CREATIVITY AND ARTIFICIAL INTELLIGENCE

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Abstract :- Creativity is a fundamental feature of human intelligence and a challenge to AI. AI techniques can be used to generate new ideas in three ways: by generating new combinations of familiar ideas; by exploring the potential of conceptual spaces; and perform transformations that allow the creation of ideas that were not possible before. The AI will have less difficulty modeling 4, new ideas than it will with automating their evaluation. 0 1998 Elsevier Science B.V. All rights reserved.

Why AI should strive to model creativity.

Creativity is a fundamental feature of human intelligence and an inevitable challenge to AI. Even tech-oriented AI cannot ignore this, as innovative programs can be very useful in the lab or in the market. And AI models intended (or perceived to be) as part of cognitive science could help psychologists understand how the human mind can be creative.

Creativity is not a special "faculty", nor is it a psychological property confined to a small class. Rather, it is a feature of human intelligence in general. It is based on everyday skills such as linking ideas, recalling, perceiving, thinking analogously, searching for a structured problem space, and self- criticism. It involves not only the cognitive aspect (new idea generation) but also motivation and emotion, and is closely linked to cultural context and personality factors [3]. Current AI innovation models focus mainly on the cognitive aspect. A creative idea is a new, surprising, and valuable idea (interesting, useful, beautiful.) But "novel" here has two very different meanings. The idea may be new just to the mind of the individual (or AI system) involved, or as far as we know it, to the whole previous story. The novelty-generating power of the first can be called P creativity (P for psychology), the second H creativity (H for history). Creativity is the most basic concept, of which creativity is a special case. AI should focus primarily on creativity. If he managed to model it forcefully, 4344 artificial creation would have happened in some cases, indeed, it did, as we shall see. (In the following, I will not use the letter prefix: in general, it is the creativity involved.)

The three types of creativity

There are three main types of creativity, related in different ways. to generate ideas in a Romanesque fashion. Each of these three leads to surprise, but only one (third) can lead to a “shock” of the surprise the owner of an idea seems to have. as improbable [2]. All categories include about 4,444 examples of creativity, but creators who are credited in the history books are generally more celebrated for their 4,444 achievements in the third category of creation. The first type involves new (impossible) combinations of familiar ideas. Let's call this "composite" creation. Examples include many poetic images, as well as the analogy in which two new ideas are linked sharing the same inherent conceptual structure. The analogy is sometimes explored and developed to some extent, for rhetorical or problem- solving purposes. But even the simple generation, or appreciation, of a proper analogy involves careful (not necessarily conscious) structural mapping, whereby the similarities structural bronzes were not only noticed but also judged on their strength and depth. The second and the third are closely related and more alike than of the first. They are “discovery” and “transformative” creations. Old is concerned with generating new ideas by exploring structured conceptual spaces. This often leads to structures (“ideas”) that are not only new but also unexpected. We immediately see, however, that they satisfy the rules of the relevant style of thought. The second type involves transforming one (or more) spatial dimensions, so that new structures can be created that were not possible before. The more fundamental the dimension of relevance and the stronger the transformation, the more surprising the new ideas will be. These two forms of creativity are intertwined, and since the exploration of space can consist of a minimal "adjustment" of rather superficial constraints. The distinction between a refinement and a transformation is to some extent a matter of judgment, but the more clearly defined the space, the clearer the distinction is. Many people, including (for example) most professional scientists, artists, musicians and jazz musicians, rightfully make a living from discovery creativity. It is that they inherit an accepted style of thought from their culture, then seek it, and perhaps modify it superficially, to discover content, limits and potential its capacity. But humans sometimes transform the accepted conceptual space, changing or removing one (or more) of its dimensions, or adding a new one. Such a transformation makes it possible to generate ideas (related to this conceptual space) previously impossible. The more fundamental and/or more fundamental the transformation to which the dimension is transformed, the more different possible new structures will be. The shock of the surprise that accompanies such ideas (previously impossible) is much larger than the surprise caused by mere random things, however unexpected they may be. If the transformations are extreme, the relationship between the old space and the new space will not be immediately clear. In such cases, new constructs will be difficult to understand and most likely rejected. Indeed, it may take some time for the relationship between the two spaces to be recognized and accepted collectively.

