

# Creativity in Comparative Analysis between Artists and Text-to-Images

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## Abstract

Creativity has been a topic of interest for philosophers, psychologists, and neuroscientists. It is a fundamental human characteristic that facilitates problem-solving. This discussion has been further expanded with the growing interest in artificial intelligence, particularly in the field of generative AI. This paper presents a comparative analysis of the creative processes of human artists and text-to-image models, with a specific focus on the cognitive mechanisms and neural substrates that underpin the process. The research explores the cognitive aspects of creativity, including memory and the creative process, to gain insight into the interplay of conscious and unconscious mental processes in creative ideation. The objective of this study is to compare state-of-the-art AI architectures with human creative endeavors in order to identify similarities and differences between the two systems. The study emphasizes the collaborative nature of creative expression and highlights the symbiotic relationship between human input and machine output in the realm of text-to-image generation. The aim of this study is to contribute to the ongoing dialogue surrounding the nature of creativity and its manifestation across different modalities.

## 1 Introduction

Since the 1950s and 1960s, computer scientists have been developing computer programs to simulate human cognitive processes. However, defining and measuring creativity has been a persistent challenge, leading to ongoing debates that highlight the inherent complexity of this phenomenon. Creativity has long been a construct of interest to philosophers, psychologists and neuroscientists because of its mysterious nature and recognition of a crucial aspect of human endeavor, as it promotes innovation, adaptability, and problem solving in various domains [1], [2]. More recently, the emergence of artificial intelligence (AI) has added a new dimension to the study of creativity, as AI systems, in particular deep neural networks, draw inspiration from the human brain in their architecture and functioning. Although AI has made remarkable progress in various domains, such as image generation and

natural language processing, replicating human creativity remains a challenge. This may be due to the elusive nature of creativity, which defies easy definition and quantification, or to the fact that when evaluating creativity, it is important to avoid biases induced by the characteristics of the creator. People often perceive generative AI as exerting less effort than humans in creating a given artifact, resulting in less creativity being attributed to generative AI producers ([3], [4]). This review explores the cognitive processes and neural correlates of human visual creativity and how they contribute to the creation of visually compelling content. It also examines AI-driven creativity, specifically when AI generates visual content based on human textual input. This paper aims to deepen our understanding of human cognition and artificial intelligence by analyzing the parallels and differences between human and AI-driven creativity. The neural architecture underlying human visual creativity and its AI coun-

terparts will be explored. By elucidating the interplay between creativity, cognitive processes, and neural mechanisms, this paper aims to contribute to ongoing discussions surrounding the nature of creativity and its manifestation in both human and artificial systems.

**Defining Creativity** Assessing creativity remains a contentious subject in the creativity research. Numerous frameworks and assessment tools have been devised over time to establish standardised definitions and metrics for creativity. These frameworks aim to provide a meaning and tools for evaluating creativity, facilitating comparisons not only among individuals but also between different modalities of creative expression, including generative models ([5]) and biological brains ([6], [7]). In the research field, some consensus has emerged around a definition that appears to link two main concepts, creativity refers to the production of something both novel and useful within a given social context ([8]). It remains difficult though execute scientific test in rigorous way, in fact, most of the tests analysed in this review were judged by human beings, independent judges with objectiveness but each with a different perception of significance ([9]–[12]). Psychometricians emphasise the importance of validity and reliability in the evaluation of creative abilities ([13]). Validity and reliability serve as principles in the researches. A test is considered valid if it effectively captures the intended aspect of creativity. Conversely, reliability refers to the consistency of results obtained when the same test is administered to the same individual on multiple occasions.

**Refining Comparative Parameters** To conduct a thorough comparative analysis between these two systems, it is essential to define specific parameters to ensure the accuracy and validity of the results. This comparative examination focuses on a specific creative task rather than a broad examination of creativity as a whole. The approach is based on the

fact that human creativity varies depending on the task ([14]). Therefore, it is necessary to make specific comparisons between each type of artificial architecture and each biological one for each creative activity. This investigation focuses on the increasing use of artificial intelligence (AI) systems that can transform text into visual representations. To ensure a fair and informative comparison, it is important to consider the unique characteristics, limitations, and capabilities of each system. This is essential to avoid any appearance of bias or superficiality in the analysis. The study aims also to investigate also whether artificial neural networks can exhibit creative agency similar to that observed in human cognition.

