How AI Can Be Applied in Creative Fields

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Abstract. Defining creativity has been a question for centuries. Artificial Intelligence methods are mainly applied in well specified fields of studies, which can be evaluated in an objective way. This paper focuses on research in creative fields, such as visual, linguistic, and musical creativity. The connection to general AI is also described. Finally, we also question if these methods can be considered as creative.

Keywords: Machine creativity, Artificial intelligence, Neural Network.

1. Introduction

Machine creativity is one of the few topics where humanities and computer science meet. It serves several purposes. Experimentation in this field can be used both for creating something new, and for finding out more about human creativity. This paper describes some areas where current research is happening, but first it is important to define machine creativity and to talk about the history of it.

According to the Association of Computational Creativity, machine creativity is defined as the following [3]: *"Computational creativity is a multidisciplinary endeavour that is located at the intersection of the fields of artificial intelligence, cognitive psychology, philosophy, and the arts. The goal of computational creativity is to model, simulate or replicate creativity using a computer, to achieve one of several ends:*

- *to construct a program or computer capable of human-level creativity*
- *to better understand human creativity and to formulate an algorithmic perspective on creative behavior in humans*
- *to design programs that can enhance human creativity without necessarily being creative themselves*

The field of computational creativity concerns itself with theoretical and practical issues in the study of creativity. Theoretical work on the nature and proper definition of creativity is performed in parallel with practical work on the implementation of systems that exhibit creativity, with one strand of work informing the other."

This is the most precise definition that can be found but it still leaves plenty of questions. What is human-level creativity? How can creativity be measured? If a machine only does actions that were told by a human, is it even doing anything creative [2]? In the following sections this paper will try to find answers to these questions, but before that it is important to talk about when research started in the area.

The science of creativity as we know it today first appeared in 1950 when a paper by JP Guilford was published [10]. Guilford was an expert in psychometrics who separated the term creativity from intelligence, and he defined it as a measurable psychological power or propensity. As the Turing test appeared in the 50s, we can say that testing creative aspects of machines has been common for a long time. Research professor Margeret Boden published two relevant books about AI: Artificial Intelligence and Natural Man. What made these books interesting was the reactions it received - some users found the topic of creativity to be out of place [9]. As Artificial Neural Networks gained popularity in the 1980s the innovation aspect of computers got more relevant. The first time someone used Neural Nets for this purpose was in 1989 by Peter Todd [33]. The network generated music in an uncontrolled manner. In 1992 this was extended using a so-called distal teacher approach, which is based on using 2 neural networks. These 2 steps were highly important, as multiple neural network architectures (like Generative Adversarial Networks [14]) continue to be the most commonly used methods in research. In the following section some of these papers will be discussed in more detail, while also touching up on related questions.

2. Relevant Works

Types of artistic creative products can be distributed in groups; the paper does this for convenience.

2.1. Visual and artistic creativity

Visual and artistic creativity is mainly related to abstract and representational art. Mathematic formulation of visuals, already appeared in the 17th century – René Descartes and Pierre Fermat created what we today know as Cartesian geometry [29]. Harold Cohen is considered as one of the pioneers of generative art. He was British artist, who created AARON, a computer program which creates artistic images [16]. He began the development in 1968 at the University of California, San Diego, but he continuously worked on it throughout his life. Cohen does not consider the art it generates creative, as it just follows the style that he had previously hand-coded, but it influenced research for the next decades.

Art, Creativity, and the Potential of Artificial Intelligence by Marian Mazzone and Ahmed Elgammal [24] tries to find the answer to both machine creativity on its own and related to human creativity. As stated in section 1, GANs are a very commonly used methodology for generating something new. In this paper a similar idea was introduced: CANs (Creative Adversarial Networks). The main difference is that there is no curation on the dataset to enforce creativity. The author's goal was not to create something similar to human art, but to create something completely new. The network chose everything for generation, including style, texture, colours, and subject. Reactions to the generated images were rather positive, most people couldn't tell that the paintings weren't human made and were interested who the artist was. The latest image collection can be seen at figure 1.

