Chapter 6
On the Role of Computers in Creativity-Support Systems

Bipin Indurkhya

Abstract We report here on our experiences with designing computer-based creativity-support systems over several years. In particular, we present the design of three different systems incorporating different mechanisms of creativity. One of them uses an idea proposed by Rodari to stimulate imagination of the children in writing a picture-based story. The second one is aimed to model creativity in legal reasoning, and the third one uses low-level perceptual similarities to stimulate creation of novel conceptual associations in unrelated pictures. We discuss lessons learnt from these approaches, and address their implications for the question of how far creativity can be tamed by algorithmic approaches.

6.1 Introduction

Even though the last few decades have seen a steady progress in the development of computer systems that produce artifacts in the domain of visual art [8, 43], music [7, 40, 44], literature [39, 51]; and so on, generally they have received a negative press as regard to their creativity: computers cannot have emotions, programs do not have intents, creativity cannot be algorithmic, and so on [4, 57]. Even designers of computational creativity systems seem to take an apologetic tone when it comes to ascribing creativity to their systems. For example, Colton [9] argues that it is not enough to generate an interesting or creative artifact, but one must also take into account the process by which the artifact was generated. Krzeczkowska et al. [38] took pains to project some notion of purpose in their painting tool so that it might be perceived as creative. Such views blatantly expose the implicit assumptions underlying creativity: namely that it crucially needs a creator with emotions, intentions, and such. A consequence of this view is that creativity is considered an essentially human trait, and cannot be ascribed to computer programs or AI systems (or to animals like elephants and gorillas).

B. Indurkhya (✉)
Department of Computer Science, AGH University of Science and Technology, Cracow, Poland
e-mail: bipin@agh.edu.pl

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We critically examine this traditional view in the light of our previous experiences in designing creativity-support systems and modeling creativity. We present three very different case studies here, each of which incorporates a different mechanism of creativity. These systems are based on our previous research, and we will mention here only the main ideas behind each of the systems and the results. After a brief discussion of these systems, we will present our views on the role of computers in supporting and modeling creativity.

6.2 Some Case Studies of Computer-Based Creativity-Support Systems

We have been studying and modeling different aspects of creativity for over twenty years [23–34]. During this time, we have also explored various computational approaches to creativity, and have developed some computational systems that stimulate imagination and emergence of novel ideas and associations in the users, or model such processes. We present here three such systems in order to provide some concrete examples of how computers can play a crucial role in supporting creativity.

6.2.1 Stimulating Creativity in Generating Stories

We implemented a system *Story Telling from Pictures* [34] inspired by an idea *Little Red Riding Hood in a helicopter* from Rodari's fascinating book *The Grammar of Fantasy* [54]. In this technique, children are given a list of five or six words, and are asked to make a story that involves all of them. Rodari's idea was that if all but one of the words in the list are chosen so that they remind the children of some familiar story, and one unrelated but familiar word is thrown in with them, children's imagination is stimulated in incorporating the unrelated concept in the familiar story. Children enjoy this activity, and produce a great many imaginative variations of the original story.

For example, suppose children are given the words 'grandmother', 'wolf', 'forest', 'cape', and 'helicopter'. The first four words remind the children of the story *Little Red Riding Hood.* However, the last word is completely unrelated. We must emphasize here two necessary conditions for this technique to work. The first is that the children must be familiar with the story *Little Red Riding Hood.* If they do not know the story, or if the words used in the list do not remind them of the story, for there are several versions of the story, then this technique is not so effective in terms of stimulating imagination. The second condition is that the children must be familiar with the unrelated word as well. If they have no idea what a helicopter is, then the technique does not work either.

In this technique, the children find it interesting and challenging to make a story that incorporates the strange but familiar element (the helicopter) in the familiar story. Each child tackles this task in her or his own way. Their imagination is stimulated, and they enjoy the activity. They listen to each other's stories, and react to them enthusiastically.

Our creativity-support system based on this technique was implemented in three stages. In the first stage, we showed a number of pictures to the children and asked them to describe each picture. Our aim here was to find out the concepts with which our target user group (the children) was familiar. In the second stage, we created a library of *picture elements*, where each picture element depicted an object familiar to the children. Picture elements were also organized in a semantic association network to reflect which ones of them are related and which ones are not. In the third stage, we composed a picture by combining picture elements such that all the picture elements were associated except one that was semantically distant or unrelated. So, for example, the system might generate a picture of a cow in a classroom by combining some classroom-related picture elements like desks, blackboard, notebooks, children and teacher, and add the unrelated picture element cow. On evaluating the system, we found that the children found writing about such pictures more interesting, and they wrote longer stories.

This system was a straightforward implementation of Rodari's technique. The point we would like to emphasize is that it is not so difficult for a computer program to add an unrelated object in a scene. However, this task is harder for people, for as soon as a concept or word is given, all the associated concepts and their corresponding words get automatically activated—it is difficult to suppress these activations and to look beyond them to find an unrelated word or concept.

The T-puzzle (Fig. 6.1) provides an excellent example of how our past experiences, and perceptual and conceptual associations constrain us. The puzzle has four simple wooden pieces, and the objective is to arrange them in the form of the letter T. However, people have a very hard time solving this puzzle because their prior perceptual experiences keep them trying the same combinations over and over again [62].

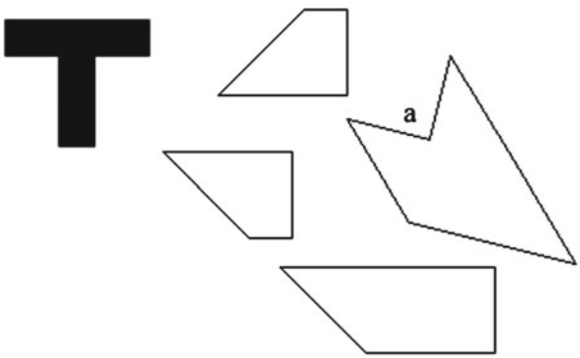

Fig. 6.1 The T-puzzle

On analyzing many of Rodari's techniques to stimulate creativity and imagination, we find that they are essentially elaborate ways to get some unrelated combination of words or concepts. When people try to connect these unrelated concepts in their imagination, their creativity is stimulated. For example, in one method, two children are asked to go to different rooms, close their eyes, open a dictionary at a random page, and put their finger at some point on the open page. This produces two random words, and then the children make a story connecting these two words. In another activity, each child is asked to bring a picture from some newspaper or magazine. The children sit in a circle, and all the pictures are put face down in the middle. Children take turns at random (by drawing lots), and the child whose turn it is turns over one of the pictures, and starts a story based on that picture. Each child (in random order) repeats this process, except that all the subsequent children have to continue the story generated so far by incorporating the picture they just turned over. This process is akin to generating novel and creative metaphors by combining unrelated words or concepts together [29].

