (hours), Price (min US\$), Weight (lbs). Note that there is subjectivity, stemming from the preferences of users – an elderly person using the laptop for email and Web surfing may care very much about weight, price and battery, and may not even know that

processor speed is a characteristic, much less having a preference on it. So, while Csikszentmihalyi (1996) suggests that value is a social construct and determined by the “gatekeepers,” these gatekeepers and preferences will, of course, vary among observers, as will the attributes that these observers associate with preferences. We have not specified aesthetic and affective features of creativity as a separate factor since these are domain dependent and therefore may be included in what we call value. For example, in many areas of design, people correlate the aesthetic of increasing complexity of images or ideas with creativity; in such cases, complexity is a characteristic that would be included in the measurement of value.

In this initial work on assessing creativity quantitatively, we use distances as relative measures within the design space. For example, given two designs, $X^{(1)}$ and $X^{(2)}$ each described along numeric attributes, $X_i^{(k)}$, the Euclidean distance is the square root of the sum of squared differences in the corresponding attributes (after normalization) of each design: $\sqrt{\sum(X_i^{(1)} - X_i^{(2)})^2}$. Even when we commit to distance as a means of measuring novelty, there are multiple ways to operationalize this approach.

- As above, we can measure the distance of a design in terms of its distances to other *specific* designs in the conceptual space; for example, equating novelty of design X as the distance to its *nearest neighbor* in the conceptual space is an example of a individual-link approach.
- However, if we were to measure novelty of X by the ratio of X’s distance to its nearest neighbor, divided by the average of nearest-neighbor distances of all other designs (excluding X), then this would be an example of a family-link measure, since information about ALL designs, through the average of nearest neighbor distances, would be taken into account.
- Yet another family-link strategy is to measure the distance between X and the *centroid* of designs in the conceptual space. The centroid is a theoretical point in the space, created by averaging the attributed values across all designs in the space. X’s novelty could be operationalized as its distance to the centroid, or some ratio involving the centroid.
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Continuing along these lines, it is natural/desirable for cognitive agents to organize their observations into rich conceptual structures. When new designs are observed, they are not (necessarily) assessed relative to an unorganized collection of previous designs, but against a backdrop of conceptual structures over these designs. Clustering has been proposed and used as an organizing principle for an autonomous agent’s conceptual structures (e.g., Fisher, 1996; the use of SOMs in Marsland et al., 2000). We will use the well-known K-means clustering algorithm, using Euclidean distance and centroids, to organize the known designs. When a new design is observed, its distance to the nearest cluster centroid will inform assessments of novelty, value and surprise.

4.2 Measures of novelty, value and surprise in a conceptual space

Novelty, value and surprise are distinct perspectives on the location of a new design in a conceptual space of possible designs. We treat novelty and value as arising from different perspectives of the conceptual space (as noted in 4.1); novelty stems from a comparison (e.g., based on distance) in a *descriptive space*, and value is based on attributes that have utility preferences associated with them.

Importantly, while novelty and value are assessed in different (descriptive and performance) spaces, we assume that both can be assessed through distance – distance in descriptive space and distance in performance space. In addition, of course, value not only has a magnitude component (distance), but a directional component too. We don’t address the directionality component here other than to note that

a measure like Euclidean distance cannot capture it per se; and just as there were choices in how to use distance (e.g., centroid vs neighbour), choices in directionality must also be addressed (e.g., is positive score in one performance dimension more important than others).

It is possible for something to be novel and valuable, but not be surprising. Surprise is a feature that is based on expectations, which can themselves be represented as a subspace of possible designs – thus, surprise is based on anticipating patterns or trends in the space of both actual designs and possible designs, leading to violated expectations.

We illustrate our approach to evaluating these three characteristics for the Bloom laptop, relative to a space of previous Mac laptops (i.e., MacBook, 11-inch MacBook Air, 13-inch MacBook Air, 13-inch MacBook Pro, 15-inch MacBook Pro, 17-inch MacBook Pro). The values for descriptive and performance attributes for the Mac laptops were taken from the apple.com technical specifications, and the values for the Bloom laptop were found in Bhobe et al (2010). The laptops have been conceptually organized using the K-means algorithm (with $K=2$, with attribute normalization). Distances between the Bloom and nearest centroids inform measures of novelty, value and surprise.

Novelty: Table 1 shows the full set of descriptive attributes (column 1), the cluster number (second to last row), and the distance from each design to the centroid of its cluster (last row). The Bloom's (rightmost column) Euclidean Distance to the centroid of its cluster is an order of magnitude larger than the distance of the Mac designs to the centroid of their respective clusters. This larger distance indicates that the Bloom is novel with respect to the other designs in this space, in large part because of the large differences in Body Parts (row 1), Removable Trackpad (row 2), and Removable Keyboard (row 3). In fact, there was no variance on these three variables before Bloom's introduction, and they would likely not have been used in descriptive analyses at all – Bloom's introduction added these variables in effect.