The Creative Model of the Computer

The Creative Model of the Computer includes examples of all three types. So far, focuses on the latter category (exploration) as the most successful. This is not to say that discoverability is easily reproducible. Instead, it often takes a great deal of domain expertise and analytical ability to define the concept space in the first place and identify its potential discovery procedures. But combinatorial creation and transformation is even more elusive. In short, the reason for this is the difficulty in accessing the abundance of human memory associations, and the difficulty in determining our values and expressing them. in the form of a computer. The first difficulty interrupts the attempt to simulate combinatorics. This last difficulty concerns efforts directed at any kind of creativity, but is particularly difficult in relation to the third problem (see section 4 below). Combined creativity is studied in AI through the study of (examples) jokes and analogies. Both of these require some sort of semantic network, or an interconnected knowledge base, as a foundation. Obviously, extracting random links from such a source is straightforward. But the link may be undisclosed or inappropriate in context. For all combinatorial tasks that are not "freely linked", the nature and structure of the associative association is also important. Ideally, each product of the combinatorial program should be at least minimally matched, and the originality of the different combinations should be evaluated by the AI system. A recent and relatively successful example of AI-generated humor (composite) is Jape, a program that produces puns [1]. Jape creates jokes based on nine general sentences, such as: What do you get when you combine X with Y?; What kind of from X to Y?; What type of Y could X be?; What is the difference between X and a Y? The semantic network that the program uses integrates knowledge of phonology, semantics, syntax, and orthography. Various combinations of these aspects of the word are used. Separately, to create each kind of joke.

These are examples of puzzles created by Jape:
(Q) What kind of killer has a string?
(A) A grain killer;
(Q) What do you call the strange market?
(A) A bizarre market place;
(Q) What do you call the bored train?
(A) A weak engine; and
(Q) What is the difference between sheets and a car?
(A) One slams and rakes, the other accelerates and brakes.

These may not bring us good laughs, although in a relaxed social setting, one or two 4, of them might. But they're all hilarious enough to elicit sarcastic and grateful laments.
Binsted conducted a series of systematic psychological tests, comparing people's reception of Jape's quizzes with their responses to man-made jokes published in storybooks. laugh. She also compared Jape products to "no joke" products created by random combinations. For example, she found that children who liked this humor the most, could reliably distinguish between jokes (including Jape's riddles) and non-jokes. While they often find man-made jokes funnier than Jape's, that difference disappears if Jape's output is stripped down, to remove elements generated by poorly successful schemas more public. The puzzles published in human joke books are highly selective, as only those that the author finds reasonably humorous appear on paper. Binsted has set himself a difficult task: to make sure that every Jape joke is hilarious. His subsequent research showed that although none of the sentences were considered particularly humorous, very few generated any reaction. This is in contrast to the other creation models, such as AM [16], where a high proportion of the newly created structures are not considered interesting by humans. It does not follow that all Modeling of Creation should imitate Binsted's ambition. This is especially true if the system is intended to be used interactively by people to support their own creativity by prompting them to come up with ideas they might not otherwise consider. Certain "failed" products must be allowed under any circumstances, because even human creators often create second-rate or even inappropriate ideas. Jape 's success is due to the fact that his joke models and fusion schemes are very limited. Binsted identifies some aspects of the real-life puzzle that are not parallel in Jape, and a (reliably) implementation is unlikely for the foreseeable future. Incorporating these aspects in such a way as to produce believably humorous jokes raises conundrums assessment questions (see section 4).
As for the analogy AI models, most of them generate and evaluate the analogies using domaingenera1 mapping rules, applied to pre- structured concepts (e.g. [7,12, 13]).
The creators of some of these models compared them with the results of the psychological experiments, which claim a substantial amount of evidence in support of their common-domain approach [8]. In these models, there is a clear distinction between representing one concept and mapping it to another. Two concepts commonly associated with do not change by analogy.
Some AI analogies allow for more flexible representation of concepts.
An example is the program Copycat, an association system that primarily looks for similarities between alphanumeric strings [11,18]. Copy concepts are contextual descriptions of strings like "mmpprr" and "klmmno". The two ms of the first sequence just listed will be described by Copycat as a pair, but the ms of the second sequence will be described as the end of two different triples.
One could say that Copycat would describe them "finally" this way. For its concepts evolved over time. This research is guided by the theoretical assumption that seeing a new analogy is like perceiving something in a new way. Thus, Copycat is not based on ready-made and fixed representations, but builds its own in a contextual way: new analogies and new realizations grow together. A partial description seems to correspond well to the stub analogy still maintained, and further developed. Anyone who seems to be coming to a dead end will be left out, and an alternative begins to exploit different aspects. The model allows for the generation and evaluation of a wide range of analogies (less or bold). The degree to which the analogies are obvious or far-fetched can be changed using one of the parameters. of the system. Whether the approach used in Copycat is preferable to more conventional forms of mapping (domain generics) remains controversial. Hofstadter [11] criticizes other AI similarity models for arguing that concepts are immutable and inflexible, and for ensuring that the forced similarity (among others) will be found by focusing on small