In terms of computational modeling, at least this aspect of creativity is easily modeled algorithmically [31]. This is because it is very difficult to model common-sense conceptual associations on the computer, and it has been a challenging research areas since the advent of Artificial Intelligence. This implies that it not difficult for a computer program to break or ignore these conceptual associations and generate a combination of two unrelated words or concepts. For us humans, on the contrary, conceptual associations are an unalienable part of us, and so elaborate methods have to be devised to look past those existing associations.

6.2.2 Modeling Creativity in Legal Reasoning Computationally

We now move to a completely different topic and present another piece of previous research where we studied creativity in legal reasoning, and sought to model it computationally [23, 25]. The main idea behind this approach was that creative insights often come from applying the high-level structure (or gestalt) of one situation to the low-level details of another situation. The distinction between the levels (high and low levels) is important, for if both the situations are considered from a high level, then only traditional analogy can result, which, as far as creativity is concerned, is counterproductive (see [24, 29] for detailed arguments with examples). We explain this approach with an example below.

We focused on situations where new categories are brought in to analogize or distinguish between prior cases and a new case in order to argue for a particular resolution of the new case. Our domain was a particular tax law in the US, which allowed taxpayers to deduct their home-office expenses from their taxable income under certain conditions. These exception conditions were based on factors such as whether the home office was the *principal place of business* (*PPB*) (e.g. when a doctor saw patients regularly at a home clinic), whether the employer provided office space for the employee, and so on.

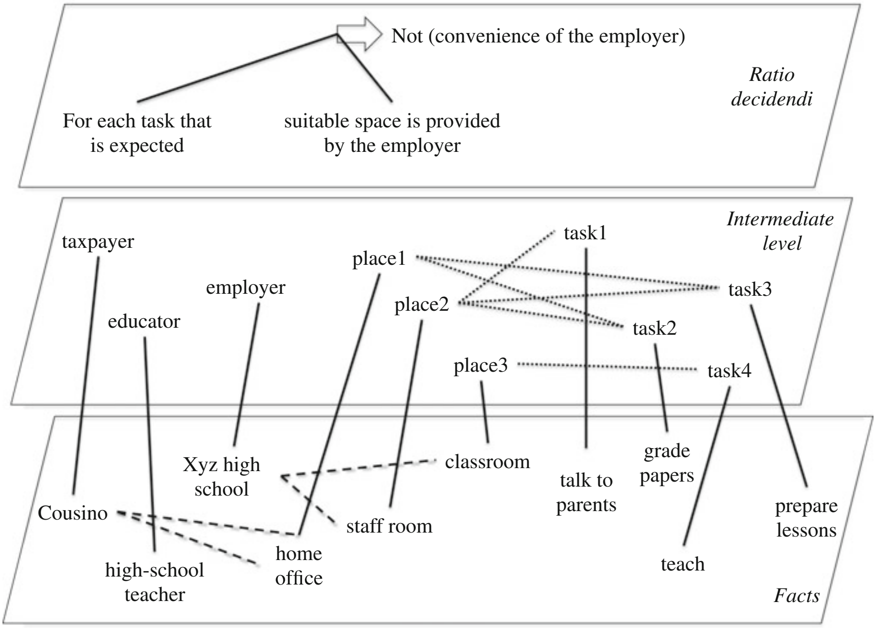

Fig. 6.2 A partial representation of the *Cousino case* (*Dashed lines* means *provided by* and *dotted lines* mean *designated space for*.)

In particular, among the precedents, there was a case of a high-school teacher Cousino, who claimed home-office deduction, but the courts denied him because the school provided him a *suitable space:* a classroom where he could teach, and an office equipped with a phone and office supplies. Let us refer to this as the *Cousino case*. A partial representation of the *Cousino case* is shown in Fig. 6.2.

In this figure, three levels of representations are shown. The *Facts* level corresponds to the low-level or perceptual features and the *Ratio decidendi* level corresponds to the high-level conceptual or the gestalt features. At the *Ratio decidendi* level, the justification for the decision is presented in abstract legal terms. An *intermediate* level of representation is also shown, which mediates between and connects the high-level representation to the low-level representation. (See [25] for more details.)

Another case among the precedents concerned a concert violinist Drucker. He claimed tax deduction for a studio he maintained at home where he practiced regularly. The courts allowed him the deduction arguing that for musicians, their principal activity is rehearsal, and the employer did not provide any space where the musician could rehearse. Let us call this the *Drucker case*. A partial representation of the *Drucker case* is shown in Fig. 6.3.

Now consider the case of a college professor Weissman, who claims tax deduction for an office he maintained at home. In the *Weissman case,* the college provided him a shared office. But the taxpayer argued that because many staff members shared the