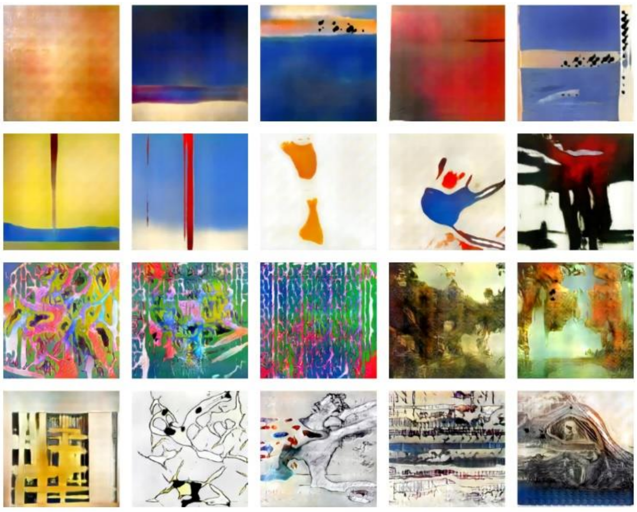

Figure 1: Examples of generated images [24]

In Sketch-to-Art: Synthesizing Stylized Art Images from Sketches, the authors decided to combine two tasks into one: Sketch-to-image synthesis and Style transfer [5]. They suggest that the method can reduce repetitive work and could speed up artist's work. As these are generative tasks, a GAN was used here as well. In the model they implemented three novel components: Dual Mask Injection (a trainable layer that increases content faithfulness), Feature Map Transfer (an adaptive layer that extracts only the style information of an input image) and Instance De-Normalization (to effectively disentangle the style and content information). The model was trained on Wikiart images of different artistic styles. Using human evaluation, they concluded that their architecture yields consistent performance.

Creative Machine Performance: Computational Creativity and Robotic Art by Petra Gemeinboeck and Rob Saunders [13] focuses on an even more physical approach, where robots create actual material art. It takes place in an installation called Zwischenraume, where autonomous robots are placed, and try to create something artistic from a room that looks quite common. The robots rely on colour histograms, blob detection and frame differencing. The method is not as common - it uses a neural network for reinforcement learning, to be more exact - implementing Q learning. The machines are equipped with a motorised hammer, chisel or punch, and a camera to interact with the other machines. The robots try to sculpt something from the walls and get reward from the network by creating something new. It is important to note that this is a more human oriented approach, as the response of the audience is also taken into aspect by the neural net, it's evaluated in the so-called state. The research was successful, it received several awards. In figure 2 a creation of the robots, and its vision is shown.

Figure 2: Zwischenraume [13]

2.2. Musical creativity

As music can be easily mathematically formalized, it is no surprise, that algorithmic composition has a long history. Mozart’s Musikalisches Würfelspiel (German for “musical dice game”) is a more than 3 century old example [28]. In this piece, precomposed sections are placed after each other, and randomness is introduced – through dice throws. The pioneer of ambient music – Brian Eno – created the album “Ambient 1: Music for Airports”, which can also be considered as generative art. It used a series of semi-unpredictable processes, which caused it to play differently every time someone listened to it. Another critically acclaimed musician, Icelandic singer and songwriter - Björk, teamed up with Microsoft, and used an AI, which collected data about the weather using a visual input, to use the results as parameters to determine the choral arrangements in a piece of music [8]. People coming from scientific background are also still active in the field, in the following the improvements, and new approaches from recent years will be discussed.

Flow Machine technologies, created by the company Sony, aided the first AI-human collaborated album – *Hello world* [25]. These algorithms can be used for multiple purposes, such as generation of melodies chords and music bases. The creators of Flow Machine emphasize that their product was not created to generate music but is a tool for creators to get inspiration. They mainly rely on statistics for the algorithms (such as Markov models), which could imply that they cannot be creative on their own but aim to help humans doing creative work. SKYGGE, a French pop artist used these methods to create an entire album, with the help of other musicians coming from various backgrounds and genres, with one goal – to prove that AI can be used to create music that is enjoyable for humans. The author of the paper *Artificial Intelligence & Popular Music: SKYGGE, Flow Machines, and the Audio Uncanny Valley* believes that using artificial intelligence in the field will get more and more common and draws an interesting comparison – not such a long time ago Auto-Tune was considered as cheating, but in today's music it is completely legitimized and used in obvious ways.