representations have the necessary conceptual structure and built-in mapping rules. Opposition camp denies these allegations [8].

They argue that to define similar thinking with higher cognition, as Hofstadter did, is to use a vague and misleading metaphor: similarity mapping, they insist, is a general domain processes must be distinguished analytically from the conceptual representation. They point out that Copycat's most detailed published account [18] provides only such an analysis, describing representation-building procedures as distinct from representation comparison modules, although despite interacting with them. They report that the Structural Mapper (SME), for example, can be successfully used on "very large" representations of duplicates, some of which are built by other systems for independent purposes. They compared Copycat's alphabetical micro world to the 'cubic world' of 1970s scene analysis, which omitted most of the interesting complexity (and noise) of in the real world.

Although their early models did not allow for conceptual structure changes as a result of analogy, they refer to for working on learning (using SME) involving abstract processes. schema visualization, inference, projection and representation [9]. In addition (as noted above), they claim that of their psychological experiences support their simulation approach.

For example, they say that there is evidence that access to memory, where an analogue (not present) is remembered, depends on psychological processes and the like, other significantly different from those with respect to the mapping between two concurrently presented analogs.

The jury is not out of this controversy. However, it may not be necessary to completely round for both sides. My hunch is that the Copycat approach is much closer to with the flexible Complexity of human thinking. But the general principles of analogy in this regard are perhaps very important.

And they are probably enriched by many domain-specific processes. (Certainly, psychological studies of how humans retrieve and interpret analogies can be helpful.) In short, even combinatorics is a very complex subject.

Exploratory and transformative creative types can also be modeled by AI systems. As for conceptual spaces, and how to explore and modify them, can be described by computational concepts. Sometimes an “innovative” program that will apply to many fields, i.e conceptual spaces like EURISKO for example, do [16]. But to make this general program useful in a particular field, such as genetic engineering or VLSI design, considerable expertise needs to be provided if it does not produce much pointless ideas (the opposite is just boring). All in all, delivering a program with the representation of an interesting conceptual space and with appropriate exploratory processes requires considerable domain expertise on the part of the programmer. at least from the person he is dealing with. (Unfortunately, the institutional structure closely associated with most university subjects opposes this type of interdisciplinary study.)

For example, EMI (experiment on musical intelligence) is a program composing in the style of Mozart, Stravinsky, Joplin and others. [6]. To do this, it uses powerful musical grammars represented in the ATN. In addition, he used a list of "signatures":

Samples of melodious, harmonic, metric and decorative music typical of each composer.

Using general rules to alter and intertwine these, he often composes a musical phrase that closely resembles an unsigned signature. This shows the systematicity of 4, individual compositional styles.

Personal musical style was also covered in a pioneering program where improvised jazz in real time, although the technique could be applied to other types of music.

Currently, the most developed version produces jazz in the Charlie Parker style, and the (ignoring the lack of expressiveness and quality of the synthesizer sound) it truly resembles Parker. In addition to an in-depth (and relatively general) knowledge of musical dimensions such as harmony and rhythm, and the musical conventions characteristic of jazz, the system has access to a Parker's range of signature models can be varied and the can be combined in a number of ways. (The programmer is a successful jazz saxophonist: without strong musical skills he would not be able to identify the patterns involved, nor evaluate the suitability of particular processes. to use them.) Exploring this conceptual space, the program is often a source of interesting musical ideas that jazz professionals can tap into in their own performance. In its current form, however, it never leaves Parker space: its creative possibilities are simply to explore, not transform.

