Creativity in AI: Progresses and Challenges

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Creativity is the ability to produce novel, useful, and surprising ideas, and has been widely studied as a crucial aspect of human cognition. Machine creativity on the other hand has been a long-standing challenge. With the rise of advanced generative AI, there has been renewed interest and debate regarding AI's creative capabilities. Therefore, it is imperative to revisit the state of creativity in AI and identify key progresses and remaining challenges. In this work, we survey leading works studying the creative capabilities of AI systems, focusing on creative problem-solving, linguistic, artistic, and scientific creativity. Our review suggests that while the latest AI models are largely capable of producing linguistically and artistically creative outputs such as poems, images, and musical pieces, they struggle with tasks that require creative problem-solving, abstract thinking and compositionality and their generations suffer from a lack of diversity, originality, long-range incoherence and hallucinations. We also discuss key questions concerning copyright and authorship issues with generative models. Furthermore, we highlight the need for a comprehensive evaluation of creativity that is process-driven and considers several dimensions of creativity. Finally, we propose future research directions to improve the creativity of AI outputs, drawing inspiration from cognitive science and psychology.

1 Introduction

> Computers can't create anything. For creation requires, minimally, originating something. But computers originate nothing; they merely do that which we order them, via programs, to do.
>
> *Ada Lovelace*

Creativity, the ability to produce novel, useful, and surprising ideas [Boden 2004], is one of the major hallmarks of human intelligence [Guilford 1967]. Since the invention of the first known general-purpose mechanical computer (known as Analytical Engine) designed by Babbage [Babbage 1837], the question of whether machines can truly think or create anything new has intrigued the scientific community [Newell et al. 1959; Turing 1950; Wang et al. 2024b]. Ada Lovelace, recognized as the first programmer by many, famously stated that the Analytical Engine *has no pretensions to originate anything* [Lovelace 1843] and Alan Turing, who laid the foundations of computer science, asserted that *machines can never take us by surprise* [Turing 1950]. Nevertheless, alongside the development of personal computers and advancements in Artificial Intelligence (AI), several symbolic-based and stochastic approaches were developed to endow machines with story generation [Lebowitz 1983; Meehan 1977; Turner 1994; y Pérez and Sharples 2001], poetry writing [Masterman 1971; Racter 1984] and music composition skills [Brooks et al. 1957; Hiller and Isaacson 1958]. However, these early approaches could not generalize beyond a set of limited domains [Colton et al. 2012; Ji et al. 2020; Yao et al. 2019].

Fast-forward to now, the advent of the Transformer architecture [Vaswani et al. 2017] and the development of large language models (LLMs) [Zhao et al. 2023c] in the past decade ushered a new age of intelligent systems with remarkable generative, reasoning, coding, mathematical and
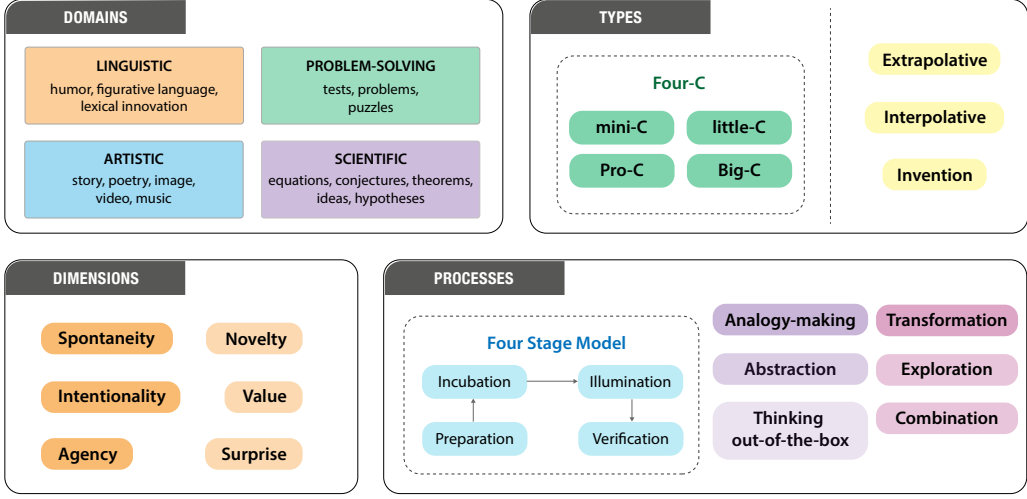
Fig. 1. A summary of domains, dimensions, types and processes of creativity covered in this survey.

multimodal capabilities [Bubeck et al. 2023; Gemini 2024; Wei et al. 2022]. Transformer-based models can now produce long stories in various domains [Yang et al. 2022; Yao et al. 2019], write poems about diverse topics [Chakrabarty et al. 2022a; Ormazabal et al. 2022a], compose high-fidelity songs [Dhariwal et al. 2020], generate impressive high-quality images and videos [Betker et al. 2020; Brooks et al. 2024] and discover new scientific knowledge [Jumper et al. 2021].

While these remarkable achievements can be seen as signs of the presence of creative capacity in transformer-based language models, it should be noted that these models rely on an astronomically large number of parameters and are trained on massive amounts of public and private data [Brown et al. 2020a]. Hence, it is not entirely clear whether the seemingly extraordinary outputs of these models are the result of a truly creative inner process and robust generalization or the result of powerful interpolation and strong memorization skills [Bender et al. 2021; Bender and Koller 2020; Carlini et al. 2022; Hupkes et al. 2022; Marcus 2020; McCoy et al. 2023]. Recent works have shown that language models fail at real-world commonsense reasoning and compositionality tasks [Dziri et al. 2023; Ismayilzada et al. 2023], occasionally copy large amounts of text from their training data [McCoy et al. 2021], significantly lag behind experts in creative writing [Chakrabarty et al. 2023a], produce less diverse content [Anderson et al. 2024a; Padmakumar and He 2023], struggle with creative problem-solving [Tian et al. 2023] and abstract reasoning [Gendron et al. 2023; Mitchell et al. 2023] and suffer from factual inconsistency and hallucination issues [Banerjee et al. 2024; Elazar et al. 2021]. While previous works have reviewed developments on some aspects of AI creativity [Amin and Burghardt 2020; Elzohbi and Zhao 2023; Franceschelli and Musolesi 2021b; Lai and Nissim 2024; Oliveira 2017; Rowe and Partridge 1993], a more holistic and broader review of the field is necessary to understand its rapid advancements.

In this work, we provide the general AI audience with a timely summary of the state of the creative capabilities of the latest AI systems. While creativity is a broad concept that can be explored in a wide range of areas, in this survey, we focus on four main areas where machine creativity has been extensively investigated: **Linguistic Creativity** (§3), **Creative Problem-Solving** (§4), **Artistic Creativity** (§5) and **Scientific Creativity** (§6). These areas capture four

crucial pillars of creative thinking in humans: linguistic creativity enables us to manipulate language in novel ways for effective communication of ideas; creative problem-solving helps us find efficient solutions by thinking out-of-the-box; artistic creativity allows for the expression of emotions, ideas, and aesthetics through various media; and scientific creativity drives innovation by enabling the formulation of new hypotheses, theories, and discoveries. Together, these areas represent distinct yet interconnected facets of creativity, providing a comprehensive framework for studying how machines can emulate or assist human-like creative processes across different domains. For each area, we survey representative tasks, resources, methods, and major findings and present a taxonomy of these works in Figure 2. Our review indicates that although the latest AI models are generally proficient in generating linguistically and artistically creative outputs, such as poems, images, and music, they face challenges with tasks demanding creative problem-solving, abstract reasoning, and compositionality. Their outputs often lack diversity and originality, exhibit long-term incoherence, and are prone to hallucinations. We also briefly discuss the emerging challenges brought by generative models concerning **copyright** and **authorship** of artworks (§7). Finally, in the last section (§8), we argue for a comprehensive evaluation of creativity in AI that considers several dimensions of creativity and the creative process at its core. Furthermore, we discuss **future research directions** to enhance the creativity of AI systems, potentially drawing ideas from cognitive science and psychology.

Our goal in this survey is to provide a high-level yet comprehensive overview of the state of creativity in AI. We expect our survey to provide researchers working on machine creativity with comprehensive background knowledge and encourage them to explore new avenues for developing intelligent systems that can do creative generation.

2 Creativity

2.1 Definitions

While creativity as a concept seems intuitively easy to understand on the surface, there is still no consensus on what constitutes true creativity. This is primarily due to the subjective nature of creativity, as what is deemed novel and of quality can vary significantly across cultures, disciplines, and periods. Aleinikov et al. [2000] lists more than 100 proposed definitions, and the number keeps growing. Despite the lack of global consensus, there is one definition of creativity that has seen wide adoption by many philosophers and psychologists and has been dubbed as the *"standard definition"* [Barron 1955; Runco and Jaeger 2012; Stein 1953]. According to this definition, creativity requires **novelty** (a.k.a originality, uniqueness, etc.) and **value** (a.k.a utility, effectiveness, usefulness, appropriateness, relevance, meaningfulness, etc.).

The novelty criterion is typically self-explanatory to the point that people equate it to creativity in everyday life. This is generally known as *intrapersonal* or *personal* creativity (often denoted as **P-creativity**), i.e. the product is novel within the frame of a person's life [Boden 2004; Stein 1953; Weisberg 1986]. Researchers distinguish it from the *interpersonal* or *historical* creativity (often denoted as **H-creativity**), i.e. the product is novel with respect to the entire history of people such as Einstein's general relativity theory.

Many theorists have argued that novelty is insufficient for creativity, and value dimension is needed to filter out original nonsense, such as something generated by a truly random process. While value is generally understood as something inherently "good" for the respective audience, there appears to be such a thing as malevolent or "dark" creativity. For instance, one can be creative in producing torture instruments or in committing terrorist atrocities [Gaut 2010]. Therefore, the interpretation of the value of a product as being "effective" towards its intended end, regardless of whether that end is morally good or bad, has been suggested as a better alternative [Livingston

2018]. However, we should note that evaluating utility or value still requires an outside judgment which is subjective, can be faulty or biased and can change over time and across cultures. This is especially apparent in arts as there are many great artists (Bach, Van Gogh etc.) whose "value" have only been recognized longtime after their death. Moreover, sometimes novelty *is* itself the value created by the artist because no one has done it before, particularly, in visual arts. Hence, some researchers have recently argued to drop the value criterion altogether from the definition of creativity [Brandt 2021; Weisberg 2015b].