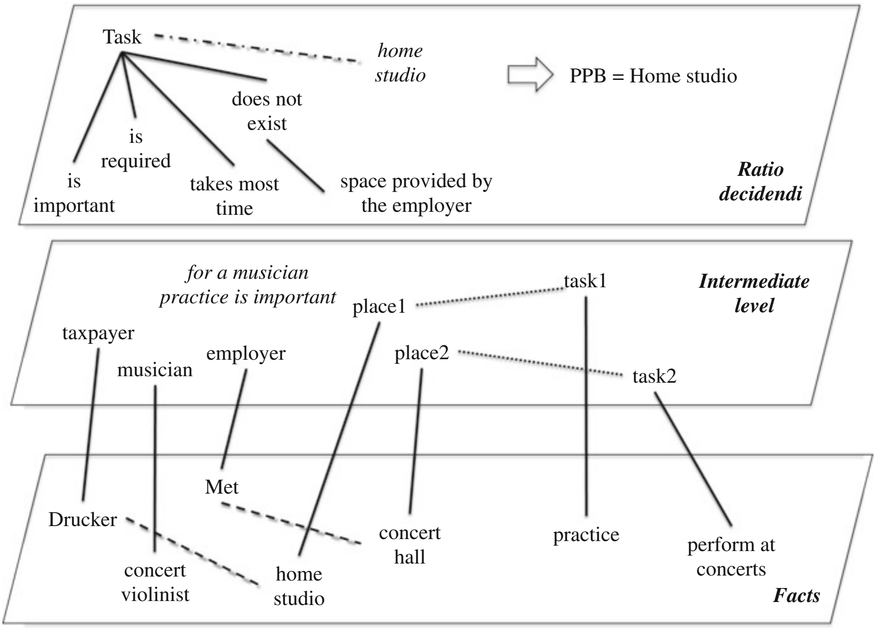

Fig. 6.3 A partial representation of the *Drucker case* (*Dashed lines* means *provided by, dotted lines* mean *designated space for,* and *dot-dash lines* means *performed at.* PPB is *principal place of business*.)

office, he could not leave his books and other material safely there. Let us consider this to be the new case.

With this background, the *Cousino case* is very similar to the *Weissman case* (the new case) and supports a decision against Weismann. When the *Drucker case* is applied to the facts of the *Weissman case,* we also get a decision against Weissman, because for each task that the college professor had to perform as part of his duties, there was some place (the shared office) provided by the employer. This situation is shown in Fig. 6.4.

However, when the *Cousino case* is activated, the category *suitable space* comes into play. Now we can reinterpret the *Drucker* using this category to argue that the decision favored the taxpayer because the employer did not provide any *suitable space* to carry out the activity. This reinterpretation of the *Drucker case* is shown in Fig. 6.5.

With this reinterpretation, the *Drucker case* is rendered similar to the *Weissman case* (the new case), and supports a decision in favor of Weissman as shown in Fig. 6.6. (See [25] for details, and also [23].)

It may seem a small semantic quibble to some readers, but legal arguments often hinge on such quibbles. There is another example discussed in [25] that hinges on introducing the term *substantial.* We should also add that all the analyses and

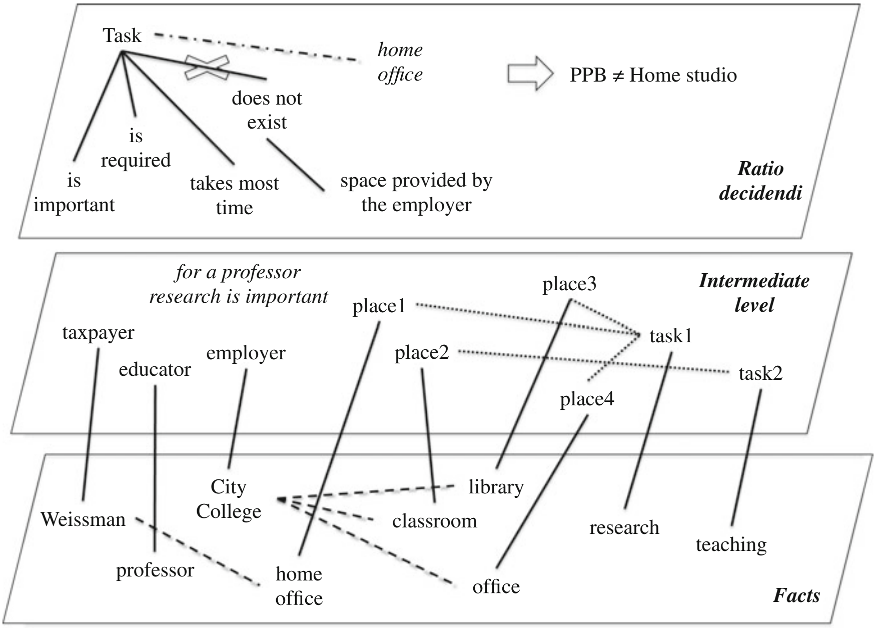

Fig. 6.4 *Drucker case* applied to the *Weissman case* (*Dashed lines* means *provided by, dotted lines* mean *designated space for,* and *dot-dash lines* means *performed at.* PPB is *principal place of business*.)

representations used in these examples were derived from actual opinions written by the judges when rendering their decisions.

The implications of this for computational systems is that we need to be able to model the process of reinterpretation, by which concepts and categories are applied to different data (for which they may not have been intended) in novel ways. This is consistent with recent research that suggests *psychological distance* as a mechanism for enhancing creativity [60]. Moreover, it has been demonstrated that psychological distance can be induced by such simple devices as taking another person's perspective or thinking of the problem as if it is unreal [35].

It is interesting to point out that the ability to get a new insight or perspective was one of the advantages claimed for case-based reasoning when it was promoted by Riesbeck and Schank ([53, pp. 9–14]). They compared and contrasted three modes of reasoning: (1) reasoning with ossified cases (rules or abstract principles), (2) reasoning with paradigmatic cases (cases with a given interpretation), and (3) reasoning with stories (cases with many possible interpretations and capable of re-interpretations). They argued that it is the third mode of reasoning that displays the most flexibility and power of having a knowledge base containing cases. However, most approaches to case-based reasoning in the 1990s and early part of the 2000s worked largely with indexed cases, which precludes this reinterpretation step. (See, for instance [6].) But in recent years, advances in data mining and unsupervised learning techniques pro-