Audio mastering is the process of enhancing a piece of music in post-production with things such as increasing loudness, making it clearer, and augmenting it in such a way that it sounds similar on different sound systems. This task is on the verge of a creative task, as it heavily relies on a branch of physics – acoustics, but in a lot of cases the songs can be improved with clever ideas, and there are famous mastering engineers with a well distinguishable style. AI is starting to get more relevant in this field as well, with companies such as LANDR and Cloud-Bounce proposing to master songs without the help of humans and relying purely on algorithms [32]. Currently these methods cannot compete with human engineers, but it is a much cheaper and more accessible way for artists to meg their music mastered. As they allow users to finetune the masters using a few knobs, they can also be used by musicians to create an initial master so that they can later show an engineer what sound they are going for. Using AI in this field is a fresh concept, so it is possible that in the future algorithms will be on par with engineers.

Granular Sound Synthesis is an audio generation technique that makes use of previously existing audio by slicing it into so-called grains and rearranging them to create something new. Adrien Bitton, Philippe Esling and Tatsuya Harada created a Neural Network for this [7]. They used 3 datasets:

- Individual note recordings of instruments (Oboe, Flute etc.)
- Drum and percussion recordings
- Recordings of animal sounds

This was research of a smaller scale but it is interesting to see raw audio being generated with controls for composition purposes, by using a generative model. The aim of it was to enrich the creative use of neural nets in musical sound synthesis.

Ants Can Play Music by Christelle Guéret, Nicolas Monmarché and Mohamed Slimane [15] is a music generation tool focusing more on the melody element, which is influenced by how ant colonies work. The method (in most cases) is guiding the search agents (-the ants) towards promising solutions using a global memory. The idea is to create a graph of which the ants must choose an edge, which corresponds to a certain musical note. This is shown in figure 3.

As in other artforms – evaluating generated music is not a trivial question. Relying on human evaluation is a common choice, in *Are you ready for artificial Mozart and Skrillex? An experiment testing expectancy violation theory and AI* music [21] they decided to do this. They recruited participants from age 19 to 73 to give their opinions on generated pieces from two genres: classical and EDM. They separated these two cases because of multiple differences between them, such as harmony, tempo, style and structure, but also because usually people

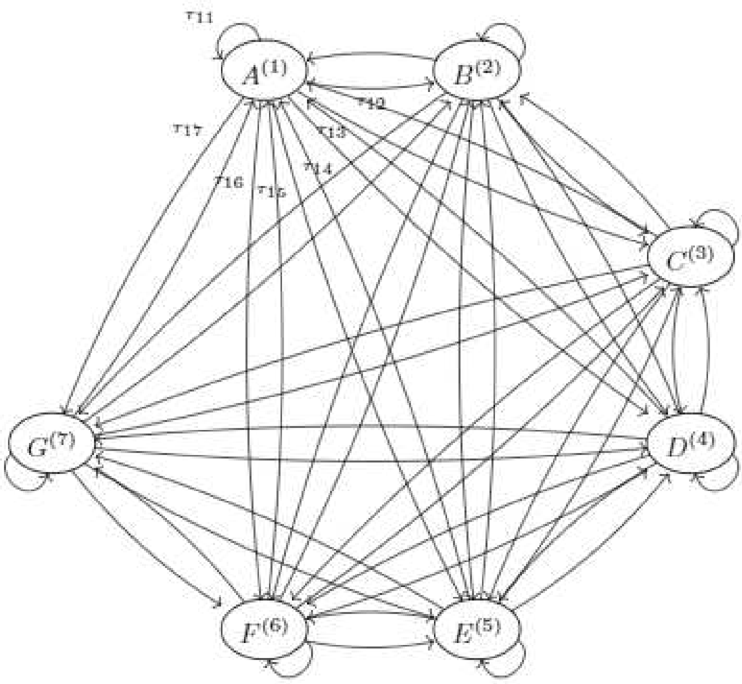

Figure 3: Chosen notes by the ants in the graph representation [15]

consider classical music as less digestible to the general public, opposed to EDM. They decided to use three measures:

- Expectancy violation scale: how much the quality deviates from what the participant expected
- Evaluation of music: assess the musical quality
- Attitudes toward creative AI: assess how much the participant believes in existence of machine creativity

The study showed that people who correctly expected not to enjoy the music hated it less than the people who expected to like it, but did not – the opposite was also true. It also became clear that the genre heavily influenced the results, as the partipicants had formed preconceptions in their minds beforehand. In conclusion the authors say that appreciating new things comes from an open-minded attitude.