Despite its wide adoption, the sufficiency of the novelty and value conditions for creativity has also been challenged [Arnheim 2001; Gaut 2010; Weisberg 2015a]. It has been argued that ***agency***, a capacity to have beliefs, desires or intentional states, is a required attribute of creativity. For example, Gaut [2010] mentions the tectonic movement of the earth's crust that can produce valuable (financially and aesthetically) and sometimes original (new variation) diamonds, but we would hardly call tectonic movements creative. However, mere agency without ***intentionality*** is also insufficient. Gaut [2010] illustrates this with an example where a person walking in a studio accidentally knocks over a set of paints, which spill onto a canvas and happen to create a beautiful and original painting. Weisberg [2015b] has gone even further to suggest that creativity is simply *intentional novelty*.

While the creative process should be intentionally initiated, others have argued that the creative process should involve an element of ***spontaneity*** [Kronfeldner 2009]. This allows the creative product to induce a *surprise* in the audience since the output of the process is not foreseen from the beginning. Being ignorant of the end at the outset of the creative process opens the room for creativity as opposed to a mechanical routine or algorithm that, by definition, is exact and excludes any type of spontaneous modifications. To illustrate this contrast Perkins [2001] makes a distinction between *reasonable* problems (i.e. that can be reasoned out step-by-step such as anagrams) and *unreasonable* problems (i.e. that are hard to describe with a step-by-step thinking).

The element of ***surprise*** has been further developed by [Boden 2004] into a widely recognized third dimension of the "standard definition" of creativity. This new definition can be seen as an elaborated version of the three criteria (i.e. new, useful and non-obvious) used by the United States Patent Office to determine whether an invention can come under patent protection[1] [Simonton 2012]. In this survey, we will also take this extended definition as our working definition throughout the paper.

2.2 Types

While creativity manifests itself in various forms across domains, even within a particular domain, different *types* of creativity can be distinguished based on the difficulty level of the inherent creative process involved. **Four-C** model of creativity is one such popular theory that differentiates between four types of creativity corresponding to four levels of difficulty involved in producing creative artifacts [Kaufman and Beghetto 2009]. The first major type of creativity is known as **little-c** creativity which is what we find in everyday life as solutions to minor problems. Examples might include combining unusual ingredients to make a new type of meal or using a hand-held vacuum cleaner on the ceiling to remove flies. Almost everyone possesses this type of creativity in one way or another. The second main type of creativity in this model is the **Big-C** creativity that includes major works of scientific, technological, social, or artistic importance. Examples could be Darwin's theory of evolution, the invention of the printing press, or Leonardo Da Vinci's painting of the Mona Lisa. In addition to these two major categories, Kaufman and Beghetto [2009] also defines two minor categories of creativity. First is the **mini-c** creativity for very small-scale cases of

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[1]http://www.uspto.gov/inventors/patents.jsp

creativity such as young children's drawing or their creative experiments with Lego pieces. Second is the **Pro-C** creativity which is proposed for work produced by professional but non-prominent practitioners such as professional musicians or artists who generate novel work, but do not make historical contributions.

Recently, there has been a suggestion to differentiate three types of creativity corresponding to three major levels of innovation that can be achieved [Hassabis 2018]. First can be achieved through **interpolation** where a prototypical creative artifact is produced by averaging all the artifacts of the same class seen before. While it is an original product that did not exist before, it still relies heavily on the other existing products. An example would be to come up with a novel winning strategy in chess that is a combination of existing different strategies. Consequently, a second type of innovation can be achieved through **extrapolation** where a creative artifact extends the boundaries of what has been seen before, but is still of the same class. A completely new chess move that is not related to any existing moves can be seen as an example of extrapolative creativity. Finally, the highest level of creativity can be termed as **invention** where a creative artifact introduces a novel class of its own. Inventing chess itself or any major scientific invention is a perfect example of this type of creativity.

2.3 Evaluation

Evaluating creativity remains a challenging task in artificial intelligence due to its inherently subjective nature [Lamb et al. 2018]. Interestingly, some research work even argued against the quantitative evaluation of creativity, suggesting it is either too domain-specific to be measured effectively [Baer 2012], or that creativity is an inherently human trait that cannot be accurately modeled computationally [Boden 1991; Minsky 1982]. However, an overwhelming majority of the scientific community favors the possibility of computational modeling and evaluation of creativity [Veale and Cardoso 2019]. Hence, numerous evaluation methods have been proposed in the past [Lamb et al. 2018]. However, most of the proposed metrics are either formal frameworks that are hard to implement in practice or manual psychometric creativity tests that require costly human involvement [Kim 2006] or automated metrics that are too domain-specific [França et al. 2016]. We refer the reader to Franceschelli and Musolesi [2021b] and Lamb et al. [2018] for more details on formal evaluation frameworks, and here we briefly summarize some of the relevant manual and automated metrics for creativity.

2.3.1 Manual Evaluation. Since creative products vary greatly in their forms and are hard to characterize with objective measures, the simplest and most common way to evaluate them is to ask other humans to manually rate them based on some criteria associated with creativity, which differs from task to task [Lamb et al. 2015]. For example, in story generation, humans are typically asked to rate a generated story on aspects such as **interestingness**, **coherence**, **relevance**, **humanlikeness** and etc. [Goldfarb-Tarrant et al. 2020; Rashkin et al. 2020; Yang et al. 2022]. In other tasks where the goal is to produce multiple responses such as common psychometric creativity tests *Alternative Uses Task (AUT)* [Guilford 1967] and *Torrance Tests of Creative Thinking (TTCT)* [Torrance 1974], evaluation is centered around four dimensions of creativity: ***fluency*** (the total number of meaningful, and relevant ideas generated in response to the stimulus), ***flexibility*** (the number of different categories of relevant responses), ***originality*** (the uniqueness or rarity of responses) and ***elaboration*** (the amount of detail in the responses).

While it is common and straightforward to conduct human evaluation with ordinary humans, some have argued that people who are not experts on a kind of creative artifact might not be good judges of those artifacts [Gervás 2019; Lamb et al. 2015, 2018; Mirowski et al. 2022; Veale 2015]. This typically results in poor interrater reliability and even when they agree, their judgments do

not correlate well with expert judgment [Lamb et al. 2018]. Therefore, it is generally recommended to employ **Consensual Assessment Technique** [Amabile 1983], an evaluation method that relies on the collective judgment of experts in a given field.

2.3.2   Automated Evaluation. While creativity is generally evaluated by humans, several attempts have also been made to devise automated measures of it [Cook and Colton 2015; França et al. 2016; Jordanous et al. 2015; Maher and Fisher 2012]. These measures often target a specific dimension of creativity. Below, we review some automated measures for three dimensions of creativity: novelty, value, and surprise.

Novelty. It is typically defined as the measure of how different an artifact is from other known artifacts in its class [Maher 2010]. Then a distance metric is established to quantify this difference based on the attributes of the artifact and the task space. For example, in the text generation task, a notion of ***semantic distance*** is commonly employed as a distance measure [Beaty and Johnson 2020; Dunbar and Forster 2009; Harbison and Haarmann 2014; Johnson et al. 2022; Prabhakaran et al. 2013]. More specifically, the text is embedded into a vector in semantic space and some distance or dissimilarity metric (e.g. typically `1-cosine_similarity`) is used to compute how much semantically different is one text from another. However, the granularity of the text can differ from task to task. For example, in the story generation task, Karampiperis et al. [2014] defines the novelty of a story as the average semantic distance between the dominant terms included in the textual representation of the story, compared to the average semantic distance of the dominant terms in all stories where distance is measured based on the embeddings of terms.

Novelty can also be characterized by the degree an artifact differs from the previously produced works that one has already seen [Elgammal and Saleh 2015; Gunkle and Berlyne 1975]. This definition has inspired the development of Creative Adversarial Networks (CANs) [Elgammal et al. 2017] similar to the popular Generative Adversarial Networks (GANs) [Goodfellow et al. 2014a]. In CANs, the generator tries to fool the discriminator into thinking its generation is "art" and at the same time, the style of its generation is nothing known to the discriminator. Consequently, the score assigned by the discriminator (more specifically, `1-score`) can be used to measure the novelty of the generated artifact as suggested by Franceschelli and Musolesi [2022].

Value. This dimension is generally the hardest to evaluate as it depends on the subjective utility or performance of the artifact which is typically judged by domain experts of that artifact and can radically change across domains [Maher 2010]. In visual arts, this might correspond to "beauty", whereas in science to "logical correctness". Therefore, a metric appropriate for its domain should be employed. For example, in open-ended story generation, a minimally useful story can be defined as a relevant, coherent, and meaningful story. In this sense, automated metrics measuring the overall quality of a story can be leveraged [Chen et al. 2022b; Guan and Huang 2020; Xie et al. 2023a], however, it is often challenging to measure coherence [Laban et al. 2021; Zhao et al. 2023b]. Another more general evaluation of utility has been suggested by Franceschelli and Musolesi [2022] based on the discriminator score in GANs.

Surprise. Also known as unexpectedness, surprise measures the artifact's degree of deviation from what is expected [Maher 2010]. Therefore, automatic metrics for surprise tend to be *information-theoretic* [Bunescu and Uduehi 2022; Kuznetsova et al. 2013] and estimate the violation of expectation based on uncertainty reduction [Frank 2010; Hale 2006]. However, semantic distance-based measures of surprise have also been suggested. For example, in the story generation task, Karampiperis et al. [2014] conceptualizes surprise as the average semantic distances between the consecutive fragments of a given story. Recent work has also suggested an automated measure based on the Bayesian theory of surprise [Baldi and Itti 2010; Franceschelli and Musolesi 2022].