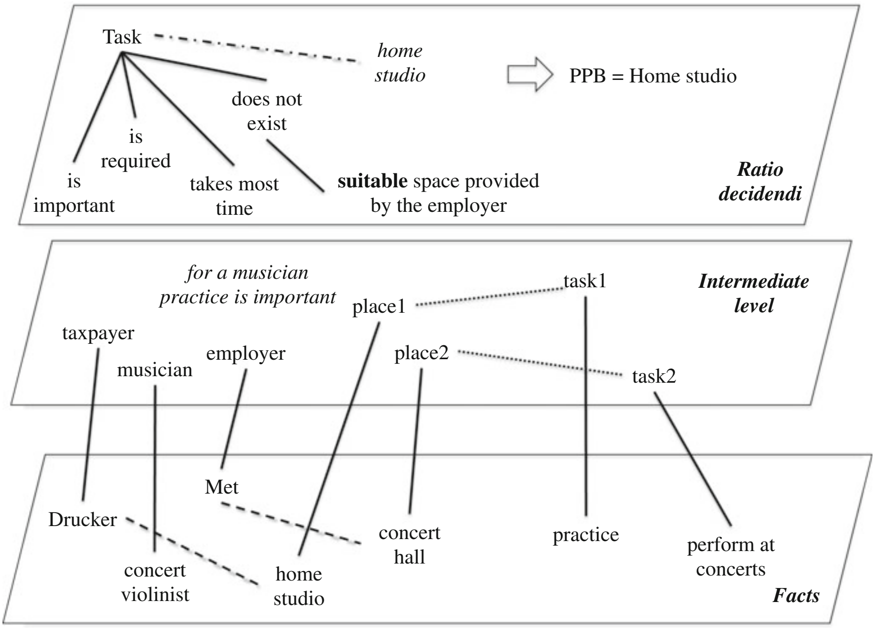

Fig. 6.5 *Cousino case* applied to reinterpret the *Drucker case* by introducing the category *suitable space* (*Dashed lines* means *provided by, dotted lines* mean *designated space for,* and *dot-dash lines* means *performed at* PPB is *principal place of business*.)

vide us with many new approaches to model the reinterpretation process. (See, for example [21, 65, 66].)

6.2.3 Role of Low-Level Perceptual Similarities in Stimulating Novel Conceptual Associations

Finally, we present a third approach to creativity in which we assessed the role of low-level perceptual similarities—namely similarities with respect to shape, color, texture, etc.—on emergent features when two images are juxtaposed. A feature related to a metaphor is considered *emergent* if it is not normally related to either of the two terms of the metaphor alone. For example, in "Her gaze, a flash of diamond", 'seduction' is an emergent feature as it is not normally related to 'gaze' or 'diamond' [16]. A major methodological problem in working with images is in determining the degree of low-level perceptual similarities between two given pictures. One alternative is to ask the participants to rate the degree of perceptual similarities between pairs of pictures, but the drawback is that when we look at a picture, conceptual and perceptual features interact heavily, and it is difficult to be certain that only perceptual

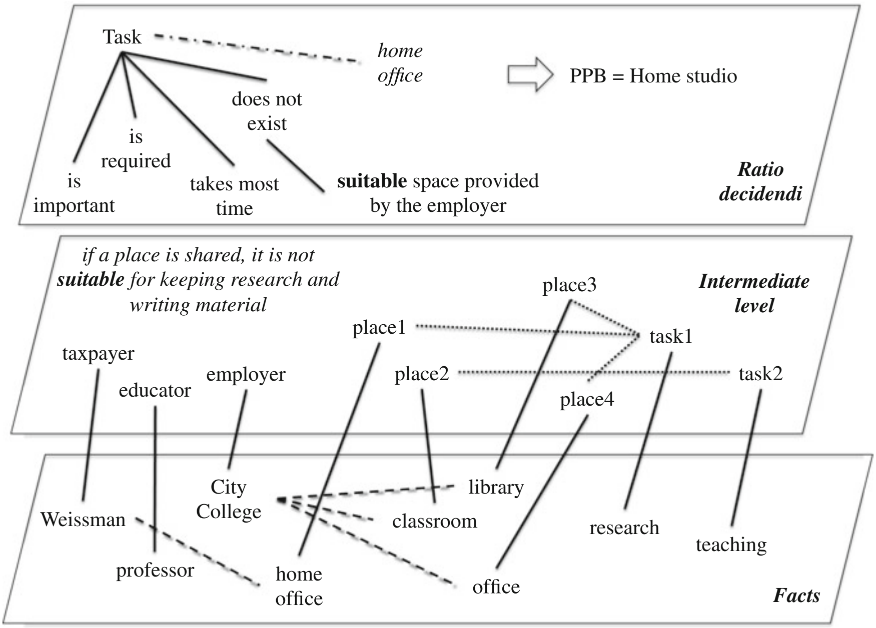

Fig. 6.6 Reinterpreted *Drucker case* applied to the *Weissman case* to support a decision in favor of Weissman (*Dashed lines* means *provided by, dotted lines* mean *designated space for,* and *dot-dash lines* means *performed at* PPB is *principal place of business*.)

features were used in determining the degree of similarity. To address this problem, we turned to image-processing programs.

In the field of machine vision, a number of algorithms have been developed for low-level visual processing. These algorithms extract features (like color, shape, texture, and so on) of images, which are analogous to features found in the early stages of visual processing in humans. So a similarity measure based on these features would reflect perceptual similarity.

We used one such image-based search system called Fast Image Search in Huge Database (FISH), which compares two images based on low-level perceptual features like color, shapes, texture, etc., to get a similarity index for them [64]. We refer to this as *algorithmic perceptual similarity*. For example, consider the pair of images shown in Fig. 6.7. The image on the left is of the world-famous marble mausoleum *Taj Mahal* that was built by the Moghul emperor Shah Jahan in the 17th century. The image on the right is of wine bottles. These two images were given a high perceptual similarity index by the FISH system. In fact, the wine bottles image was retrieved by the system as a *similar* image when queried by the *Taj Mahal* image. If we examine them carefully, we can see the perceptual similarities: the tall slender minarets of the *Taj Mahal* are analogous to the shape of the wine bottles. However, when people

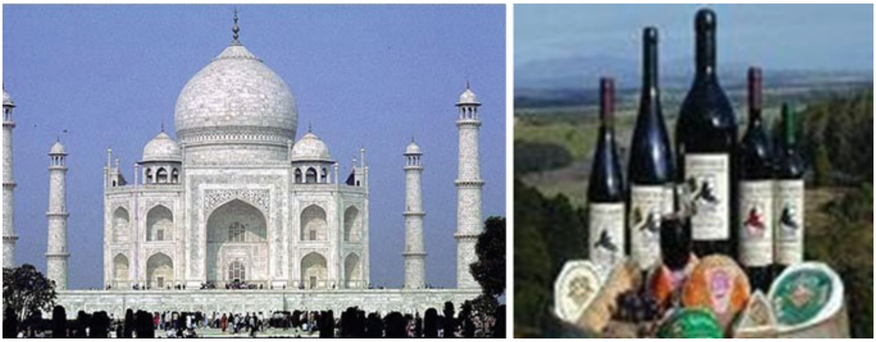

Fig. 6.7 An example of algorithmic perceptual similarity

look at these two images, they tend to focus on conceptual aspects, and fail to find any significant similarities, if they find them similar at all.