Music is a creative field where collaborations are quite common, in these cases all artists have legal authorship over a piece of music, but how does this change if one of artists is an algorithm [20]? This debate dates back to at least 50 years, and legal scholars still did not find an answer they agreed on. An authorship is considered to be original if it owes its origin to the author; and possesses some creative spark. Is this the case if a musician relies on an algorithm? On the other hand – can a machine's work possess a creative spark if it is restricted to create art between the boundaries of what it thinks could be a part of the database? The paper draws an interesting comparison that human musicians also limit themselves by their experiences, for example western artists rely on using 12 musical notes, eventhough using more would be physically possible, and has been done in other regions. The author of *O.K. Computer: The Devolution of Human Creativity and Granting Musical Copyrights to Artificially Intelligent Joint Authors* says that making AI joint authors would be the best choice. This implies that AI needs to be given rights and needs to be regulated. This however raises the question: what would a robot do with its payment? An AI marketplace could require financial support, but it still is not trivial how an entity could administer transaction costs. A solution, the

Collective AI Rights Organization is functioning in the same way that Performing Rights organizations do and is comparable to a relationship that human authors have with their publishers. In conclusion the author says that the law should remove barriers to authorial equity and make collaborations with AI as easy as possible.

2.3. Linguistic creativity

Usually for people not in the field, a machine is considered intelligent when it can explicitly communicate with a human. Natural Language Processing is the segment of AI that is solving problems connected to this. The Turing test (originally "imitation game") was created by English mathematician, Alan Turing, to test a machine if it is capable of exhibiting intelligence that is indistinguishable from human intelligence [34]. ELIZA is a famous NLP program, created in 1966 that Turing's test was done on [36]. It could communicate with humans, using a simple hard-coded structure. This program cannot be considered creative, but perhaps it influenced more research in the field. In the following I will give current examples.

Hierarchical Neural Story Generation by Angela Fan, Mike Lewis, and Yann Dauphin [12] was not the first research group trying to write stories. They saw the errors in previous methods, namely that a lot of stories didn't follow a narrative or weren't consistent at all. They decided to fuse two methods that have been used before by other researchers:

- Convolutional Network
- Sequence two sequence model

They gave the model a big database of texts to learn how to write. After teaching they were hoping to have a model that worked as the following: they gave the model a prompt that they got from reddit's writingprompts forum, and the computer continued the story, that was consecutive and followed the given idea. The network could produce fine results, but it had a few errors, mainly: grammar errors, and producing generic results compared to human prompts. The latter came from the model relying on probabilities of the chosen word, and this caused rare words to be an unpopular choice, for example many stories start with *"the man"*. However, the research team concluded that their model was an improvement overall.

Story generation tasks are usually inconveniently evaluated by humans. The authors of *Evaluating Story Generation Systems Using Automated Linguistic Analyses* [26] proposed a method to make this easier. The following metrics are calculated on the outputs of the story generation algorithms:

- Story-Independent Metrics
  - Sentence Length: number of words in a sentence
  - Grammaticality: calculated using a rule-based system
  - Lexical Diversity: unique words divided by all words
  - Lexical Frequency: measure of uncommon words
  - Syntactic Complexity: number and length of syntactic phrases in a sentence
- Story-Dependent Metrics
  - Lexical Cohesion: Jaccard similarity and embedding similarity of the sentences occurring in a given story
  - Style Matching: comparing sentences by counting how many times a given word category appears, using part-of-speech (POS) tagging
  - Entity Coreference: proportion of noun phrases in the sentence that co-referred to an entity in the corresponding story

They evaluated different story generation methods using these values and showed that there is a statistic difference between them, which implies that these metrics could be used to highlight differences between algorithms.

PoeTryMe is a modular Portugese poetry generation architecture, that was created in 2012. In 2014 a Spanish version was created, which Multilingual extension and evaluation of a poetry generator [19] extended to the English language. The architecture is shown in figure 6. A lot of parts of the original architecture could be kept, but the resources surrounded in dashed lines were updated:

- Lines Grammar: either handcrafter or discovered from human-created text using a semantic network
- Semantic Network: where words are connected according to labelled relations (e.g., synonymy)
- Polarity Lexicon: where words are associated with their typical polarity
- Morphology Lexicon: properties such as POS and lemma
- A tool for syllable division and rhyme identification