Creativity in AI

- **Linguistic Creativity (§3)**
  - **Humor (§3.1)**
    - **Datasets:** **Humorous headlines** [Horvitz et al. 2024; Hossain et al. 2019, 2020b], **Puns** [Miller et al. 2017; Yang et al. 2015], **Jokes** [Jain et al. 2024; Meaney et al. 2021; Tang et al. 2022; Weller and Seppi 2019; Zhang et al. 2019b; Zhong et al. 2023], [Hasan et al. 2019; Mihalcea and Strapparava 2005]
    - **Methods:** **Humorous content** [Arora et al. 2022; Hessel et al. 2023b; Kayatani et al. 2021; Peyrard et al. 2021; Ravi et al. 2024; Xie et al. 2023b], [Amin and Burghardt 2020; Annamoradnejad and Zoghi 2020; Bertero and Fung 2016; Chen and Soo 2018; Liu et al. 2018b; Ziser et al. 2020], [Radev et al. 2016; Raskin and Attardo 1994; Stock and Strapparava 2005; Taylor and Mazlack 2004; Yang et al. 2015; Zhang and Liu 2014] [Hasan et al. 2019], **Pun** [He et al. 2019; Mittal et al. 2022; Yu et al. 2018], **Sarcasm** [Chakrabarty et al. 2020a, 2022c], **Joke** [Jentzsch and Kersting 2023; Meaney et al. 2021; Ren and Yang 2017; Shahaf et al. 2015; Weller and Seppi 2019; Xie et al. 2021]
  - **Figurative Language (§3.2)**
    - **Datasets:** **Metaphor** [Chakrabarty et al. 2022c, 2023e; Mohammad et al. 2016; Mohler et al. 2016; Stowe et al. 2021, 2020], **Simile** [Chakrabarty et al. 2021a, 2022c] **Idiom** [Chakrabarty et al. 2021a, 2022c]
    - **Methods:** **Metaphor** [Chakrabarty et al. 2023e, 2021b; Stowe et al. 2021, 2020], **Simile** [Chakrabarty et al. 2021a, 2020b; He et al. 2023], **Idiom** [Chakrabarty et al. 2021a], **Hyperbole** [Tian et al. 2021]
  - **Lexical Innovation (§3.3):** **Novel compound** [Butnariu et al. 2009; Coil and Shwartz 2023; Dhar and van der Plas 2019; Hendrickx et al. 2013; Kuznetsova et al. 2013; Vecchi et al. 2017], **Neologism** [Das and Ghosh 2017; Lencione et al. 2022; **Morphological Productivity** [Anh et al. 2024; Ismayilzada et al. 2024; Weissweiler et al. 2023]
- **Creative Problem Solving (§4)**
  - **Convergent Thinking (§4.1):** **NYT Connections** [Samadarshi et al. 2024], **MacGyver** [Tian et al. 2023], **The Only Connect Wall** [Naeini et al. 2023], **RiddleSense** [Lin et al. 2021]
  - **Divergent Thinking (§4.2):** **BrainTeaser** [Jiang et al. 2023], **UnCommonsense** [Zhao et al. 2023a], **MacGyver** [Tian et al. 2023], **DAT** [Chen and Ding 2023], **AUT** [Góes et al. 2023b; Hubert et al. 2024a; Koivisto and Grassini 2023; Stevenson et al. 2022], **TTCT** [Góes et al. 2023b; Guzik et al. 2023; Zhao et al. 2024]
  - **Abstraction (§4.3.1):** **ConceptARC** [Mitchell et al. 2023; Moskvichev et al. 2023; Odouard and Mitchell 2022], **ARC** [Chollet 2019; Gendron et al. 2023; Mirchandani et al. 2023; Odouard and Mitchell 2022; Opiełka et al. 2024; Xu et al. 2022, 2023; Zhang et al. 2021], **RAVEN** [Ahrabian et al. 2024; Gendron et al. 2023; Odouard and Mitchell 2022; Santoro et al. 2018; Zhang et al. 2019a], **Kandinsky Patterns** [Holzinger et al. 2019; Lorello et al. 2024] **Serial Reproduction** [Kumar et al. 2022], **Bongard Problems** [Bongard 1970]
  - **Analogy (§4.3.2):** **Word Analogies** [Gladkova et al. 2016; Marquer et al. 2022; Mikolov et al. 2013; Ushio et al. 2021], **Scientific Analogies** [Czinczoll et al. 2022; Yuan et al. 2023], **Visual Analogies** [Bitton et al. 2023; Opiełka et al. 2024; Zhang et al. 2019a], **Story Analogies** [Jiayang et al. 2023; Nagarajah et al. 2022; Sourati et al. 2023; Sultan and Shahaf 2022], **Sentence Analogies** [Wijesiriwardene et al. 2023; Zhu and de Melo 2020], **Analogical Reasoning** [Lewis and Mitchell 2024; Musker et al. 2024; Petersen and van der Plas 2023; Hu et al. 2023; Webb et al. 2022; Yasunaga et al. 2023]
- **Artistic Creativity (§5)**
  - **Story Generation (§5.1)**
    - **Datasets:** **StoryWars** [Du and Chilton 2023], **Visual WritingPrompts** [Hong et al. 2023], **STORIUM** [Akoury et al. 2020], **RolePlayingGuild** [Louis and Sutton 2018], **WritingPrompts** [Fan et al. 2018]
    - **Methods:** **Re3** [Yang et al. 2022], **Creativity Support** [Chakrabarty et al. 2023c], **TTCW** [Chakrabarty et al. 2023b], **Dramatron** [Mirowski et al. 2022], **PEER** [Schick et al. 2022], **WordCraft** [Yuan et al. 2022], **TaleBrush** [Chung et al. 2022], **PlotMachines** [Rashkin et al. 2020], **Aristotelian Rescoring** [Goldfarb-Tarrant et al. 2020], **Story Centaur** [Swanson et al. 2021], **Plug and Play** [Dathathri et al. 2019; Pascual et al. 2021], **Plan-And-Write** [Yao et al. 2019], **Reward Shaping** [Tambwekar et al. 2018], **Hierarchical** [Fan et al. 2018], **UNIVERSE** [Lebowitz 1984], **TALE-SPIN** [Meehan 1977] **COINS** [Paul and Frank 2021]
  - **Poetry (§5.2)**
    - **Datasets:** **Gutenberg** [Jacobs 2018], **CoPoet** [Chakrabarty et al. 2022b], **Acrostic Poems** [Agarwal and Kann 2020], **UniM- and MultiM-Poem** [Liu et al. 2018a]
    - **Methods:** **Heuristic-based** [Colton et al. 2012; Manurung 2004; Manurung et al. 2000, 2012; Oliveira 2012], [Masterman 1971; Milic 1970; Racter 1984], **Neural-networks** [Ghazvininejad et al. 2016; Lau et al. 2018; Liu et al. 2018a; Zhang and Lapata 2014], **Language models** [Belouadi and Eger 2022; Chakrabarty et al. 2022b; Ormazabal et al. 2022b; Popescu-Belis et al. 2023; ?], [Agarwal and Kann 2020; Tian and Peng 2022; Van de Cruys 2020]
  - **Visual Creativity (§5.3)**
    - **Image Editing:** **Style transfer** [Abdal et al. 2019; Dumoulin et al. 2016; Gatys et al. 2015; Johnson et al. 2016; Karras et al. 2018, 2019], **Super-resolution** [Dong et al. 2014; Ledig et al. 2016], **Colorization** [Zhang et al. 2016a], **In-painting** [Pathak et al. 2016], **Generic Image-to-Image** [Huang et al. 2018a; Isola et al. 2016]
    - **Text-to-Image:** **Creativity-VLA** [Shen et al. 2024], **InstructDiffusion** [Geng et al. 2023], **DALL-E** [Betker et al. 2020; Ramesh et al. 2022, 2021], **Imagen** [Saharia et al. 2022], **Make-A-Scene** [Gafni et al. 2022], **StableDiffusion** [Rombach et al. 2021], **GLIDE** [Nichol et al. 2021], **StackGAN** [Zhang et al. 2016b], **CreativeSynth**, **Dream Art** [Huang et al. 2022; Ruiz et al. 2022], **InstructPix2Pix** [Brooks et al. 2022], **StyleCLIP** [Patashnik et al. 2021], [Chakrabarty et al. 2023e; Hertz et al. 2022; Mansimov et al. 2015; Reed et al. 2016a,b; Yan et al. 2015]
    - **Video Generation:** **Sora** [Brooks et al. 2024], **W.A.L.T** [Gupta et al. 2023], **VideoPoet** [Kondratyuk et al. 2023], **VideoFusion** [Luo et al. 2023], **Video Diffusion** [Ho et al. 2022b], **Imagen** [Ho et al. 2022a], **Make-A-Video** [Singer et al. 2022], **ViViT** [Arnab et al. 2021], **VideoGPT** [Yan et al. 2021], **MoCoGAN** [Tulyakov et al. 2017; Vondrick et al. 2016] [Xing et al. 2023]
  - **Musical Creativity (§5.4):** **MusicGen** [Copet et al. 2023], **MusicLM** [Agostinelli et al. 2023], **Jukebox** [Dhariwal et al. 2020], **Pop Music Transformer** [Huang and Yang 2020], **MuseNet** [Payne 2019], **LakhNES** [Donahue et al. 2019], **Music Transformer** [Huang et al. 2018b], **MusicVAE** [Roberts et al. 2018], **MidiNet** [Yang et al. 2017], **MuseGAN** [Dong et al. 2017] **EMI** [Cope 1996], **GenJam** [Biles et al. 1994], [Ames 1987; Brooks et al. 1957; Eck and Schmidhuber 2002; Farbood and Schöner 2001; Hiller and Isaacson 1958; Lavrenko and Pickens 2003; Todd 1989]
- **Scientific Creativity (§6)**
  - **Equation discovery Symbolic Regression:** [Chen et al. 2022a; Garcon et al. 2021], **AI Feynman** [Udrescu et al. 2020], [Cranmer et al. 2020; Petersen and Landajuela 2019; Schmidt and Lipson 2009], [Dzeroski and Todorovski 1993; Koza 1994; Rzevski et al. 1987; Todorovski 1997], **BACON** [Langley 1977]
  - **Knowledge discovery:** **conjectures** [Buchberger et al. 2006; Chen et al. 2016; Fajtlowicz 1988; Raayoni et al. 2021; Wu and Tegmark 2019], **theorem-proving** [Hubert et al. 2024b; Trinh et al. 2024], **concepts** [Hakuk and Reich 2020; Iten et al. 2020; Lenat and Brown 1984], **molecular structures** [Abramson et al. 2024; Jumper et al. 2021; Lindsay 1980; Zambaldi et al. 2024]
  - **Scientific process automation:** **literature review** [Skarlinski et al. 2024], **idea generation** [Baek et al. 2024; Girotra et al. 2023; Si et al. 2024; Wang et al. 2023, 2024a], **hypothesis generation** [Ghafarollahi and Buehler 2024; Majumder et al. 2024; Qi et al. 2023; Sybrandt et al. 2020; Wang et al. 2024a; Yang et al. 2023], **paper writing** [Altmäe et al. 2023; Wang et al. 2019], **AI Scientist** [Boiko et al. 2023; Ifargan et al. 2024; King et al. 2009; Li et al. 2024b; Liu et al. 2024; Lu et al. 2024a]
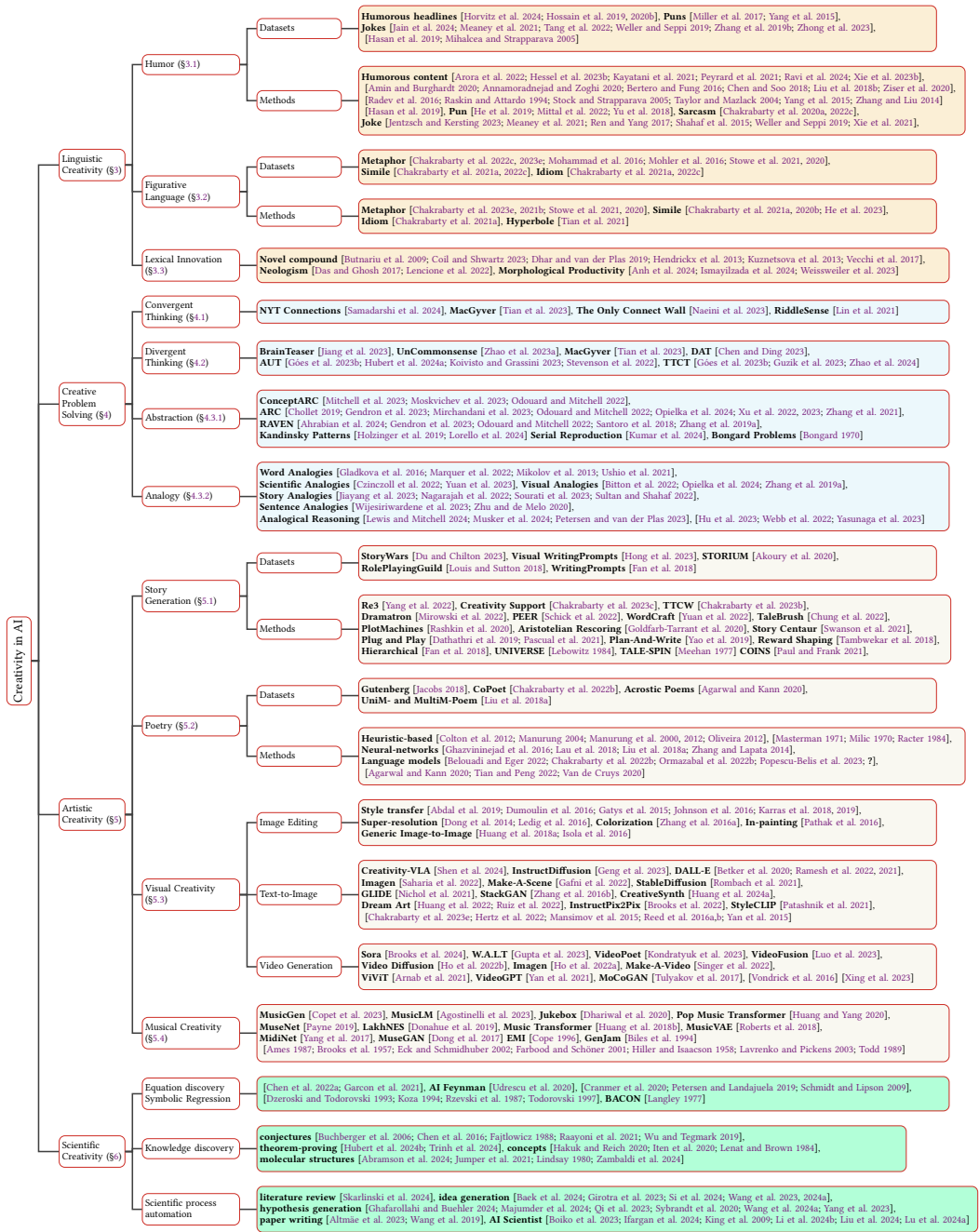
Fig. 2. Taxonomy of creativity in AI covering areas of linguistic creativity, creative problem-solving, artistic and scientific creativity. Note that this taxonomy is not exhaustive, but rather a representative view of the key works.