Using such stimuli, we experimentally studied how perceptual similarities correlate with people's ability to interpret pairs of images metaphorically, and with emergence of new features that are not a part of either image [46]. Our results show that a pair of perceptually similar images (in terms of color, shape, etc.) is more likely to be given a metaphorical interpretation. Here are some examples of the interpretations given to the pair of images in Fig. 6.7 by the participants: 'Becomes better as it grows old', 'Standing pillars of tradition', 'Beauty in taste', 'Taste of history', 'Taj for eyes, wine for tongue', 'What a waste of time.' We also found that perceptual similarity correlates positively with emergent features.

An implication of these results is that they provide yet another way in which computational approaches can aid creativity. If this hypothesis—namely that low-level perceptual similarities facilitate novel conceptual associations (among people)—is correct then a computational system based on an algorithmic approach to perceptual similarity will be quite effective in stimulating creative imagination in the viewer. Systems based on such approaches can be used for creating persuasive ads, intuitive educational material, aesthetic pleasing art, and so on [32].

6.3 Is Creativity Computational?

We now return back to the question we raised in the introduction: Can creativity be algorithmic? Or is it essentially a human quality? To examine such questions, let us consider two different characterizations of creativity. The first one focuses on the process by which a human being engages in a creative pursuit. If we try to think of creative people, who comes to mind? Perhaps Einstein, Mozart, Michelangelo or Leonardo da Vinci. In the modern times, we might think of Steve Jobs. But what do we mean when we say that they are creative?

Perhaps music came naturally to Mozart. In a letter to his father on Nov. 8, 1777, he wrote: "I cannot write in verse, for I am no poet. I cannot arrange the parts of speech with such art as to produce effects of light and shade, for I am no painter. Even by signs and gestures I cannot express my thoughts and feelings, for I am no dancer. But I can do so by means of sounds, for I am a musician." Perhaps one could say that his brain was structured in a certain way that generated musical patterns naturally. Of course, what makes his work great is because of the way people have responded to his music over more than two centuries. (See also [37, 47].)

Or consider mentally different people, like the case of Stephen Wiltshire, discussed in [55]. Sir Wiltshire has an amazing ability to draw a landscape from memory after seeing it only once. Though he is diagnosed with autism, his work is highly regarded both by critics and general population. He was awarded *Member of the Order of the British Empire* for services to art in 2006. So he is no doubt a very creative person, no matter which criterion one chooses to apply.

But let us think about it a minute. What do we mean by saying that he is creative? His work has a certain style, level of details that most people cannot reach, aesthetic appeal, and all that. As with Mozart, we can go further and say that perhaps this is the way he expresses himself naturally: just like you and I might describe what we did on our last summer vacation, he draws fantastic landscapes.

We can now throw in here examples of people with schizophrenia or brain damage, savants or manic-depressive people, and so on [57]. When these people produce work that is considered creative, often this is their mode of being, and it could not have been otherwise. (See also [1, 17].) Many times the intention is missing as well.

Einstein's brain was preserved after his death so that people can study it to get any clues about the biological basis for creativity. But it is not like he was creative every day of his life. It is the impact of his theory of relativity, and its eventual acceptance by the scientific community that was a key factor in him becoming an icon of scientific creativity of the twentieth century. Moreover, Einstein was also dogmatic at times, perhaps the most famous case being his rejection of Alexander Friedmann's expanding universe hypothesis [61].

If we were to model Einstein's creative process, what would we model? There have been some computational models of scientific discovery, but they almost always greatly simplify the process by putting a number of assumptions in place as to what is significant and what is not. At that point, it is not clear at all if they are modeling the actual mental process of the creative person at the time of the creative act. (See also [5].)

Such examples suggest that the so-called creative humans use a variety of heuristics, some of them consciously and some subconsciously, for creating artifacts or for problem solving. Many of these heuristics can be mechanized, and in principle there seems to be no reason to consider any of them non-algorithmic.

The second characterization of creativity focuses on the nature of creative artifacts. It takes only the audience's perspective, so the creator is not even mentioned. We refer to Barthes' [3] articulation: "We know that to restore to writing its future, we must reverse its myth: the birth of the reader must be ransomed by the death of the Author," though he traced this view to even earlier scholars. Though not everyone subscribes to this extreme position, most accounts of creativity do acknowledge the role of the audience [12, 13, 22, 41].

In the audience-based view of creativity, it is generally accepted that in order for an artifact to be deemed creative, it must be *novel* and *useful*. We have argued above (Sec. 6.2.1) that *novelty* is cognitively difficult for people because we are constrained by our previous conceptual associations. Researchers who study creativity have come up with various techniques to overcome this difficulty. However, computers and AI systems, which do not have any such associations, have a great advantage here, for they can search the unchartered areas of novel concepts and conceptual combination more systematically [19, 31].

However, to automatically assess the *usefulness* of created artifacts is a different cup of tea altogether. As the usefulness is necessarily from a human point of view, the question becomes: Can an algorithm capture usefulness to humans? Here, we can distinguish two different aspects of usefulness. One is aesthetics, which relates to artistic creativity. In this regard, there has been some research to suggest that at least some of our aesthetic values are hardwired in the structure of the brain [52, 68]. Moreover, machine-learning techniques have been applied to *learn* about the cultural preferences of an audience based on the past data. For instance, Ni et al. [45] trained their program with the official UK top-40 singles chart over the past 50 years to learn as to what makes a song popular. A program like this might successfully predict, for instance, the winner of the future Eurovision competitions. However, a limitation of these approaches is that they cannot predict drastic changes in the aesthetic values and tastes: for example atonal music, or abstract art. Moreover, creativity is not the same as popularity. So to be able to predict whether a song, or a book, or a video will become popular [63] is not the same thing as evaluating their creativity.