## 2 Human architecture

**Creative Process** The simplest model of the creative process is a two-stage model sometimes called the balloon, an expanding stage of divergent thinking [15] where many possibilities are generated, followed by convergent thinking as you converge on the one best idea. This process it's been studied multiple times and they've observed that creativity tends to occur in a sequence of more stages [16]–[20]. The creativity process in our brain can be broken down into eight distinct stages [13]. First, the individual identifies and frames the problem. This first step involves the task of identifying a problem that is not only significant, but also framed in a way that is conducive to a possible creative solutions. Next, individuals employ the acquisition of relevant knowledge to the identified problem. Creativity relies heavily on the accumulation of expertise, mastery, and practice relevant to the given domain [21]–[23]. After acquiring relevant knowledge, individuals broaden their scope by gathering a variety of potentially related information. This is different to the previous step because here comes into play information that are not strictly related to the topic. Next, the incubation phase comes into play. During this phase, the unconscious mind processes and asso-

ciates acquired knowledge and seemingly unrelated information in unpredictable ways, setting the stage for creative insights to emerge. After the accumulation and incubation, individuals generate a multitude of ideas, what we defined divergent thinking [15]. The next stage involves merging ideas in unexpected ways. Innovative solutions often result from the novel combination of existing mental concepts or ideas. Inside the creative process, individuals must exercise discernment by selecting the most promising ideas. Given the plethora of potential solutions, successful creators must have the ability to apply relevant criteria to identify ideas worthy of further pursuit, the so called convergent Thinking. Finally, creativity is externalized using various materials and representations. The conscious mind plays an important role in the creative process. Stages 1, 2, and 3 are mainly conscious and directed. Even Stage 4, incubation, only occurs in the context of ongoing conscious work. You can benefit from incubation only if you work hard on a problem beforehand and then continue to work hard on it afterward. [24]. As a commission to an artist, the first point is not relevant. However, it is worth noting that creativity researchers have found that exceptional creativity often arises when individuals work in areas where problems are not pre-defined. Success in such areas depends on the ability to formulate good questions.[25], [26]. This means that a commission alone may be less creatively stimulating for an artist than starting a new project independently. Furthermore, research identified twelve attributes that individuals consider when evaluating ideas [27]. These attributes include the perceived riskiness of the idea, its ease of understanding, originality, completeness (i.e., whether the idea provides detailed steps for implementation), complexity, consistency with existing social norms, likelihood of success, ease of implementation, potential benefits to a large number of people, alignment with desired societal outcomes, as well as the time, effort, and complexity required for implementation. This process in a commission is agreed with the contractor, either

explicitly or indirectly through feedback of the final work.

**Role of the memory** The Gestaltist theory suggests that the mind is capable of sudden restructuring, leading to a moment of insight known as the Eureka moment [28]. However, studies have disproved this theory, showing that the mind gradually approaches the correct solution [29]. This aligns with the associationist theory, which proposes that creativity emerges from the fusion of pre-existing ideas. This theory explains how these associations facilitate novel connections and innovative ideas. Creative ideation begins with the workings of semantic memory, where concepts, ideas, and experiences connect to form a web of associations. This theory explains how these associations facilitate novel connections and innovative ideas. To explore the role of semantic memory in creativity, we assume that knowledge is organized in a map, space, or network, in which concepts are related to each other. Search processes operate across this semantic space, resulting in memory search, retrieval, and creative combination. The theory of creativity suggests that individuals with higher creativity possess a more extensive semantic memory structure, enabling them to conduct a broader search in their memory. [21]. Humans have different types of memory and either short-term memory (STM) and Long-term memory (LTM) are involved. In particular: semantic memory [30], episodic memory [31], association [32] and combination [33] have been identified as cognitive components of the creative process. STM is involved in creative processes because they require the temporary storage of information [34], [35]. LTM has been linked to creativity because it stores information about prior knowledge. [36]. LTM can be classified into two types: declarative memory and non-declarative memory. Declarative memory is the type of memory that can be consciously accessed, the most related to the activity and is further divided into semantic memory and episodic memory. Studies examine seman-