3 Linguistic Creativity

The creative aspect of language in linguistics has been discussed since the early days [Chomsky 1965]. Chomsky, in this paper, attributes creativity mainly to the essential property of language to provide means to express many thoughts indefinitely. However, several linguists since Chomsky have argued against using this characterization since it does not align with the everyday definition of creativity [Bergs 2019; Sampson 2017; Zawada 2006]. Chomsky's theory of grammar might generate an infinite number of sentences; it, however, relies on a fixed set of rules, while creativity requires deviation from rules. In this sense, Sampson [2017] suggests distinguishing between **F-creativity** (fixed) and **E-creativity** (extending), where F-creativity refers to the Chomskian interpretation of linguistic creativity (a.k.a productivity in morphology) and E-creativity corresponds to the real linguistic innovation such as metaphors, jokes, neologisms, etc. Some recent works have explored the F-creativity of large language models and found that this task is challenging in general and even harder in more morphological complex languages [Anh et al. 2024; Ismayilzada et al. 2024; Weissweiler et al. 2023]. Most past works however have focused on studying the E-creativity of AI systems which we review in the following sections.

3.1 Humor

Humor is one of the most common ways humans creatively use language to express their ideas and feelings. Early works to model humor focused on hand-crafted linguistic templates and wordplay [Raskin and Attardo 1994; Stock and Strapparava 2005; Taylor and Mazlack 2004]. Subsequent works have leveraged language's lexical and syntactic properties as humor-specific features for humor detection [Liu et al. 2018b; Yang et al. 2015; Zhang and Liu 2014]. The growing interest in computational humor in recent years has resulted in several shared tasks organized by the NLP community [Castro et al. 2018; Hossain et al. 2020a; Meaney et al. 2021; Miller et al. 2017; Potash et al. 2017; Van Hee et al. 2018]. Latest works have developed methods based on neural networks and language models to generate and detect **humorous content** [Amin and Burghardt 2020; Annamoradnejad and Zoghi 2020; Arora et al. 2022; Bertero and Fung 2016; Chen and Soo 2018; Hossain et al. 2019; Peyrard et al. 2021; Ravi et al. 2024; Ziser et al. 2020], **jokes** [Horvitz et al. 2024; Ren and Yang 2017; Tang et al. 2022; Weller and Seppi 2019; Xie et al. 2021], **puns** [He et al. 2019; Mittal et al. 2022; Yu et al. 2018], and **sarcasm** [Chakrabarty et al. 2020a, 2022c]. Several datasets have also been proposed to benchmark the humor capacity of LLMs in several languages including English [Horvitz et al. 2024; Hossain et al. 2019, 2020b; Jain et al. 2024; Meaney et al. 2021; Miller et al. 2017; Tang et al. 2022], Chinese [Zhang et al. 2019b], Italian [Buscaldi and Rosso 2007], Spanish [Castro et al. 2017], Dutch [Winters and Delobelle 2020] and Russian [Blinov et al. 2019]. Computational humor has also been explored in multimodal settings involving images, audio, and video in addition to text [Bertero and Fung 2016; Hasan et al. 2019; Hessel et al. 2023a; Radev et al. 2016; Shahaf et al. 2015; Xie et al. 2023b]. While the latest methods particularly LLMs show an impressive ability to generate and detect humorous content, recent work has also shown that these models still fail to *reliably understand* humor [Borji 2023a; Góes et al. 2023a; Hessel et al. 2023a; Kocoń et al. 2023] and generated jokes typically *lack diversity* [Jentzsch and Kersting 2023] which has been attributed to training on less diverse humor datasets [Baranov et al. 2023]. Creative training frameworks have also been developed to improve the humor generation capabilities of LLMs [Zhong et al. 2023]. We refer the reader to Amin and Burghardt [2020] for an in-depth survey on computational humor.

POEMS

FRENCH NOVEL

By Richie Hofmann

April 1, 2019

You were my second lover.
You had dark eyes and hair,
like a painting of a man.
We lay on our stomachs reading books in your bed.
I e-mailed my professor. I will be absent
from French Novel due to sickness. You put on
some piano music. Even though
it was winter, we had to keep
the window open day and night, the room was so hot, the air so dry
it made our noses bleed.
With boots we trekked through slush for a bottle of red wine
we weren't allowed to buy, our shirts unbuttoned
under our winter coats.
The French language distinguishes
between the second
of two and the second
of many. Of course
we'd have other lovers. Snow fell in our hair.
You were my second lover.
Another way of saying this:
you were the other,
not another.

In the quiet dawn, love softly sings,

A whisper carried on morning's wings.

It paints the sky in hues so bright,

Guiding hearts through day and night.

In a glance, a spark ignites,

Two souls merging in gentle light.

Through storms and calm, it endures,

A bond that's timeless, pure, and sure.

With every touch, a story unfolds,

In love's embrace, our hearts we hold.

Eternal, tender, ever true,

In you, I find my endless muse.

Fig. 3. Illustration of a qualitative difference between poetry written by humans and machines. **Left:** Poem about love published on New Yorker. **Right:** Poem about love generated by GPT-4o. While New Yorker poem draws deep metaphoric parallels between linguistic features of French and love, the GPT-4o generated poem merely describes love using cliché phrases. A similar comparison was made between Grok and the same New Yorker poem in [Chakrabarty et al. 2023d].