This problem becomes more severe when we move beyond arts, and consider creativity in problem solving, and in science and technology. Here the usefulness of a novel and creative idea comes down to simply whether it works. This clearly has an objective component, for in a sense it is the reality that determines whether the idea works or not. History of science and technology is full of many interesting and novel ideas that did not work. Prehistory of flight [20] is a rich domain of examples where many novel ideas that were based on numerous observations, experimentations, and in which inventors had complete faith, did not work at all. The following examples provide further support for this argument (see also [28, 48]):

1. Schön [58, 59] described the case of a product-development team in the 1940s, which was working to develop a synthetic-fiber paintbrush that would yield smoothly painted surfaces like the natural-fiber paintbrush did. They came up with an innovative and successful design using the *painting-as-pumping* metaphor. However, during the problem-solving phase, they also considered *painting as masking-a-surface* metaphor, which was quite a novel idea, but it led to no useful insight.
2. Yolanda Baie, a food stand operator and owner, petitioned to have the kitchen of her house, where she prepared food sold at the food stand, qualify as a *home office* for the purpose of tax deduction (Baie vs. C.I.R., 74 T.C. 105), using the argument

that her kitchen was a *manufacturing facility* for her business. The judges, while finding the argument 'ingenious and appealing,' ruled it 'insufficient' nonetheless.
3. John Casti ([5, pp. 7–10]) comments on the fate of Immanuel Velikovsky's theory as outlined in Worlds in Collision, which hypothesized Earth's encounters with a large comet expelled from Jupiter and provided explanations for many biblical events. Velikovsky's theory proposes a novel understanding of the Solar system, but the scientific community has not accepted it.

Considering such examples, we suggest that this *usefulness* aspect of creativity remains essentially non-algorithmic, but not because humans are special, and cognitive processes cannot be computational, but because nature is not bounded by the limits of our cognitive models. To elaborate this further, whether an object flies or not (which is the *usefulness* of the idea) does not depend on how beautiful or elegant the theory is, or how much effort and emotional energy the creator has invested in the object, and so on. In other words, usefulness cannot be addressed from within the cognitive model, but it must be applied and tested in the real world.

Thus, creativity, in our view, represents the open-endedness of our interaction with the environment, and cannot be captured in a cognitive or computational model. Nonetheless, we can have computational models of creativity in limited domains, and computational systems can be designed to stimulate and enhance general creativity in people.

We can contrast our position with some other approaches to model creativity, notably among them being the FACE and IDEA models proposed Colton and his colleagues [10, 11, 49, 50]. The FACE model formalizes novelty by explicitly identifying eight dimensions along which an object can be considered novel. To complement this, the IDEA model formalizes the impact of the artifact (so the *usefulness*) by assuming how it affects an ideal audience. Two dimensions are identified to measure the impact on the audience: one refers to how the well being of the audience has changed in response to the artifact or the work, and the other refers to the cognitive effort required to appreciate the artifact.

Our position is consistent with the FACE model, except that the FACE model is more detailed in its explicit identification of various ways in which novelty can be generated. However, the position we have articulated here with respect to *usefulness* essentially implies that the goal of the IDEA model is not attainable. First of all, it is very difficult to characterize an *ideal audience.* Moreover, as the character of the audience—and here we include both the nature of the individual members of the audience and the membership of the audience—changes as a result of interacting with the artifact, and changes in quite unpredictable ways, it is nearly impossible to measure the two parameters posited in the IDEA model. One only has to consider the history of art genre like atonal music, minimalist music, abstract visual art, conceptual art, and how they gradually became accepted by the audience to appreciate this point. Finally, for scientific creativity and real-world problem solving, the audience is the nature or the real world, which ultimately accepts or rejects the artifact, and this response cannot be modeled, as we have argued above. Nevertheless, in restricted domains, it may be possible to make certain assumptions about the audience, and so IDEA model can be useful in a limited way.

6.4 Conclusions

To summarize the main arguments of this chapter, we would like to rearticulate them in another way. It is generally accepted that the two main characteristics of creativity are originality and intelligibility: the product must be novel or the process must generate a new perspective; and the product or the generated perspective must be intelligible in order to be useful for at least some audience [2, 56, 67]. For novelty, research on real-world creativity shows that it is difficult for people to step out of their conventional and habitual conceptual associations. To overcome this inertia, several methods like making the familiar strange [18], concept displacement [58], bisociation [36], lateral thinking [14], estrangement [54], conceptual blending [15], and so on, have been proposed in the literature. However, computers do not have this inertia, and so they can be very effectively used to generate novel ideas. This argument has been presented in more detail elsewhere [31]. Our experience in developing creativity-assistive systems (reviewed in Sect. 6.2) lends supports to this hypothesis.

However, when it comes to incorporating usefulness of the generated perspective or idea, we have argued that, in general, it is not possible to capture this aspect of creativity algorithmically. The reason is simply that when a new object or style is introduced, people react to it in different ways. Sometimes they adapt to it right away; at other times they do not find it interesting or useful at first, but the same object or style introduced at a later time becomes a big success; and sometimes they do not find it useful at all, in spite of the efforts made by the creators to convince them otherwise.

Nevertheless, one cannot rule out the possibility that in limited domains we might be able to characterize usefulness algorithmically, and to design and implement computer systems that can generate statistically a larger number of useful and interesting artifacts and ideas. So combining this with novelty-generating systems, we can have computer systems that are creative. Systems like Aaron exemplify this approach.

However, even in a limited domain, once usefulness is characterized algorithmically, it loses its novelty, and gradually ceases to be creative. (See, for instance, the model of literary style change proposed by Martindale [42].) So while, we may be able to model some aspect of creativity within a style (with respect to usefulness), it remains doubtful whether creative changes in styles can be modeled successfully in a universal way. Again, to emphasize, novelty can be modeled—it is relatively easy to computationally generate new styles, but the problem is to incorporate which styles will be successful (meaning people will adapt to them and find them useful). Therefore, we claim that this usefulness aspect of creativity will always remain the last frontier for computational modeling techniques.