tic memory search processes that support higher creative thinking, identifying clustering as correlated with divergent thinking and switching with the ability to combine distant associates. The results suggest that clustering is more associated with divergent thinking, while switching is associated with convergent thinking and a more efficient semantic network [37]. Another study suggests that the semantic memory network of people with low creative ability appears to be more rigid than that of people with high creative ability, in the sense that it is more spread out and divided into more sub-parts [38]. Conceptual combination is the mental act in which imagination brings concepts together to produce new ideas in creative processes [39]. These creative combinations probably have properties that aren't held by the component concepts. This retrieval and combination of previous memory processes can stimulate imagination [31]. Other findings have also been promoted, such as that highly creative people are more likely to use remote association during a creative process [40]. Memory is one of the fundamental elements of creativity [41], [42]. Creativity cannot occur *ex nihilo*, but is a process in which novel ideas are generated by searching [43], interacting [44] and associating [45] existing memories. Objects, rather than features, are generally considered to be the elementary building blocks of our visual representations, not only for perception [46], [47] but also for visual working memory (VWM) [48], [49].

**Brain flow and structure** Creativity is not specifically associated with any single area of the brain [50]. Thus, understanding the distribution of information throughout the brain is considered a crucial factor [11]. As the source of new ideas, memory has been identified with the activity of amygdale by fMRI [51]. Results from numerous fMRI studies consistently highlight the central role of the prefrontal cortex in both hemispheres [52]–[56], presumably due to its involvement in working memory and executive attention processes. This observations aligns with the framework of associative think-

ing, wherein semantic understanding of words precedes the activation of memory for visualisation. Recent research has challenged the prevailing notion regarding the lateralisation of brain activity during the creative process. New evidence suggests that the frontal lobe, which is responsible for executive functions such as planning and action control, is involved in creativity. This contradicts the popular belief that creativity predominantly involves the right hemisphere. Functional magnetic resonance imaging (fMRI) was used by researchers to evaluate neural activity in individuals during a visuospatial creativity task [57]. This task is known to rely on divergent thinking, which is a hallmark function typically associated with the right hemisphere. Another study supports these results, comparing electroencephalogram (EEG) data with existing research on brain activation during creative cognitive tasks and finding that remote association is associated with frontal lobe activity [58]. This contrasts with some previous studies that associate it with temporal lobe activity. [59]. The variation in outcomes could be attributed to the engagement of semantic and episodic memory, indicating that distinct brain regions may be activated during remote association, potentially influenced by the type of induction task and the method of stimulus presentation. Also brain wave activity are involved, especially alpha [60], theta [61], and gamma waves [62]. In addition, leftward gaze shift when participants were required to think about an original idea and pupil dilatation [9]. When discussing drawing, additional brain structures come into play that were not studied in canonic divergent thinking, such as motor and somatosensory areas, as well as cortical regions involved in spatial and auditory perception [63]–[65]. Divergent thinking is commonly measured using the Alternative Uses Test (AUT) [15], which evaluates a person's ability to generate multiple uses for a common object or to think of novel and unusual uses for everyday items. This test cannot fully represent the artist's creative process because it does not involve physical movements or imagery.

Additionally, tasks such as imagining an apple, performing a mental rotation, or engaging in a sporting activity are often referred to as 'imagery', despite being very different. Studies have shown that the visual imagery of artists when thinking about subjects is similar to perception but with a weaker activity, and is influenced by the strength and duration of the stimulus. There is overlap in the brain between imagery and perception of previous experiences. This is due to the fact that the brain processes both in similar ways [66]. Another research has shown that participation in visual arts education can lead to changes in brain structure, particularly in the density of grey matter [12]. This highlights the importance of sensory and motor experiences in promoting creativity. Also in cognitive drawing, operationalized by internally cued drawing stimuli or objective drawing content, would be associated with activation of the prefrontal and cingulate cortices [67].