3.2 Figurative Language

Figurative language is a term in language studies encompassing various figures of speech like hyperbole, similes and metaphor [Paul 1970; Roberts and Kreuz 1994; Veale et al. 2016]. These elements can be used to achieve a range of communicative goals. Figurative language generation involves transforming a text into a specific figure of speech while maintaining the original meaning [Lai and Nissim 2024]. Generating figurative language requires an understanding of abstract concepts, commonsense reasoning, and an ability to make analogies and deviate from literal meaning. Recent works have shown that language models with injected commonsense knowledge can generate textual and visual **metaphors** [Chakrabarty et al. 2023f, 2021b], **similes** [Chakrabarty et al. 2020b; He et al. 2023], **idioms** [Chakrabarty et al. 2021a] and **hyperboles** [Tian et al. 2021]. Chakrabarty et al. [2023a] reveals that metaphors generated by large language models are often *incoherent or cliched.* Chakrabarty et al. [2023a] highlights the following example of such a metaphor generated by an LLM: *"- However, she managed to laugh louder and louder until her laughter transformed into an embrace of the sun's atmosphere."* We refer the reader to Lai and Nissim [2024] and Abulaish et al. [2020] for an in-depth survey on the automatic generation and detection of figurative language.

3.3 Lexical Innovation

Understanding and generating novel words or word compounds is a challenging linguistic task that often requires creativity, commonsense knowledge, and an ability to generalize over seen concepts [Costello and Keane 2000; Wisniewski 1997]. Similar **noun compounds** might have different meanings based on our common understanding. For example, knowing that *"chocolate*
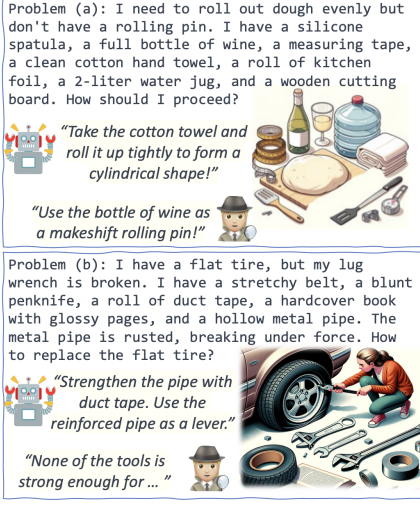
(a) Example from the MacGyver dataset for creative problem-solving [Tian et al. 2023]. Problems in this dataset require innovative usage of objects and involve both convergent and divergent thinking.
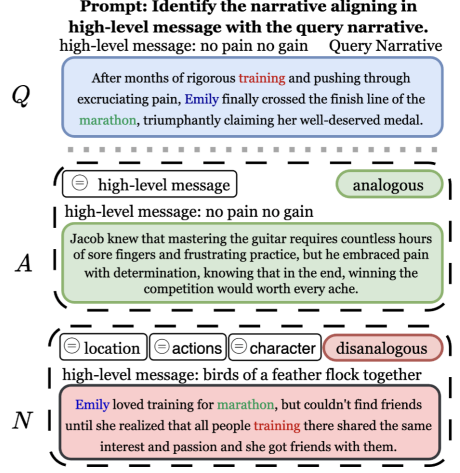
(b) Example from Analogical Reasoning over Narratives benchmark [Sourati et al. 2023]. The task is to distinguish between analogous narrative A and distractor N for the query narrative Q.

Fig. 4. Examples from Creative Problem-Solving datasets.

croissant" means a *"croissant filled with chocolate"* does not necessarily imply that *"chocolate bunny"* would mean *"a bunny filled with chocolate"*, but rather a bar of *"chocolate in the shape of a bunny"*. Several works have evaluated and analyzed language models on the task of interpreting and predicting the emergence of these noun compounds and found that models generally show a moderate performance [Coil and Shwartz 2023; Dhar and van der Plas 2019; Kuznetsova et al. 2013]. Other works have successfully trained neural networks to generate **neologisms** (i.e. newly coined words or phrases) [Das and Ghosh 2017; Lencione et al. 2022]. On the other hand, previous works have also shown that large language models can fail at *linguistic generalization* tasks such as morphologically deriving new words from nonce roots [Ismayilzada et al. 2024; Weissweiler et al. 2023] and can occasionally *duplicate* large amounts of text from its training data [McCoy et al. 2021]. Similarly, a recent work explores the linguistic creativity of both large language models and humans by reconstructing their text output from the existing text snippets on the web and finds that the seemingly remarkable creativity of model outputs may be in large part attributable to the remarkable creativity of human-written texts on the web [Lu et al. 2024b].

4 Creative Problem-Solving

Creative problem-solving is the mental process of searching and coming up with creative solutions to a given problem [Duncker and Lees 1948]. It is a challenging task for machines as it not only requires creativity but also commonsense reasoning, and compositional generalization [Davidson et al. 2022]. In addition, creatively solving a problem is usually characterized by two kinds of thinking, namely, **convergent** and **divergent** thinking, and involves deep **abstraction and analogy-making** abilities.

4.1 Convergent Thinking

Convergent thinking models creativity in terms of an ability to produce a single optimal solution for a given problem [Guilford 1967]. This type of creativity requires one to be able to associate seemingly remote ideas and converge to a unified solution. To evaluate this type of thinking in humans, psychologists have come up with several creativity tests such as **Remote Associates Test (RAT)** [Mednick 1962] and **insight problems** [Webb et al. 2017]. For example, the goal in RAT is to connect several unrelated words with one concept, e.g. words *"broken", "clear"* and *"eye"* can be connected with the word *"glass"*.

Language models have recently been evaluated on problems that require convergent thinking. Lin et al. [2021] tests language models on solving riddles that require creativity and commonsense and finds a *significant gap* between model and human performance. Naeini et al. [2023] uses the popular British quiz show Only Connect's Connecting Wall that mimics RAT formulation with built-in, deliberate red herrings (i.e. misleading stimuli or distractors) and evaluates large language models such as GPT-4 on these problems. They report poor model performance and show that models are highly *susceptible to distractors* in the input and manifest a form of **fixation effect** (a.k.a functional fixedness or Einstellung effect). This type of cognitive bias forces the model to fixate on its past knowledge and prevents it from thinking "out-of-the-box". The same effect is also found when models are evaluated on everyday problems involving unconventional use of objects [Tian et al. 2023]. Very recently, large language models such as GPT-4o have been evaluated on the popular New York Times game *Connections* and have been found to struggle with *associating* encyclopedic and linguistic knowledge at an abstract level [Samadarshi et al. 2024].

4.2 Divergent Thinking

Divergent thinking requires one to conceptualize multiple, often seemingly disconnected ideas [Guilford 1967]. It essentially plays the opposite role to convergent thinking and therefore, the goal is to start with a unified idea and diverge from this idea into the space of all ideas to find the ones that are relevant to the task at hand. Psychologists have also devised creativity tests to evaluate humans' divergent thinking abilities, such as **Alternate Uses Test (AUT)** [Guilford 1967] and **Torrance Tests of Creative Thinking (TTCT)**. AUT tests creativity based on whether the participant can come up with unusual (creative) uses for an everyday object and the results are typically evaluated either manually or using *semantic distance*. For example, a *"brick"* can be used as a *"paperweight"* or *"to break a window"* and *"coffee cup"* can be used as *"small bowl"*, or *"a hat for an elf"* etc. TTCT consists of several verbal and non-verbal tasks such as imagining impossibilities or the consequences of actions. Works evaluating GPT-3 [Brown et al. 2020b] and GPT-4 [OpenAI 2023] on these tests report near-human performance results [Góes et al. 2023b; Guzik et al. 2023; Hubert et al. 2024a; Koivisto and Grassini 2023; Stevenson et al. 2022; Zhao et al. 2024]. Other tests that highly correlate with human creativity measured by AUT have also been proposed such as the task of **naming unrelated words** [Olson et al. 2021]. Chen and Ding [2023] uses this test to evaluate the creativity of large language models and finds that models outperform humans.

While language models perform strongly on AUT-like divergent thinking tasks, they, however, struggle when these tasks require some form of **lateral thinking** or **"thinking out-of-the-box"**. For example, recent works have found that defying default commonsense associations and modeling *unexpected* or *unlikely* situations are challenging for large language models [Jiang et al. 2023; Tian et al. 2023; Zhao et al. 2023a]. Figure 4a illustrates a creative problem-solving example from Tian et al. [2023] that involves unconventional use of everyday objects.

Fig. 5. Example from the Abstraction and Reasoning Corpus (ARC) [Chollet 2019] designed to test the abstractive thinking capabilities of both humans and machines.

4.3 Abstraction and Analogy-Making

Conceptual abstraction and analogy-making lie at the core of human cognition and intelligence [Chollet 2019; Hofstadter 2001; Mitchell 2021]. These are abilities that enable humans to generalize to new domains, invent novel concepts, and make useful and often surprising connections between concepts. In other words, abstraction and analogy-making serve as foundational building blocks for creative thinking.

4.3.1 Abstraction. As the cornerstone of human intelligence, abstraction, and abstract reasoning are typically evaluated using visual IQ tests in humans. Popular examples of these tests are **RAVEN progressive matrices** [Raven 1938], **Bongard problems** [Bongard 1970] and recently introduced **Kandinsky Patterns** [Holzinger et al. 2019], **Abstraction and Reasoning Corpus (ARC)** [Chollet 2019] and its variations [Moskvichev et al. 2023]. These tests require the participants to identify and complete an abstract visual pattern based on given examples. Although several attempts have been made to solve these tasks using both symbolic-based and neural network-driven approaches [Hu et al. 2023; Lorello et al. 2024; Mirchandani et al. 2023; Santoro et al. 2018; Xu et al. 2022], modern AI systems still struggle with solving *RAVEN-like* [Ahrabian et al. 2024; Gendron et al. 2023; Odouard and Mitchell 2022; Zhang et al. 2019a] and *ARC-like* tasks [Mitchell et al. 2023; Moskvichev et al. 2023; Odouard and Mitchell 2022; Xu et al. 2023; Zhang et al. 2021]. Analysis of abstraction via a **serial reproduction task** [Langlois et al. 2021] where participants are asked to produce a textual stimulus for the next participant upon observing a visual stimulus and vice versa, has suggested that GPT-4 unlike humans relies heavily on linguistic representations even in vision-only paradigm [Kumar et al. 2024]. Figure 5 illustrates an example from the ARC task [Chollet 2019]. The problems in this corpus are quite hard to solve to the extent that this task has been recognized as the de facto benchmark for measuring progress towards Artificial General Intelligence (AGI) and a public competition with a grand prize of $1, 000, 000 has recently been launched[2]. At the time of writing this paper, the highest score is 49.5% far from from the passing threshold of 85% (human-level).