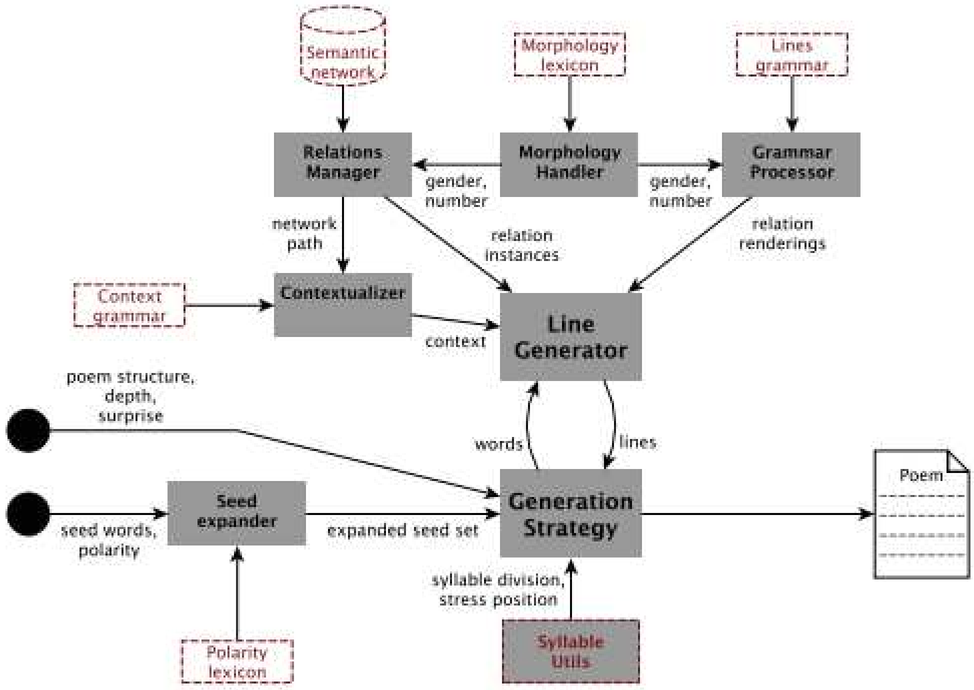

Figure 6: PoeTryMe architecture [19]

When evaluating a poem, it is an important aspect that a poem must fulfil certain structural conditions. The authors aimed at assessing three aspects:

- Poetic Features: the conformance with the metre or the rhymes
- Structure variation: to assess that the system can generate different results
- Topicality: the topic of the poem should have a semantic connection to the words provided in the poem

Children's Evaluation of Computer--Generated Punning Riddles by Kim Binsted, Helen Pain and Graeme Ritchie [6] tried to find out if a computer can generate puns. They developed a generator called

JAPE which created puns based on a database of joke collection books. It mainly relied on ambiguity in the English language:

- Juxtaposition: placing confusable segments near each other
- Substitution: substituting a confusable segment for another
- Comparison: explicit comparison of two confusable texts

In the first tries the puns were evaluated by adults. Interestingly they found quite controversial jokes, in the aspect that some of them found the puns hilarious while others didn't find them funny at all. In the final test 122 primary school aged children evaluated the puns by 3 aspects: *"jokiness"*, *"funniness"* and *"heard before"*. They were given generated puns, puns written by humans, and non-jokes. The response on the generated puns looked like the following:

- Jokiness: They found the puns to be less *"jokey"* than the ones written by humans, but more *"jokey"* than the non-joke ones. The latter was expected.
- Funniness: Similarly, to *"jokiness"* the children found puns by humans funnier and non-jokes less funny than the generated ones.
- Heard before: Interestingly some children said that the generated puns seemed familiar. This could mean that already existing puns were regenerated (or at least the concept of it was similar to an already existing one).

Although the research wasn't successful, it is still interesting to see that young children seem to agree much more on what they find funny, than adults.

As riddles are believed to be one of the earliest forms of oral literature, *RiddleSense: Reasoning about Riddle Questions Featuring Linguistic Creativity and Commonsense Knowledge* [4] is also a paper that deals with AI and literature. Answering riddles is a challenging cognitive process. The authors present a multiple-choice question answering task, which comes with a large dataset. They also evaluated commonly used language processing models. There was a large gap between computized and human performance, which suggests an intriguing future in the field.

Research by Florian Pinel and Lav R. Varshney [30] doesn't fully fall into the category of linguistic creativity, as they tried to make use of computational creativity to create culinary recipes. It made use of analytic algorithms and disparate data sources from culinary science, chemistry and hedonic psychophysics to create recipes that are flavourful, novel, and perhaps healthy. It operates with a human-computer interaction approach. The results it produces is an ingredient list and proportions, and a directed acyclic graph to represent partial ordering of the recipe steps.