Value: Table 2 shows the performance attributes (again, a matter of subjectivity, but our example illustrates the point), the cluster number (second to last row), and the distance from each design to the centroid of cluster 1 (since the Bloom laptop is in a cluster of 1 and the distance to its centroid is 0). When comparing the Bloom to existing laptops, this distance is 2 orders of magnitude higher than the other designs, due to differences in the first three attributes/rows of Table 2.

Surprise: The large distance between the Bloom and the centroids of the 2 clusters in the description space suggests that in a 3-cluster space, the Bloom would be placed alone, and indeed K-means ($K=3$) places the Bloom in its own cluster. In value space, even in the 2-cluster solution, the Bloom is placed alone. We interpret surprise as a difference so great that the new design is effectively creating a new cluster in the conceptual space, and thereby changing expectations for new designs.

Table 1. Description space for laptop design (Data from apple.com and Bhobe et al, 2010)

	MacBook	11-inch MacBook Air	13-inch MacBook Air	13-inch MacBook Pro	15-inch MacBook Pro	17-inch MacBook Pro	Bloom Laptop Design
Body Parts	1	1	1	1	1	1	14
Removable Trackpad	0	0	0	0	0	0	1
Removable Keyboard	0	0	0	0	0	0	1
Processor Speed (GHz)	2.4	1.6	2.13	2.7	2.3	2.3	2.4
Height (in)	1.08	0.68	0.68	0.95	0.95	0.95	1.08
Display size (in)	13.3	11.6	13.3	13.3	15.4	17	13.3
Memory (GB)	4	4	4	8	8	8	4
Storage (GB)	500	128	256	500	750	500	256
HD Graphics Processor	0	0	0	0	1	1	0
Resolution-x (pixels)	1280	1366	1440	1280	1440	1920	1280
Resolution-y (pixels)	800	768	900	800	900	1200	800
Battery life (hours)	7	5	7	7	7	7	7
USB ports	2	2	2	2	2	3	2
Cluster	1	1	1	1	2	2	1
Distance to Centroid	0.14	0.16	0.12	0.18	0.03	0.03	1.8

Table 2. Value space for laptop design (Data from apple.com and Bhobe et al, 2010)

	MacBook	11-inch MacBook Air	13-inch MacBook Air	13-inch MacBook Pro	15-inch MacBook Pro	17-inch MacBook Pro	Bloom Laptop Design
Disassembly (min)	45	45	45	45	45	45	2
Removable Trackpad	0	0	0	0	0	0	1
Removable Keyboard	0	0	0	0	0	0	1
Price (min US\$)	1000	1000	1300	1200	1800	2500	1000
Weight (lbs)	4.7	2.3	2.9	4.5	5.6	6.6	4.7
battery life (hours)	7	5	7	7	7	7	7
Cluster	1	1	1	1	1	1	2
Distance to Centroid	0.0148	0.0524	0.0175	0.005	0.0164	0.0094	2.167

Before closing, we draw from Boden (2003) and Gero (2000), who note that there are several ways in which a new design can be creative: a previously unknown value for an attribute is added (which the Bloom did in the case of several attributes), a new attribute is encountered in a potentially creative design (again, with the Bloom), or a sufficiently different combination of attributes is encountered. In all of these cases, a creative design changes the organizational structure of existing designs in a conceptual space, which we show using clustering and relative distance. The Bloom illustrates *transformational* creativity in that it triggers a realignment of conceptual structures. There are many

interesting questions that need to be addressed as we design a cognitive artificial agent that can learn (cluster) designs and assess novelty, value and surprise (and creativity generally) of new designs relative to learned concepts, particular issues of how the agent is motivated to transform the conceptual space. Our point here is to sketch how clusters of designs in a conceptual space might be learned and used to assess creativity.

5. Conclusions

This paper presents an AI approach to evaluating creative designs that is independent of the design discipline and of the source of creativity. The AI models operate in a conceptual space, thereby contextualizing the evaluation and providing a relative measure of creativity rather than a binary judgment. Formalizing the criteria for evaluating creativity facilitates comparisons of computational systems that are themselves creative, as well as computational systems that enhance human creativity. The three criteria for evaluating relative measures of creativity described here are novelty, value and surprise. With metrics for these we have a common ground for evaluating creativity in human, computer, and collectively intelligent systems.

Our next steps are to evaluate our method for evaluating creative designs, which will involve first collecting attribute-value representations of successive designs in a domain such as the laptop illustration used here, and measuring how successive laptops compare to previous ones along our metrics. Ultimately we are interested in how our distance-based assessments compare with judgments by humans when presented with the same ordering of designs. In addition to having to elaborate on some smaller, but important issues, such as directionality (as well as magnitude) in assessing value, we have alluded to larger issues of conceptual *organization* of conceptual spaces that undoubtedly bias human judgements and that will ultimately guide computer judgements of creativity as well. Unsupervised machine learning approaches, while often viewed as data analysis tools, are also approaches for organizing a cognitive agent's memory of designs, products and processes (Fisher, 1996; Fisher and Yoo, 1993), creating the backdrop against which an agent can make more sophisticated assessments of creativity.

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