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[2]https://arcprize.org/

4.3.2 Analogy-Making. In its basic form, analogy-making is the ability to identify a relation between two concepts and apply it to a new concept. For example, *Paris* is to *France* as *Tokyo* is to *Japan* (i.e. capital:country relation). Early approaches to computational analogy-making were symbolic-based and required extensive hand-coded input i.e. structured representations of both the entities and their relations [Falkenhainer et al. 1989; Gentner 1983; Turney 2008]. Later, word embedding models based on neural networks were shown to exhibit analogy-making abilities at the word level [Gladkova et al. 2016; Jacob et al. 2023; Marquer et al. 2022; Mikolov et al. 2013; Petersen and van der Plas 2023; Ushio et al. 2021]. However, word-level analogies are generally simple and do not reflect the typical analogical reasoning humans perform in everyday life about complex situations. While some works have argued for *emergent analogical reasoning* abilities of large language models [Hu et al. 2023; Webb et al. 2022; Yasunaga et al. 2023], other works have shown that these models lack the *robustness and generality* exhibited by humans when it comes to **long text analogies** [Wijesiriwardene et al. 2023; Zhu and de Melo 2020], **scientific analogies** [Czinczoll et al. 2022; Yuan et al. 2023], **story analogies** [Jiayang et al. 2023; Nagarajah et al. 2022; Sourati et al. 2023; Sultan and Shahaf 2022], **visual analogies** [Bitton et al. 2022; Opielka et al. 2024; Zhang et al. 2019a] and **complex analogical reasoning** [Lewis and Mitchell 2024; Musker et al. 2024]. Figure 4b illustrates an example from the analogical reasoning over narratives benchmark [Sourati et al. 2023].

5 Artistic Creativity

Artistic creativity is the ability to produce original, imaginative, and expressive works in various art forms, such as creative writing, poetry, visual arts, music, dance, theater, and more. In this section, we will focus on the advancements made in AI to produce creative stories, poetry, visual, and musical content automatically and also point out the remaining challenges.

5.1 Story Generation

Storytelling is at the heart of human communication, a powerful tool for connecting and conveying ideas effectively [Suzuki et al. 2018]. It requires creativity, particularly when crafting an engaging and compelling narrative. Early approaches to this task focused on algorithmic planning based on character traits and social and physical constraints [Lebowitz 1984; Meehan 1977]. With the advent of powerful neural networks, the focus shifted to machine learning-based data-driven approaches [Akoury et al. 2020; Du and Chilton 2023; Fan et al. 2018; Hong et al. 2023; Louis and Sutton 2018]. While these networks are trained on large datasets of stories and prompted to directly generate a new story, often producing locally coherent narratives, they suffer from long-term coherence, irrelevance to premise, and repetitive text problems [Yao et al. 2019]. Latest approaches have addressed these problems by using *content planning* and *recursive prompting* techniques where a high-level plan of the story is first generated, followed by iterative prompting that aims to generate the story in multiple steps based on the plan [Goldfarb-Tarrant et al. 2020; Yang et al. 2022; Yao et al. 2019]. Since language models are designed for open-ended text generation, controlling the attributes of its generations (e.g. topic, characters) is another major challenge [Dathathri et al. 2019]. While several methods have been developed towards *controllable text generation* [Chung et al. 2022; Dathathri et al. 2019; Pascual et al. 2021; Paul and Frank 2021; Rashkin et al. 2020; Tambwekar et al. 2018], language models still struggle with following *constraints* [Sun et al. 2023]. In addition, *long-term factual inconsistency and hallucinations* still remain as major issues in language model generated texts [Banerjee et al. 2024; Elazar et al. 2021; Tam et al. 2022; Zhang et al. 2023].

Language models have also been evaluated on their ability to produce and judge creative content as a professional writer. Chakrabarty et al. [2023b] generates short stories from LLMs based on the plots of popular fictional stories published in the New York Times and conducts a fine-grained

expert assessment of both model-generated and original stories. Their study shows that LLMs significantly lag behind *seasoned writers* in producing inherently creative content, and in addition, they can not be used as *reliable evaluators* of creativity either.

To complement the shortcomings of LLMs in creative content generation, recently several works have developed frameworks to use these models as creative assistants for humans and these collaborative systems have shown strong performance across domains and editing tasks [Chakrabarty et al. 2023c; Mirowski et al. 2022; Schick et al. 2022; Swanson et al. 2021; Yuan et al. 2022]. However, recent works have also demonstrated that the output of human and language model collaboration lacks *lexical* and *idea diversity* [Anderson et al. 2024b; Padmakumar and He 2023]. Particularly, adapting language models with human feedback [Ouyang et al. 2022] has been found to be a main contributing factor in diversity reduction [Bai et al. 2022; Mohammadi 2024; Padmakumar and He 2023].

5.2 Poetry

Poetry is a form of literary expression that uses rhythmic and often condensed creative language to evoke emotions, convey ideas, or tell stories. Early approaches to poetry generation have been based on hand-crafted templates, heuristics, and linguistic features of the target language which were limited in their expressivity [Colton et al. 2012; Manurung 2004; Manurung et al. 2000, 2012; Masterman 1971; Milic 1970; Oliveira 2012; Racter 1984]. However, recent statistical approaches using (recurrent) neural networks [Ghazvininejad et al. 2016; Lau et al. 2018; Zhang and Lapata 2014] and language models [Agarwal and Kann 2020; Belouadi and Eger 2022; Chakrabarty et al. 2022b; Ormazabal et al. 2022b; Popescu-Belis et al. 2023; Tian and Peng 2022; Van de Cruys 2020] have been shown to generate high-quality poems. While these generations almost always follow natural poetic style with appropriate rhyme and meter, they typically fail to express a *poetically deep meaning* [Chakrabarty et al. 2023d]. Figure 3 illustrates the qualitative difference between human and machine-generated poems. We refer the reader to [Elzohbi and Zhao 2023; Oliveira 2017] for an in-depth survey on automatic poetry generation.

5.3 Visual Creativity

Humans have been producing visual content to convey emotions, concepts, and narratives since ancient times, from cave paintings and hieroglyphics to classical and Renaissance art masterpieces. For centuries, visual creativity was primarily the domain of professional artists, however, the invention of photography in the 19th century and the traditional image editing software, such as Adobe Photoshop in the past few decades enabled ordinary individuals to produce visually creative outputs without the need for formal artistic training. The advancements of AI have further transformed the landscape of visual creativity, pushing the boundaries of what can be created and who can create it. Early works employed Generative Adversarial Networks (GAN) [Goodfellow et al. 2014b] and Convolutional Neural Networks (CNN) [LeCun et al. 1989] to model images [Li and Wand 2016; Radford et al. 2015; van den Oord et al. 2016b,a] and **generate images** by applying specific transformations such as **style transfer** [Abdal et al. 2019; Dumoulin et al. 2016; Gatys et al. 2015; Johnson et al. 2016; Karras et al. 2018, 2019], **super-resolution** [Dong et al. 2014; Ledig et al. 2016], **colorization** [Zhang et al. 2016a] and **inpainting** [Pathak et al. 2016] or **learning a generic mapping between two images** [Huang et al. 2018a; Isola et al. 2016; Richardson et al. 2020] or **conditioning on text** [Mansimov et al. 2015; Mirza and Osindero 2014; Reed et al. 2016a,b; Yan et al. 2015; Zhang et al. 2016b]. In recent years, the development of Transformer architecture [Vaswani et al. 2017] and Diffusion models [Ho et al. 2020] has further pushed AI-driven art to new heights. Trained on large amounts of multimodal data, these models are capable of generating from *arbitrary* instructions not only **high-quality images** [Brooks et al. 2022; Chakrabarty et al. 2023e;

Spatial relationship

A book *on the left* of a bird

Attribute-color

A *red book* and a *yellow vase*

Comparative

A bowl has **fewer** strawberries than cucumbers

Negation

"One boy is sleeping and one boy is not sleeping"

Commonsense

A **bat** is flying over baseball stadium

A robot couple fine dining with Eiffel Tower in the background.
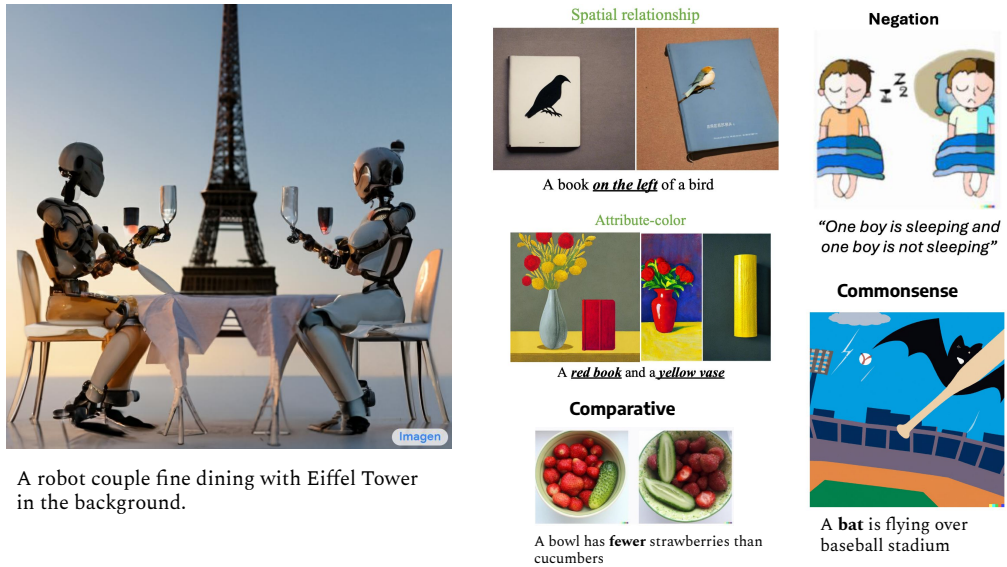
Fig. 6. Illustration of progress and challenges in image generation. **Left:** A creative image made by Imagen [Ho et al. 2022a] based on text instruction. **Right:** Various model generations showing failures in compositionality [Huang et al. 2023], commonsense [Rassin et al. 2022], object relationships [Marcus et al. 2022], and negation [Murphy et al. 2024].