5. General Artificial Intelligence

General Artificial Intelligence exists only hypothetically, it is the idea that a machine could learn any intellectual task that a human can [18]. The concept is quite common in science fiction, but it is also heavily connected to creativity. *Theory Blending as a Framework for Creativity in Systems for General Intelligence* [23] says that human mechanisms like analogy-making, concept blending, and computing generalizations rely heavily on creativity. Visions about AI in the past were more optimistic, the General Problem Solver [17] was created in 1959, hoping that research in the area will evolve in the near future. However, AI today is oriented towards completing specific tasks, research with creativity gives hope that general AI will exist sometime.

6. Abstraction and Reasoning

The measurement of artificial intelligence is a complex task, as solely measuring the skill of a machine at a certain task is heavily modulated by prior knowledge and experience [9]. The Abstraction and Reasoning Corpus dataset (abbreviated as ARC) was created to innate human priors and is a better choice to measure human-like intelligence. The goals of ARC are the following:

- Be approachable by humans and machines - should be solvable by a human without any prior knowledge
- Measure generalization, not task-specific skill
- Feature highly abstract tasks that need to be understood using only a few examples
- Provide a fixed amount of data from which new data is not easily generated
- Describe a complete set of priors it assumes

The dataset consists of images in which patterns need to be found. See figure 4. The tasks were tested by higher IQ humans who seemed to solve the tasks successfully. Although this measure still has shortcomings, and still does not fulfil every goal, arguably it is currently the best choice to compare machine and human intelligence.

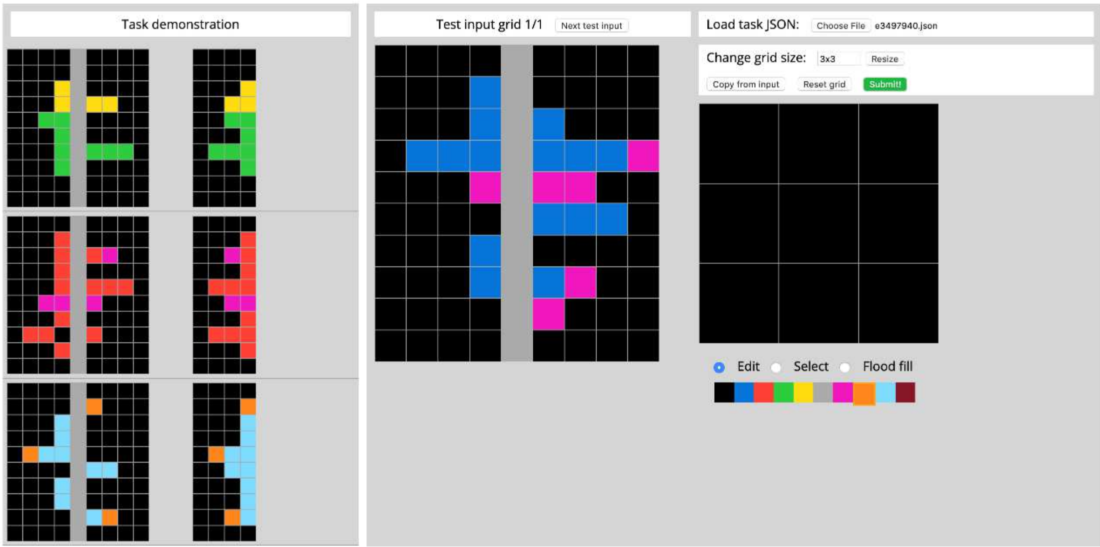

Figure 4: ARC [9]

6. Discussion and Conclusions

Not everyone agrees upon that a computer can be creative [31]. Harold Cohen rejects the claim of machine creativity even though his program has been hailed to be one of the most creative AI programs. The following quote describes his opinion well: *"It is easy, in short, to assert that machines think, and equally easy to assert that they do not. If you do not know exactly what the machine did, both are equally fruitless in carrying our knowledge, including our self-knowledge, forward."* Other researchers in the topic try to separate types of creativity, like Margaret Boden. She says that creativity can be distinguished into:

- Interactive art: some or all of the creativity is attributed to the programmer or the human participants.
- Standing alone art:
    - Generative art: *"the programmer tweaks no knobs while it is running"*
    - Evolutionary art: the computer produces results by capitalizing on the evolutionary principle of random variation and selective retention