### 3 Artificial Neural networks

As explained in the Human Architecture section, the creative process relies heavily on semantic memory. However, most current architectures do not incorporate explicitly a network that emulates the human memorisation process, despite its importance. The Hopfield Neural network (HNN) [68] is known to its capacity to emulate human memory association process. Recent study introduces the use of them as a tool to emulate the creative process through concept association [69]. This approach is based on the architecture of neural networks, which mirrors the way human memory works, where multiple neural units are activated simultaneously in response to given stimuli. Using modern HNNs, it was possible to simulate in a discrete and asynchronous way the ability of human creative thinking to make meaningful connections between seemingly unrelated concepts. The research demonstrated success in implementing a neurocomputational framework for creativity-based semantic associations using both binary and modern HNNs. How-

ever, the study is limited by the low memory and nodes ratio, as only approximately 138 vectors can be retrieved from storage for every 1000 nodes ([70]). Therefore, in the field of text-to-image synthesis, the three main methodologies - Generative Adversarial Networks (GANs), autoregressive methods, and diffusion models - do not explicitly use the HNN architecture.

### Generative Adversarial Networks

Generative adversarial networks (GANs) [71] uses two neural networks that work together: one generates artificial images using a random noise vector, while the other determines whether the input image is real or artificial by comparing it to samples from the training data. Gans are renowned for their single-step formulation and efficiency. However, despite efforts to scale them up for handling large datasets [72], diffusion models have recently shown significant results that surpass the quality of GAN models [73].

### Autoregressive

Autoregressive methods for text-to-image synthesis are able to capture the details and global coherence by modeling the conditional probability distribution of image pixels based on textual descriptions. The models linearize 2D images into 1D sequences of patch representations using a Transformer [74] Model. This sequential generation differs markedly from the parallel approach employed by Generative Adversarial Networks (GANs), as autoregressive models generate images pixel by pixel. Although this sequential process results in superior global image coherence, it is more computationally expensive during both training and inference compared to GANs.

**Parti** Parti [75] is a Google research project that utilizes standard Transformers for all of its components, which are the encoder, decoder, and image tokenizer. The model is composed of two

stages: an image tokenizer and an autoregressive model. In the first stage, the tokenizer is trained to convert images into a sequence of discrete visual tokens for training and reconstruction purposes. The second stage trains an autoregressive sequence-to-sequence model that generates image tokens from text tokens. Increased prompt complexity may lead to errors such as color bleeding, omission, hallucination, duplication of details, displaced positioning or interactions. To prevent these errors, it is important to increase proportionally the number of tokens to generate a well-structured output.

**CM3Leon** Meta has developed CM3Leon [76], a transformer-based autoregressive model. The aim of this approach is to balance inference time with global image coherence. This is accomplished through retrieval augmented pretraining on a large, diverse multimodal dataset. The CM3Leon model achieves state-of-the-art performance in text-to-image generation using five times less training compute than comparable methods. In contrast to Parti, CM3Leon uses a decoder-only transformer architecture without an encoder. To merge the two token vocabularies in the decoder, a break token is used to indicate when the text tokens stop and the image tokens start. The model is trained in two stages: pre-training and supervised fine-tuning. Contrastive decoding is used to improve sample quality, and the text is replaced with the mask token from the CM3 objective to enable unconditional sampling. The CM3 objective accepts multi-modal inputs, making it a versatile model capable of infilling and autoregressive generation tasks for both images and text. This allows for guidance without the need for finetuning. CM3Leon is fine-tuned on a wide array of mixed image and text tasks, which are organized as a series of interleaved text and image examples. Notably, the model has been trained exclusively on licensed images. It is important to note that other models may not have the same policy on training.