Gafni et al. 2022; Geng et al. 2023; Hertz et al. 2022; Huang et al. 2022; Nichol et al. 2021; Patashnik et al. 2021; Ramesh et al. 2022, 2021; Rombach et al. 2021; Ruiz et al. 2022; Saharia et al. 2022; Shen et al. 2024] but also short **photo-realistic videos** [Arnab et al. 2021; Brooks et al. 2024; Gupta et al. 2023; Ho et al. 2022a,b; Kondratyuk et al. 2023; Luo et al. 2023; Singer et al. 2022; Tulyakov et al. 2017; Vondrick et al. 2016; Xing et al. 2023; Yan et al. 2021].

Despite their impressive quality, AI systems still exhibit *trivial* errors in their generations. Recent work has shown that these models struggle to effectively *compose* objects with different attributes and relationships [Conwell and Ullman 2022; Huang et al. 2023; Leivada et al. 2022; Marcus et al. 2022; Murphy et al. 2024; Thrush et al. 2022; Zarei et al. 2024], fails to reliably capture common *syntactic processes* such as negation, word order, comparatives etc. [Leivada et al. 2022; Marcus et al. 2022; Murphy et al. 2024], struggles with *representing* numbers and texts in images [Borji 2023b; Marcus et al. 2022], often fall short when it comes to accurately depicting the intricate details of *human extremities* such as hands and fingers [Borji 2023b] and lacks robust *commonsense reasoning* ability [Borji 2023b; Marcus et al. 2022; Rassin et al. 2022; Thrush et al. 2022]. Similarly, video generation models often suffer from a lack of reliable *spatial reasoning*, *appearance inconsistency*, *temporal inalignment*, *body deformation* and *occlusion* issues [Brooks et al. 2024; Lei et al. 2024].

5.4 Musical Creativity

Music is another major artistic medium that allows individuals to express emotions, ideas, and cultural narratives through sound, often transcending language barriers to connect people across diverse backgrounds and experiences. Automatic music generation using computers has also a long history dating back to the 1950s [Ji et al. 2023]. Early attempts at music generation employed rule-based methods [Hiller and Isaacson 1958], stochastic models (typically Hidden Markov Models)

[Ames 1987; Brooks et al. 1957; Farbood and Schöner 2001], evolutionary algorithms [Biles et al. 1994; Cope 1996; Lavrenko and Pickens 2003] and recurrent neural networks [Eck and Schmidhuber 2002; Todd 1989]. However, these methods suffered from *long-range incoherence* and produced only *short* pieces often with *low* music quality [Ji et al. 2020].

With the advent of powerful deep generative models, it became possible to capture the long-term structure of polyphonic music. Recent years have seen models that can compose multi-instrument polyphonic pieces using variational auto-encoders [Kingma and Welling 2013; Roberts et al. 2018], generative adversarial networks [Dong et al. 2017; Goodfellow et al. 2014a; Yang et al. 2017; Yu et al. 2016] and transformers [Agostinelli et al. 2023; Copet et al. 2023; Dhariwal et al. 2020; Donahue et al. 2019; Huang et al. 2018b; Huang and Yang 2020; Payne 2019].

While music generated by these systems often seems quite impressive, an automatic objective evaluation of music composition remains a challenge because of its subjective and complex nature [Yang and Lerch 2018]. It is not yet entirely clear whether the AI-generated pieces are *truly novel* as past work has found that deep learning-based music generation models gradually *copy* increasingly distinctive chunks from pieces in the training set [Yin et al. 2021]. Recent studies also show that humans exhibit a preference for human compositions over AI compositions and they report something *"off"* about the latter such as a lack of sense of *coherence* or *consistency*, *odd note* choices, unnecessary *complexity*, *repetition*, *uninterestingness*, and failure to come to a *resolution* [Sarmento et al. 2024].

6 Scientific Creativity

Scientific creativity refers to the ability to generate novel ideas, approaches, or solutions within the realm of science, often leading to new discoveries, theories, or technologies. Automating the process of scientific discovery [Kramer et al. 2023; Savage 2012; Waltz and Buchanan 2009] has long been a focus of AI research dating back to the 1970s when early attempts mainly targeted **automated equation discovery** and **symbolic regression** and were based on methods such as heuristic search and genetic programming [Dzeroski and Todorovski 1993; Koza 1994; Langley 1977; Rzevski et al. 1987; Schmidt and Lipson 2009; Todorovski 1997]. Recent methods, however, often employ Bayesian statistics [Guimerà et al. 2020] and neural networks [Chen et al. 2022a; Cranmer et al. 2020; Garcon et al. 2021; Petersen and Landajuela 2019; Udrescu et al. 2020].

Another line of work has focused on automating the discovery of other scientific knowledge such as generating new mathematical **conjectures** or **theories** [Buchberger et al. 2006; Chen et al. 2016; Fajtlowicz 1988; Raayoni et al. 2021; Wu and Tegmark 2019], automatically **proving theorems** [Hubert et al. 2024b; Trinh et al. 2024], discovering **new concepts** [Hakuk and Reich 2020; Iten et al. 2020; Lenat and Brown 1984] and predicting **molecular structures** [Abramson et al. 2024; Jumper et al. 2021; Lindsay 1980; Zambaldi et al. 2024] among others. A notable example in this area is the recent AlphaFold model [Jumper et al. 2021] that can predict millions of intricate 3D protein structures which has the potential to significantly accelerate research in biology.

While the above works have mainly targeted one aspect of the *scientific process*, namely the automatic discovery of particular scientific knowledge, there have also been attempts to partially or fully automate the *entire* process itself. The scientific process typically starts with a *scientific question* or an *idea* that is then used to formulate a *hypothesis*, followed up with *designing and running experiments* and *analyzing results* to test the validity of the hypothesis and ends with *communicating* the findings to the scientific community [Kramer et al. 2023]. Recently, the field has seen a surge in the development of frameworks using neural networks and especially, large language models to automate several steps of the scientific process such as **literature review** [Skarlinski et al. 2024], **idea generation** [Baek et al. 2024; Girotra et al. 2023; Si et al. 2024; Wang et al. 2023, 2024a], **hypothesis generation** [Ghafarollahi and Buehler 2024; Majumder et al. 2024; Qi et al.

2023; Sybrandt et al. 2020; Wang et al. 2024a; Yang et al. 2023] and **paper writing** [Altmäe et al. 2023; Wang et al. 2019]. Yet other works have gone further to introduce a so-called **"AI Scientist"** that automates almost the entire scientific process from the idea generation to experiment execution to even paper writing [Boiko et al. 2023; Ifargan et al. 2024; King et al. 2009; Li et al. 2024b; Liu et al. 2024; Lu et al. 2024a].

While the latest advancements in the automation of scientific creativity are remarkable, these results should be taken with a grain of salt. Most of the recent end-to-end automation frameworks are powered by LLMs, hence, they face the same challenges and issues we discussed in the previous sections such as hallucinations, lack of content diversity, novelty, and robust reasoning capabilities. For example, one of the aforementioned large-scale idea generation studies [Si et al. 2024] finds that out of 4, 000 LLM-generated ideas only 200 are unique. Their qualitative analysis also reveals some common failure modes such as *vague* implementation details, *misuse* of datasets, *inappropriate* baselines, *unrealistic* assumptions, and overall *poorly-motivated* ideas. Similarly, another study benchmarking the machine learning experimentation capabilities of LLMs reports *hallucinations* and *poor planning* as some of the major issues with these models [Huang et al. 2024b].

Another important aspect of scientific discovery is the **explainability** [Li et al. 2021] which helps humans prevent or better prepare for a possible future technological singularity [Good 1965; Ulam 1958]. However, current LLMs are largely black-box AI systems, and allowing them to make discoveries that are incomprehensible to humans may lead to a scenario where human knowledge is left far behind the machine's knowledge resulting in machines that humans can't control [Good 1965].

7 Creativity and Copyright

Our brief survey into the methods used to produce creative outputs showed that the predominant approach is currently the generative deep learning techniques, especially LLMs. These models typically have billions of adjustable parameters [Brown et al. 2020b] and are trained on massive amounts of public and private data [Raffel et al. 2023]. Consequently, these models have been found to exhibit strong memorization skills [Carlini et al. 2022, 2018] such that they can sometimes copy large passages [Chang et al. 2023; McCoy et al. 2021] or replicate images from their training data [Somepalli et al. 2022]. While this could be of little concern when the duplicated content is public and generic, however, the training datasets of popular LLMs are often undisclosed and can include private and copyrighted data leading to concerns about **copyright infringement and privacy violation** [Franceschelli and Musolesi 2021a]. Although several approaches have been developed to *detect* [Carlini et al. 2021; Duarte et al. 2024; Li et al. 2024a; Oren et al. 2023; Shi et al. 2024] and *prevent* [Hans et al. 2024; Ippolito et al. 2022; Kandpal et al. 2022; Zhao et al. 2022] unintended memorization in LLMs, major questions concerning the use of copyrighted material for training and *authorship* of the machine-generated content remain unresolved [Abbott and Rothman 2023; Franceschelli and Musolesi 2021a]. Recent lawsuit between The New York Times and OpenAI [Grynbaum and Mac 2023] and the class action[3] against Stable Diffusion, Midjourney, and DeviantArt [Brittain 2023] have further highlighted the urgency of the matter and the need for clear legal frameworks that address the complex issues surrounding intellectual property rights, ethical use, and the boundaries of fair use in AI development.

More specifically, two key questions concerning copyright and authorship are of interest and here we briefly discuss them with respect to machine-generated artworks. We refer the reader to

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[3]A class action is a type of civil lawsuit brought on behalf of many similarly situated people who have been harmed in the same way by the same entity.

Franceschelli and Musolesi [2021a] and Abbott and Rothman [2023] for a detailed discussion of these questions.

Is it copyright infringement to use protected works for the training of generative models? To answer this question, we will review the implications of the existing relevant laws from the US and EU. Under the US Law Code, reproduction of a copyrighted work can be allowed if the use can be considered a *fair use* of the work [Netanel 2011]. Analyzing the criteria used to determine fair use, Franceschelli and Musolesi [2021a] concludes that it is not straightforward to assess this for generative deep models and if these models do not add any form of novelty to their output. Their outputs may not qualify for fair use, which can potentially derail the progress in AI [Sobel 2017].