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References

1. Abraham, A., Windmann, S., McKenna, P., Güntürkün, O.: Creative thinking in schizophrenia: the role of executive dysfunction and symptom severity. Cognit. Neuropsychiatry. **12**(3), 235–2581 (2007)
2. Amabile, T.M.: Creativity in Context. Westview Press, Boulder (1996)
3. Barthes, R.: The Death of the Author. In: Barthes, R. (ed.) Image Music Text (trans. S. Heath). London: Fontana (1977). Original work published 1967
4. Boden, M.A.: Computer models of creativity. AAAI. AI. Mag. **30**(3), 23–33 (2009)
5. Casti, J.L.: Paradigms Lost: Images of Man in the Mirror of Science. William Morrow & Co., New York (1989)
6. Chalmers, D.J., French, R.M., Hofstadter, D.R.: High-level perception, representation, and analogy: a critique of artificial intelligence methodology. J. Exp. Theor. Artif. Intell. **4**(3), 185–211 (1992)
7. Chordia, P., Rae, A.: Tabla Gyan: an artificial tabla improviser. Proceedings of the International Conference on Computational Creativity: ICCC-X, Lisbon, Portugal (2010)
8. Cohen, H.: On Modeling of Creative Behavior. Rand Corporation Report Series, P-6681 (1981)
9. Colton, S.: Creativity versus the perception of creativity in computational systems. Proceedings of the AAAI Spring Symposium on Creative Systems (2008)
10. Colton, S., Charnley, J., Pease, A.: Computational creativity theory: the FACE and IDEA models. Proceedings of the International Conference on Computational Creativity (2011)
11. Colton, S., Wiggins, G.A.: Computational creativity: the final frontier. Proceedings of the 20th European Conference on Artificial Intelligence (2012)
12. Cropley, D.H., Kaufman, J.C., Cropley, A.J.: Measuring creativity for innovation management. J. Technol. Manag. Innov. **6**(3), 13–30 (2011)
13. Csikszentmihalyi, M.: Creativity: Flow and the Psychology of Discovery and Invention. HarperCollins, New York (1996)
14. de Bono, E.: New Think: The Use of Lateral Thinking in the Generation of New Ideas. Basic Books, New York (1975)
15. Fauconnier, G., Turner, M.: The Way We Think: Conceptual Blending and the Mind's Hidden Complexities. Basic Books, New York (2002)
16. Gineste, M.-D., Indurkhya, B., Scart, V.: Emergence of features in metaphor comprehension. Metaphor Symb. **15**(3), 117–135 (2000)
17. Glicksohn, J.: Encyclopedia of creativity. In: Runco, M.A., Pritzker, S.R. (eds.) Schizophrenia and Psychosis, 2nd edn. Academic Press, New York (2011)
18. Gordon, W.J.J.: Synectics: The Development of Creative Capacity. Harper & Row, New York (1961)
19. Harry, H.: On the role of machines and human persons in the art of the future. Pose **8**, 30–35 (1992)
20. Hart, C.: The Prehistory of Flight. University of California Press, California (1985)
21. Hofstadter, D.: The Fluid Analogies Research Group: Fluid Concepts and Creative Analogies. Basic Books, New York (1995)
22. Horn, D., Salvendy, G.: Consumer-based assessment of product creativity: a review and reappraisal. Hum. Factors Ergonomics Manufact. Serv. Ind. **16**(2), 155–175 (2006)
23. Hunter, D., Indurkhya, B.: 'Don't think, but look' a gestalt interactionist approach to legal thinking. Proceedings of the Workshop on Advances in Analogy Research, Sofia, Bulgaria, pp. 345–353 (1999)