Cohen's method does not fully fit into any of these. Boden makes another distinction: machines that model creativity and machines that do not. The latter type includes machines are not creative, they are just programmes that imitate creativity. She puts AARON into the former category - disagreeing with Cohen. He said the following: *"Creativity...lay in neither the programer alone nor in the program alone, but in the dialog between program and programer; a dialog resting upon the special and peculiarly intimate relationship that had grown up between us over the years."* It can be seen that this is a quite controversial question amongst people in the field. Amongst people not in the field it is a common misconception that the computer can only perform tasks that the programmer also knows how to perform [27]. From this some people draw the conclusion that a machine cannot be creative. A survey has been done about opinions on machine creativity, results of this can be seen in figure 5.

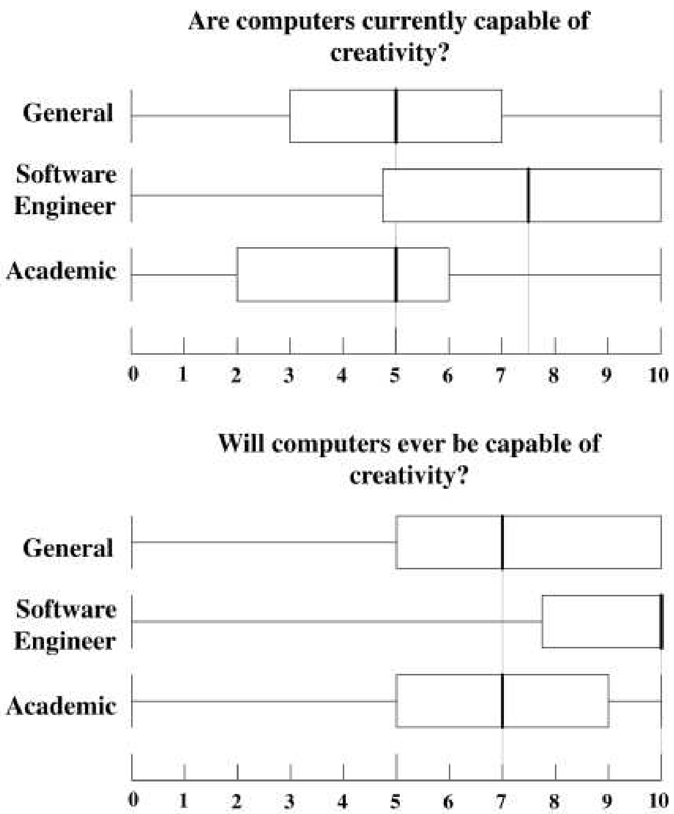

Figure 5: Survey results [27]

A quite interesting result was that in most cases people tend to consider machines that take time to "think" to be more creative. This became clear when putting a loading screen in an analogy generator program, it made people think that something is happening *'behind the curtain'*.

Another point is made by Lev Manovics in *AI Aesthetics* [2]. He says that we as humans consider creative work innovative when it is distinguishable and contains something that is distinct from other works. The problem with artificial intelligence methods (more precisely machine learning methods) is that they try to find ground truths in the database that they were given. Can these algorithms innovate the field by relying only on randomness? If a human wants to collaborate (– needs help) from a machine, will it help the human to be creative, or will it restrict the boundaries of the creative process? Maybe algorithms could make it easier for humans to start working in a new creative field, or to inspire when they are out of ideas, but it is also possible that in the long run it will just make all art less salient.

Perhaps one of the most commonly asked question - not only in machine creativity, but AI generally - is the responsibility aspect. Can the programmer who did some research in the area be held responsible if the creation starts being offensive, or even dangerous? There is no clear answer for this, but it's getting more and more relevant.

7. Future

As seen in the paper, it is very hard to draw the line where creativity starts, but in our opinion, it already exists, although it is still fully in the research phase. Perhaps the most relevant topic for a computer scientist is the question whether computer source code will be generated, and maybe even solved better by machines. We however find the humanitarian aspect more interesting, as we still know very little about the purposes of our need for creativity, and how are brains work differently when doing something creative. In our opinion machine creativity will not replace human creativity, since most people do creative activities for themselves, not just to get a certain result. Perhaps in the future machines will help us understand our creativity a bit more, but in worst case, art will be created that is enjoyable and interesting to humans.

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