Under the EU law, on the other hand, the use of lawfully accessible protected work for training is permitted as long as 1) the rightsholder of the used data has not reserved the right to withhold its data from being reproduced and 2) the accessed data is retained only for the time required for the purposes of scientific research [Franceschelli and Musolesi 2021a]. However, Franceschelli and Musolesi [2021a] also notes while the second criterion is reasonably easy to satisfy, the first criterion is hard to verify in practice because nowadays, models are being trained on large amounts of data published on the internet for which there is no centralized repository allowing to filter *reservation-free* works. Finally, whether providers of such a repository or the developers of the models should be forced to perform this check is unclear.

Who is the author (if someone) or who will own the copyright on the generated work? To answer this question, first, we have to make a distinction between the *AI-assisted* and *AI-generated* content. If the generative model is merely used as a tool to *assist* a human to produce a creative artwork, then the human will be considered the author and own the copyright. However, it becomes tricky to determine the authorship and the copyright status of the work that is *generated* mostly by AI with little human involvement (e.g. human as prompter). First, let's consider the authorship issue. Some have argued that for an author to exist there has to be a message that the author wants to convey through their work, but since no one can reliably predict the output of a generative model, *no author* exists [Ginsburg 2018]. However, if we suppose that there is an author, then there are mainly three contenders in question: 1) the person who developed the AI model (*developers*) 2) the person who used the AI model to produce creative work (*users*), and finally 3) the *AI model* itself. Since the existing laws in most countries only attribute copyright to a human, but not to a machine, the main tension is around deciding whether to attribute the authorship (also the copyright) to users or developers [Abbott and Rothman 2023; Deltorn and Macrez 2018; dos Santos and Machado 2020; Guadamuz 2017]. Some have argued that the criterion to determine authorship should center around the incentives to create and promote the work, not the ideation and creation of the work itself [Miller 1993] and since the *users* of the generative models are best positioned to do so, they should be assigned the authorship [Denicola 2016; Franceschelli and Musolesi 2021a; Samuelson 1986]. Another argument supporting this assignment is by ruling out the developer as the author since they just create the *potentiality* for the creation of the output, but not its *actuality* [Franceschelli and Musolesi 2021a; Samuelson 1986]. Using the analogy proposed by Ralston [2005], it would be similar to claim a knife manufacturer is more responsible for murder than the person who wielded the knife or assigning copyright to the teacher of the painter rather than the painter himself/herself [Franceschelli and Musolesi 2021a]. Finally, arguments in favor of AI authorship have also been made recently suggesting that this will promote transparency, efficient allocations of rights, and even counterintuitively protect human authors [Abbott and Rothman 2023].

8 Future Directions

In the previous sections, our brief exploration into the creativity of modern AI systems revealed that these systems exhibit some capacity for producing linguistically and artistically creative outputs and thinking creatively. However, true human-like creative abilities seem to be still out of reach, as indicated by challenges with tasks demanding creative problem-solving [Jiang et al. 2023; Tian et al. 2023], abstract reasoning [Gendron et al. 2023; Mitchell et al. 2023], and compositionality [Huang et al. 2023; Murphy et al. 2024]. Some studies also highlighted major issues in machine outputs, such as lack of originality [Chakrabarty et al. 2023b; Lu et al. 2024b], diversity [Anderson et al. 2024b; Padmakumar and He 2023] and incoherence [Sarmento et al. 2024; Tam et al. 2022]. From the Four-C model perspective, these models seem to manifest only mini-c or little-c type of creativity while Pro-C and Big-C creativity remain elusive. Similarly, current AI models exhibit strong interpolation and moderate extrapolation capabilities. However, they are still far from truly *inventing* a completely new type of creative artefact. In this section, we discuss potential research directions that can help us better measure and improve the creative abilities of AI systems.

8.1 Evaluating Creativity

8.1.1 Creative Process. Cognitive scientists and psychologists have proposed theoretical frameworks to evaluate creativity such as characterizing it based on ***input***, ***process*** and ***output*** [Jordanous 2012; Pease et al. 2002; Ritchie 2007] or four Ps: ***person***, ***product***, ***process*** and ***press*** [Jordanous 2016; Rhodes 1961]. A common thread across all these theories is their emphasis on evaluating the *process* aspect of creativity. However, most works in AI, including the ones we reviewed before, focus on evaluating and analyzing creativity from the *output* or *product* perspective. Creative *process*, on the other hand, is an equally (or perhaps more) important aspect of creativity that can tell us how creativity *"arises"* in the first place and what the key ingredients involved [Colton 2008]. For example, in computational creativity, one popular theory by Boden [2004] defines the creative process in terms of manipulations over a conceptual space. This theory divides creativity into three types: **combinatorial** that makes unfamiliar connections between familiar concepts (e.g. creating hybrid fictional creatures such as pegasus, sphinx, or mermaid), **exploratory** that involves an open-ended search in a conceptual space (e.g. a novel chess move) and **transformational** that requires a fundamental transformation of the existing conceptual space (e.g. non-Euclidean geometry[4]). Another popular theory by Wallas [1926] explains the creative process in four stages akin to how scientists develop their ideas: **preparation** stage where the problem at hand is investigated in all directions, information is gathered and analyzed, **incubation** stage where you step back from the problem and let your unconscious work through it in the background, **inspiration** stage where a creative insight is typically realized (an "Aha!" or "Eureka!" moment) and finally, **verification** stage where you test, evaluate and build further on your creative idea to make it perhaps useful.

While AI systems produce seemingly creative outputs, the nature of the creative process they employ (if any) remains unknown. Only very recently attempts have been made to study the creative process of machines [Nath et al. 2024] which analyzes the creative process of language models and humans to solve AUT task using ***response pathways*** (persistent vs. flexible) [Baas et al. 2013; Nijstad et al. 2010] and finds that while humans are able to follow a mixture of pathways, models are biased towards either one of them pointing to a limited capacity. Hence, analyzing the creative process of machines is an emerging and exciting area for which much work remains to be explored. We believe a strong collaboration between the computational creativity [Colton and Wiggins 2012; Veale and Cardoso 2019] and NLP communities drawing ideas from past research on

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[4]https://en.wikipedia.org/wiki/Non-Euclidean_geometry

studying human creative process and techniques from research on *(mechanistic) interpretability*[5] [Bereska and Gavves 2024; Saphra and Wiegreffe 2024] could lead to a better understanding of the creative capacity of AI systems.

8.1.2 Dimensions of Creativity. As we discussed earlier, there are many dimensions of creativity, but most works generally focus on evaluation of the *novelty* and *usefulness* dimensions. However, *surprise*, *agency* and *spontaneity* dimensions are also equally important. Humans typically communicate an emotion or a deeper meaning through creative products and their creative process is characterized by spontaneous "Aha" or "Eureka" moments coupled with deliberate decisions made at each step of the way [6]. However, current AI systems lack agency and are typically trained to generate the most likely output leaving no room for any intentional or spontaneous action [Franceschelli and Musolesi 2023]. Therefore, a holistic evaluation of machine creativity should involve consideration of all these different dimensions that characterize human creativity.

8.2 Improving Creativity

Recent years have seen a surge in human-AI creative collaboration [Vinchon et al. 2023] popularized by the introduction of chat-based products such as ChatGPT[7] and Gemini[8]. However, the poor creative capacity of current AI systems necessitates the innovation of new techniques to improve the creativity of their outputs. In this section, we discuss several possible directions to take.

8.2.1 Creative Architectures. As we argued before, current AI architectures optimized for the most likely outcome might have fundamental limitations to exhibit true human-like creativity. In fact, by definition, current AI models are optimized to model the training distribution while creating something new requires the model to *diverge* from its learned distribution. Therefore, innovating at the architecture level to endow machines with mechanisms to actively diverge from the training data and a capacity for *agency* and *spontaneity* might be a necessary step towards robust creativity. An emerging new research area called ***active divergence*** attempts to optimize models for creativity using methods such as novelty search, divergent fine-tuning, and objective functions targeting different dimensions of creativity [Broad et al. 2021; Bunescu and Uduehi 2019; Elgammal et al. 2017; Guimaraes et al. 2017].

8.2.2 Creative Prompt Engineering. Natural language-based interaction with the current AI systems has created an intuitive playground to elicit more capabilities from these systems [Qiao et al. 2022]. These so-called *prompt engineering* techniques have also been shown to enhance the creativity of large language models [Nair et al. 2024; Summers-Stay et al. 2023; Tian et al. 2023]. We can draw ideas from psychology that has shown techniques such as *brainstorming* [Osborn 1957], *competence injection* [Liu and Xu 2020] and *threatening situations* [Riley and Gabora 2019] stimulate creativity of humans. Hence, designing prompts inspired by these methods is a promising direction to get the most out of future AI systems.

8.2.3 Creative Decoding. An important component in natural language generation is the decoding strategy which is a significant contributor to the quality of the generation [Meister et al. 2022]. Past work has shown that simple greedy decoding results in repetitive and uninteresting generations [Li et al. 2023] and numerous powerful decoding algorithms have been developed to address these problems [Fan et al. 2018; Holtzman et al. 2019; Meister et al. 2023]. These decoding strategies mainly target generating human-like text and do not directly target creativity. A popular approach is

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[5]https://www.neelnanda.io/mechanistic-interpretability
[6]https://www.newyorker.com/culture/the-weekend-essay/why-ai-isnt-going-to-make-art
[7]https://chat.openai.com
[8]https://gemini.google.com

to increase the randomness of the output by increasing the *temperature* parameter, however, recent work shows that this parameter is weakly correlated with the novelty of the output [Peeperkorn et al. 2024]. A potential direction could be to devise new creative decoding algorithms that go beyond the temperature parameter by injecting **semantic planning** or intentionality [Franceschelli and Musolesi 2024] and employing information-theoretic measures of novelty, utility, and surprise [Bunescu and Uduehi 2022; Heinen and Johnson 2017; Kuznetsova et al. 2013].

9 Conclusion

In conclusion, while the rapid advancements in AI, particularly through state-of-the-art models such as large language models, diffusion models, etc., have demonstrated impressive capabilities in generating creative outputs, the question of genuine machine creativity remains unresolved. This survey has explored key areas of linguistic creativity, creative problem-solving, and artistic and scientific creativity, providing a comprehensive overview of the state of AI creativity. We also discussed pressing copyright and authorship issues with generative artworks, highlighted major challenges facing current AI systems and proposed potential research directions on how to evaluate and improve the creativity of these systems. We believe our suggestions can help future research to determine if machines can achieve a human-like creative process, ultimately enriching our understanding of artificial intelligence and its capabilities.

Acknowledgments

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