24. Indurkhya, B.: Metaphor Cogn. Kluwer Academic Publishers, The Netherlands (1992)
25. Indurkhya, B.: On modeling creativity in legal reasoning. In: Proceedings of the Sixth International Conference on AI and Law, pp. 180–189. Melbourne, Australia (1997)
26. Indurkhya, B.: An algebraic approach to modeling creativity in metaphor. In: Nehaniv, C.L. (ed.) Computation for Metaphors, Analogy and Agents. LNAI, vol. 1562, pp. 292–306. Springer, Berlin (1999)
27. Indurkhya, B.: Emergent representations, interaction theory, and the cognitive force of metaphor. New Ideas Psychol. **24**(2), 133–162 (2006)
28. Indurkhya, B.: Rationality and reasoning with metaphors. New Ideas Psychol. **25**(1), 16–36 (2007)
29. Indurkhya, B.: On the role of metaphor in creative cognition. Proceedings of the International Conference on Computational Creativity: ICCC-X, Lisbon, Portugal (2010)
30. Indurkhya, B.: Thinking like a child: the role of surface similarities in stimulating creativity. In: Stojanov, G., Indurkhya, B. (eds.) Proceedings of the AAAI Spring Symposium on Creativity and (Early) Cognitive Development, pp. 38–43. AAAI Press, Palo Alto (2013)
31. Indurkhya, B.: Computers and creativity. In: Veale, T., Feyaerts, K., Forceville, C.J. (eds.) Creativity and the Agile Mind, pp. 61–79. De Gruyter Mouton, Berlin (2013)
32. Indurkhya, B., Kattalay, K., Ojha, A., Tandon, P.: Experiments with a creativity-support system based on perceptual similarity. In: Fujita, H., Zualkernan, I. (eds.) New Trends in Software Methodologies, Tools and Techniques, pp. 316–327. IOS Press, Amsterdam (2008)
33. Indurkhya, B., Ogawa, S.: An empirical study on the mechanisms of creativity in visual arts. In: Miyake, N., Peebles, D., Cooper, R.P. (eds.) Proceedings of the 34th Annual Conference of the Cognitive Science Society, pp. 1727–1732. Cognitive Science Society, Austin (2012)
34. Ishii, Y., Indurkhya, B., Inui, N., Nose, T., Kotani, Y., Nishimura, H.: A System based on rodari's 'estrangement' principle to promote creative writing in children. Proceedings of Ed-Media & Ed-Telecom 98, pp. 1685–1686, Freiburg, Germany (1998)
35. Jia, L., Hirt, E.R., Karpen, S.C.: Lessons from a Faraway land: the effect of spatial distance on creative cognition. J. Exp. Soc. Psychol. **45**, 1127–1131 (2009)
36. Koestler, A.: The Act of Creation. Hutchinsons, London (1964)
37. Kozbelt, A.: Factors affecting aesthetic success and improvement in creativity: a case study of the musical genres of mozart. Psychol. Music **33**(3), 235–255 (2005)
38. Krzeczkowska, A., Colton, S., Clark S.: Automated collage generation—with intent. Proceedings of the International Conference on Computational Creativity: ICCC-X, Lisbon, Portugal (2010)
39. Kurzweil, R.: Cybernetic Poet. http://www.kurzweilcyberart.com/poetry/ (2001). Last accessed on 29 Jan 2012
40. López, A.R., Oliveira, A.P., Cardoso, A.: Real-time emotion-driven music engine. Proceedings of the International Conference on Computational Creativity: ICCC-X, Lisbon, Portugal (2010)
41. Maher, M.L.: Evaluating Creativity in Humans, Computers, and Collectively Intelligent Systems, DESIRE'10: Creativity and Innovation in Design. Aarhus, Denmark (2010)
42. Martindale, C.: The Clockwork Muse: The Predictability of Artistic Change. Basic Books, New York (1990)
43. McCorduck, P.: Aaron's Code: Meta-art, Artificial Intelligence, and the Work of Harold Cohen. W. H. Freeman, New York (1991)
44. Monteith, K., Martinez, T., Ventura, D.: Automatic generation of music for inducing emotive response. Proceedings of the International Conference on Computational Creativity: ICCC-X, Lisbon, Portugal (2010)
45. Ni, Y., Santos-Rodriguez, R., Mcvicar, M., De Bie, T.: Hit song science once again a science? Presented at the 4th International Workshop on Machine Learning and Music: Learning from Musical Structure. Sierra Nevada, Spain (2011)
46. Ojha, A., Indurkhya, B.: New frontiers in analogy research. In: Kokinov, B., Holyoak, K., Gentner, D. (eds.) Perceptual vs. Conceptual Similarities and Creation of New Features in Visual Metaphor. New Bulgarian University Press, Sofia (2009)

47. Painter, K.: Mozart at work: biography and a musical aesthetic for the emerging german bourgeoisie. Music. Q. **86**(1), 186–235 (2002)
48. Palmer, S.: Human Ontology and Rationality. Avebury, Aldershot (1992)
49. Pease A., Colton, S.: On impact and evaluation in computational creativity: a discussion of the turing test and an alternative proposal. Proceedings of the AISB symposium on AI and Philosophy (2011)
50. Pease, A., Colton, S.: Computational creativity theory: inspirations behind the FACE and IDEA models. Proceedings of the International Conference on Computational Creativity (2011)
51. Pérez y Pérez, R., Negrete, S., Peñalosa, E., Ávila, R., Castellanos, V., Lemaitre, C.: MEXICA-Impro: a computational model for narrative improvisation. Proceedings of the International Conference on Computational Creativity: ICCC-X, Lisbon, Portugal (2010)
52. Ramachandran, V.S., Hirstein, W.: The science of art: a neurological theory of aesthetic experience. J. Conscious. Stud. **6**(6–7), 15–51 (1999)
53. Riesbeck, C.K., Schank, R.C.: Inside Case-based Reasoning. Lawrence Erlbaum & Associates, New Jersey (1989)
54. Rodari, G.: The Grammar of Fantasy (J. Zipes, Trans.) Teachers & Writers Collaborative, New York (1996)
55. Sacks, O.: An Anthropologist on Mars: Seven Paradoxical Tales. Alfred A. Knopf, New York (1995)
56. Sarkar, P., Chakrabarti, A.: Development of a method for assessing design creativity. International Conference on Engineering Design ICED'07, pp. 28–31 August, Cite des Sciences et de L'Industrie, Paris, France (2007)
57. Sawyer, K.: Explaining Creativity. Oxford University Press, Oxford (2006)
58. Schön, D.A.: Displacement of Concepts. Humanities Press, New York (1963)
59. Schön, D.A.: Generative metaphor: a perspective on problem-setting in social policy. In: Ortony, A. (ed.) Metaphor and Thought, pp. 154–283. Cambridge University Press, Cambridge (1979)
60. Shapira, O., Liberman, N.: An easy way to increase creativity. Scientific American (Mind Matters), 21 July 2009. http://www.scientificamerican.com/article.cfm?id=an-easy-way-to-increase-c
61. Singh, S.: Big Bang. Harper Collins, New York (2004)
62. Suzuki, H., Hiraki, K. : The constraint relaxation process as theory change: toward theorizing the process of insight. (In Japanese.) Proceedings of the Japanese Cognitive Science Society's Special Interest Group on Language & Learning, vol. 97(1), pp. 33–42 (1997)
63. Szabo, G., Huberman, B.A.: Predicting the popularity of online content. Commun. ACM **53**(8), 80–88 (2010)
64. Tandon, P., Nigam, P., Pudi, V. and Jawahar, C.V.: FISH: A practical system for fast interactive image search in huge data bases. Proceedings of 7th ACM International Conference on Image and Video Retrieval (CIVR'08), Niagara Falls, Canada (2008)
65. Veale, T.: Re-representation and creative analogy: a lexico-semantic perspective. New Gener. Comput. **24**(3), 223–240 (2006)
66. Veale, T., Hao, Y.: A fluid knowledge representation for understanding and generating creative metaphors. Proceedings of COLING 2008, pp. 1–5. Manchester (2008)
67. Yong, K., Lander, M.W., Mannucci, P.V.: Novelty x Usefulness: actor-level effects and cultural influences on creativity in organizations. 35th DRUID Celebration Conference, Barcelona, Spain, June 17–19 (2013)
68. Zeki, S.: Inner Vision: An Exploration of Art and the Brain. Oxford University Press, Oxford (2000)