## Diffusion Models architectures

Diffusion models [77], [78] have become popular in image generation due to their strong performance and relatively low computational cost [79]. The main concept, which draws inspiration from non-equilibrium statistical physics, involves a gradual and systematic breakdown of structure in a data distribution through an iterative forward diffusion process of Gaussian noise. Subsequently, we acquire knowledge of a reverse diffusion process that reinstates structure in the data. The architecture of the denoising network can vary, but many diffusion models use a U-Net architecture [80]. Although initially developed for the purpose of brain segmentation in the medical field, this convolutional architecture has since been demonstrated to be highly effective in a range of computer vision tasks. At the time of inference, by reversing the forward paths of data towards noise, it becomes feasible to generate data from noise. The noise predictor estimates the noise of the image, which is then subtracted from the image. This process is not conducted in a single instance, as it was demonstrated to be less effective; instead, the process is repeated on several occasions, with a gradual reduction in noise until a clean image is obtained. This denoising process is referred to as sampling, as Diffusion models generate a new sample image at each step. The sampling method employed is known as the sampler. The noise schedule regulates the level of noise at each sampling step, with the highest noise occurring at the first step and gradually decreasing to zero at the final step. The sampler's objective at each step is to generate an image with a noise level that corresponds to the noise schedule. Multiple noise samplers exist, and the optimal one depends on the task [81]. For instance, according to some study, a linear schedule is not well-suited for low-resolution images [82]. The samplers labelled 'Karras' use the noise schedule recommended in the Karras article[83]. The study suggested that the noise step sizes should be smaller towards the end compared to the standard. This is argued to improve the quality of images. For the purpose of

reproducibility, it is important for the image to converge, even though not all samplers may converge and can run indefinitely. To generate minor variations in images, a different variational seed is used, which refers to the initial noise. Furthermore, it has been observed that there are differences in the application of noise, whether in pixel or latent space. Instead of adding noise directly to the pixel space of images and then denoising them, a latent diffusion model takes a different approach. It encodes the images into a latent space where the noise is applied and denoised. After this process, the image is decoded from the latent space, yielding an image that closely resembles the original. This method is referred to as a latent diffusion model [84], and it offers a significant improvement over the basic diffusion model. One of its key advantages is speed, as it is many times faster than denoising the raw, uncompressed data directly. The current dominant paradigms, diffusion models, and autoregressive models, both rely on iterative inference. While iterative methods facilitate stable training with straightforward objectives, they come with a significant computational overhead during inference.

**CLIP** Before discussing OpenAI’s models, it would be beneficial to first examine the CLIP technology. This technology enabled the company to make improvements to the text to image field. Although CLIP is not implemented in DALL-E 2 [85] and DALL-E 3 [86], it is present in other diffusion models. However, it should be noted that the two OpenAI models are based on it. CLIP, or Contrastive Language-Image Pre-training, is distinguished by its ability to comprehend the intricate relationship between images and text. This model comprises both an image encoder and a text encoder, which were trained on a dataset of 400 million images. The objective is to generate similar embeddings for images and captions that match, while producing distinctly different embeddings for those that do not match. This enables the model to effectively understand and relate images to their

corresponding captions. CLIP employs a convolutional neural network (CNN) as its vision encoder for image processing. The CNN extracts high-level features, which are then refined through subsequent layers. On the textual side, CLIP employs a transformer-based text encoder that captures and encodes semantic information in a format compatible with image representations. In CLIP, both images and text are processed concurrently, allowing the model to learn to establish connections between image representations and their corresponding textual descriptions. To guarantee comparability across modalities, CLIP includes normalisation and projection layers. It employs a contrastive learning objective, which encourages connections between similar image-text pairs while distinguishing dissimilar ones. This promotes meaningful associations between images and text.