Architectural design has also been formally modeled. For example, a grammar of form describing Frank Lloyd Wright's prairie homes produces all that he designed, both and others he did not design. For the eye to begin with, each of these Romanesque (discovery-creation) structures falls under this category. The grammar not only identifies important dimensions of the architectural space involved, but also shows which are relatively basic. In a house in Prairie, the addition of a balcony is superficially stylistic, as it is a decision on which nothing else (except the appearance and decoration of the balcony) depends on it. In contrast, "adding" a fireplace leads to an overall structural change, because many design decisions follow and depend on (early) decisions about households. Therefore, exploring this space by choosing different fireplaces can turn out to be more of a basic surprise than adding a balcony in unwanted places.

Perhaps the most famous example of AI creativity is AARON, a programmer, a series of programs to explore how to draw lines in specific styles [17] and more recently, coloring [5]. Written by Harold Cohen, an artist who was a renowned expert in the 1960s, AARON explores a defined space using deep field expertise.

AARON does not focus primarily on surfaces, but creates a representation of the 3D kernel and then draws a line around it. The individual multi-portrait versions use 900 control points to specify the 3Dcore, of which 300 specify the head and face structure.

The paintings in the show are highly aesthetic and have been exhibited in 4,444 galleries around the world. Until recently, the colorful images in AARON were hand-painted by Cohen. But in 1995, he showed a version of the AARON that could do it on its own. He chooses colors by tone (light/dark) rather than by hue, although he may decide to focus on a particular color group. He draws contours with a brush, but colorizes the paper by applying five circular "paint blocks" of different sizes. Some characteristics of the resulting paint pattern are due to the physical nature of the stain and paint block and not from the program instructing their use. Just like drawing AARON, AARON paint is still in the process of constant development.

Drawings (and paintings) are unpredictable due to random selections, but all drawings created by a certain version of AARON will have the same style. AARON cannot reflect its own production, nor tweak them to make them better.

She can't even transform her conceptual space, leaving aside the question of whether it leads to something "better". In this regard, it resembles most current AI programs that focus on creativity.

Another example of AI creativity discovery is the BACON suite designed to model scientific discovery 15]. The heuristics used by the BACON system are carefully preprogrammed and the data is intentionally pre-structured to match the heuristics provided. New types of discovery are not possible for BACON. It would therefore be misleading to name such programs after scientists are known to have noticed previously unnoticed -type relationships. Even the idea that there could be (for example) a linear mathematical relationship found was a tremendous creative leap.

Almost all "creative" computers today are only interested in exploring predefined conceptual spaces. They can allow very limited adjustment, but cannot have fundamental novelty or a truly shocking surprise. However, some AI systems not only attempt to explore their conceptual space, but also to transform it, sometimes in relatively unrestricted ways.

The transformation system includes AM and EURISKO [16], and some programs based on genetic algorithms. Some of them have created valuable structures that human experts say they could never have created without help: sculptor William Latham, for example, created 3D shapes in a way he could not have imagined for himself [22].

Most GA programs only explore a certain space, looking for the "optimal" position in it. But some also modify their creation mechanism in a more or less fundamental way. For example, GA work in graphics can allow a modification of the conceptual spatial appearance, resulting in images that, although new, clearly belong to the same family as earlier images [22]. Or it could expand and complicate the core of the image generation code, so that the new images don't show family resemblance even to their parents, let alone their more distant ancestors. [21]. Likewise, certain jobs in the field of evolutionary robotics have created new sensory anatomy and control systems created by GAS that can modify the length of the “genome” [4]. It should not be assumed that transformation is always creative, or even in the modern state that AI systems that can transform their rules are superior to those that cannot.

Notably, some AI modelers deliberately avoid giving their programs the ability to change the core of their code. That is, they prevent fundamental transformations in the conceptual space, allowing only relatively superficial explorations and adjustments. One of the reasons for this is that humans may be more interested in exploring a given space than transforming it in unpredictable ways. A professional sculptor like Latham, for example, might want to explore the potential (and limits) of a particular family of 3D structures, before considering others [22]. Assessment automation.

Evaluating New Ideas

One of the main reasons why most current AI creation models only try to discover and not transform, is that if the space is transformed, the resulting structures may have no interest or value. Such ideas are of course new, but not innovative. (We saw in Section 1 that "creativity" implies a positive rating.)