**DALL-E 2** OpenAI employed this CLIP architecture as a preliminary step in developing the DALL-E 2 architectures for text-to-image synthesis. Consequently, the model is also referred to as unCLIP, as it accepts input from the CLIP embedding and generates the final result. The unCLIP model is based on a prior and a decoder. The prior takes as input the CLIP image embedding and produces another image embedding. This process is the main difference between the first DALL-E [87] architecture. The prior process was added because it offers more diversity and correlation of text input. While this could be achieved through an autoregressive or diffusion process, the diffusion method was favoured for its efficiency. The autoregressive approach employs principal components analysis (PCA) to reduce the image embeddings to a lower dimension, 319 dimensions. This not only optimises the mathematical process but also improves training stability. This reduced embedding pass is incorporated into a classical autoencoder of transformer, which outputs the new image embedding. In contrast, the diffusion process provides the transformer with the encoded text, the CLIP embedding, the noisy embedding

with the relative timestamp, and returns the new image embedding as the output. In order to achieve this, the researchers employed the cosine noise schedule [82]. The schedule addresses early noise issues in the forward noise process and improves sample quality and training efficiency as the number of timesteps increases. The decoder is a previous model, Glide [87], modification. The decoder model takes two inputs: the new latent vector generated by the prior, representing the target image, and the initial caption text. The caption text is incorporated into the diffusion process to refine the image generation and align it with the text's semantics. This integration increases the relevance of the generation

**DALL-E 3** DALL-E 3 [86] is an improvement over its predecessor because it includes an additional process to elevate captions accuracy. DALL-E 2 was trained using self-supervised images and their corresponding captions. However, the captions often lacked descriptive detail. The new process trains CLIP with another model that analyzes the image and creates a synthetic descriptive caption, improving the quality of the data fed. This addition improves the final performance.

**Imagen** Imagen is the diffusion model developed by Google [79]. For further details, please refer to the cited source. Architectural is similar to the latent diffusion model of stable. Its principal innovation is that it employs a substantial pretrained NLP model called T5-XXL, which is taken already trained, instead of using a text encoder trained on image captions. This allows the model to understand language more deeply, as it has seen more diverse and complex texts than just image captions. Nevertheless, the model still encounters difficulties with regard to feature blending, omission or duplication of details, displaced positioning of objects, counting, and negation in text prompts, as the presence of the word is interpreted as a feature that has been requested and displayed. The text-to-image diffusion model is based on the U-Net architecture

and is adapted for  $64 \times 64$  resolution images. This model is conditioned on text embeddings using a combined pooled embedding vector and diffusion timestep embedding. Furthermore, cross-attention is employed over text embeddings at different resolutions, and layer normalisation is incorporated to increase the performance of text embeddings.

**Stable Diffusion** Stable Diffusion [84] is a model introduced by StabilityAI in 2022. It was the first model to have the ability to generate images based on specific text prompts or other conditioning inputs. This is achieved by introducing conditioning mechanisms into the inner diffusion model, which has also been referred to in the literature as Classifier-Free Guidance (CFG) [88]. The model takes an image and sends it to a variational autoencoder, where it is processed with diffusion in the latent space. In fact, the model was designated the Latent Diffusion Model (LDM) and was the inaugural system to demonstrate the potential for computational savings in the latent space. To facilitate conditioning, the denoising U-Net of the inner diffusion model employs a cross-attention mechanism, which enables the model to process inputs in a more efficient manner. The model has been improved, resulting in the third version, which incorporates the Rectified flow [89]. This is a generative model formulation that establishes a direct connection between data and noise. It employs a stochastic differential equation (SDE) as a sampling method. The rationale behind this approach is that SDE facilitates a transition from data distribution to noise distribution. The architectural framework comprises the following steps: the caption is taken, multiple encoders are employed to encode the information, and the resulting outputs are combined to construct an intermediate representation, which is then concatenated with the three outputs. These three encoders are two types of CLIP model and T5. Removing T5 has no effect on aesthetic quality ratings, and only a small impact on prompt adherence. However, its contribution to the capa-



bilities of generating written text is more significant. The model's robustness is increased, and the issues associated with CLIP are mitigated. Furthermore, a pooled vector is employed to store the same information in a more lightweight manner. This representation, in conjunction with the sinusoidal encoding of time, represents high-level text information in time. The text representations and the latent representations are then processed with transformers, undergoing multiple cross-attention operations. The model was trained on an open-source dataset comprising unlabeled images, which were recaptured in a manner similar to that employed by DALL-E 3 [86].