Fig[1]https://celtra.com/wpcontent/uploads/2019/09/20190905_BlogIll o_CreativeAI-Art

It doesn't matter if the AI system can perceive the poor quality of the new structure and 'give up (or give up (or give up). modified) convert accordingly. A true automated AI creator will have powerful enough evaluation mechanisms to do this.

Currently, this happens very rarely (one exception is the artificial evolution coefficient where the fitness function evolves with the different species involved [19]). It is well known that AF produces more useless things than powerful mathematical ideas, and although it has a built-in heuristic "hobby", its evaluations are often wrong by the standards. of human.

And some "bold" conversion programs do not incorporate any evaluation criteria, the evaluation is performed interactively by humans [21]. n principle, there is no reason to. why 'AI future models don't incorporate evaluation criteria that are strong enough to allow them to transform their conceptual space in effective creative ways (including H creative). But to be able to do such computer self-criticism, programmers must be able to express the relevant values clearly enough for them to be implemented. Although the values are not predefined, is instead represented as a growing fitness function, the characteristics involved must be implemented in and is recognized by the (GA) system.

This can be implicitly achieved, to some extent, by defining a conceptual space so successful that any structure can be created. by program will be accepted by humans as valid [5,14].

But structures created inside the newly converted spaces will require (at least partially) different types of evaluation from those hidden in the original space or previously provided in the explicit form.

It's harder to express (verbally or by computer) what we love about a Bach fugue or Impressionist painting, than to recognize something as an acceptable member of one of these categories. And it's even harder to say what we like (or even dislike) in a new or previously unknown form of music or painting. It is difficult to define the criteria we use in our reviews. It is even harder to justify, or even explain (causally), our confidence in these criteria. For example, just reasons why we like or dislike something often have a lot to do with motivational and emotional factors that Al currently has almost nothing to say.

To make matters worse, human values and therefore novelties that we are prepared to accept as "creative" + passed on from one culture to another and by the time.

In some cases, they do it in unpredictable and irrational ways: think of the fashion industry, like, or rogue memes like the baseball cap in the back. changes in value are not limited to trivial cases like this: even Bach, Mozart and Donne have been ignored and/or criticized at certain times by.

Scientific criteria for theoretical coherence and coherence, and empirical verification, are less variable than artistic values. But that doesn't mean they're easy to identify or implement. (An attempt to do this, for some sort of mathematical symmetry, was made by the BACON team.)

Furthermore, science has its equivalent of fashion and fashion. Even the discovery of 4, dinosaurs was not a cut-and-dry event, but the culmination of a scientific and political-nationalist negotiation process that lasted for several years [20]. Critical point is what scientists consider "creative" and what they call "discovery" largely depends on anarchic values, which include social considerations of various kinds different. 4,444 These social assessments are often invisible to scientists. Of course, they are not represented in the AI models.

CONCLUSION

A number of innovative ideas have been generated by AI programs, although often through purely exploratory (or combinatorial) procedures. The uniqueness of transformational AI is just beginning.

The two main bottlenecks are:

(1) domain expertise, which is required to map the concept space to be explored and/or transformed; and

(2) valuing the outcome, which is especially necessary and especially difficult for the transformation program.

These two bottlenecks interact, because a sophisticated evaluation requires knowledge substantial domain expertise. Evaluations, so far, have mostly been hidden in common procedures used by programs, or imposed interactively by humans.

Only a few AI models can critically evaluate their own original ideas, and almost none can combine evaluation and transformation. The ultimate justification for creativity is not a program to generate new ideas which at first baffle or even repel us, but can convince us that they really are worth, We are very far from it.

What’s next?

Evaluating new ideas is one of the biggest bottlenecks in AI creativity: after exploring and transforming space, how can a computer understand and automatically evaluate its results? How can he know, out of all the songs he's written, which one to keep? Especially for space conversion applications, this can be particularly complicated, but is even more relevant. Recent advances in AI show that computers are capable of creating high-level artwork, often capable of making humans believe it was created by another human. Do we ever let the computer do this on its own without our intervention? Not in the near future. Will we ever stop consuming artificial art? Sure is not.

However, we can begin to appreciate both. The framework presented here is suitable not only to understand and evaluate new discoveries in the field of AI, but also to shape new problems and propose solutions to them.

“The ultimate vindication of AI-creativity would be a program that generated novel ideas which initially perplexed or even repelled us, but which was able to persuade us that they were indeed valuable. We are a very long way from that.” — Margaret A. Boden

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