**SDXL** This is another StabilityAI models architecture [90] that tries to combine the sample quality of diffusion models with the inherent speed of GANs. The development of this architecture commenced with a variational autoencoder, where it was processed with diffusion in the latent space. In the latent space, the image underwent two UNets, designated as base and refined, and was then decoded by the variational decoder. The base UNet executed the standard procedure, whereas the refined UNets introduced noise into the output of the first UNet, with fewer steps. This allows the model to raise the quality of the initial image produced, as the features are not altered to the same extent. Furthermore, they have resolved a significant shortcoming of their LDM paradigm, namely that training a model necessitates a minimum image size due to its two-step architecture. Rather than discarding the images and losing information, or upsampling the low-resolution images and introducing artefacts, they have devised a solution whereby the UNets can accept the image's dimensionality as input. Similarly, the image resolution of the final result can be augmented by incorporating height and weight. Furthermore, in comparison with the initial versions of Stable Diffusion, two encoders have been added and concatenated. As improvement, they proposed a novel technique called Adversarial Diffusion Dis-

tillation (ADD) [91], capable of reduce the overhead of inference in pre-trained diffusion models. ADD is a method of distilling pre-trained diffusion models into high-fidelity. The method achieves this by condensing the typically multi-step sampling process of diffusion models into just 1-4 steps while ensuring high sampling fidelity and potentially raising overall model performance. This technique leverages score distillation [92] to use large-scale off-the-shelf image diffusion models as a teacher signal combined with an adversarial loss to ensure high image fidelity even in scenarios with one or two sampling steps. The ADD student is trained as a denoiser that receives diffused input images and outputs samples. It is trained to improve two objectives: an adversarial loss and a distillation loss. The adversarial loss is designed to fool a discriminator and the distillation loss is designed to match the denoised targets of a frozen diffusion model teacher. Firstly, the adversarial loss instructs the model to generate samples that are directly aligned with the manifold of real images during each forward pass. This directive minimises the occurrence of undesirable artefacts such as blurriness, which is commonly encountered in other distillation methods. [93]. Secondly, the distillation loss utilises the knowledge encoded in a separate, pretrained diffusion model, which acts as a fixed teacher. By distilling this knowledge into the student model, ADD capitalises on the extensive learned representations of the diffusion model, thereby preserving the robust compositionality characteristic of large-scale diffusion models. This streamlined process enables the efficient generation of high-quality samples with reduced computational overhead. The model's limitations include its inability to generate a pure black image or a pure white image, as well as its inability to place subjects onto solid backgrounds [81].

**MidJourney architecture** Regrettably, despite its significant role in the current state of the art, little is known about this architecture due to the absence of published papers.

**Playground** Playground is a Latent Diffusion Model that uses two fixed, pre-trained text encoders (OpenCLIP-ViT/G and CLIP-ViT/L) and follows the same architecture as SDXL. The latest version of the model, Playground v2.5 [94], offers three insights that aim to improve the aesthetic quality of text-to-image generative models. The first insight concerns the significance of the noise schedule in training a diffusion model, which has a profound impact on realism and visual fidelity. The new model, in fact, changed the noise schedule using the Ediffusion model noise schedule [83]. The second insight addresses the challenge of accommodating various aspect ratios in image generation. It emphasises the importance of preparing a balanced bucketed dataset. The third insight investigates the crucial role of aligning model outputs with human preferences. This ensures that generated images resonate with human perceptual expectations. To archive this, they developed a system that enables them to automatically curate a high-quality dataset from multiple sources via their platform users' ratings. The model was subjected to an evaluation process, during which it was demonstrated to outperform SDXL in all aspect ratios and to exhibit superior aesthetic quality when compared to DALL-E, MidJourney 5.2 and SDXL.

## Hybrid architectures

**Meta make a scene method** Meta's approach to image generation is designed to increase accuracy and relevance through the use of meta-feedback. This approach enables users to sketch their desired outputs and refine generated images. It was developed in response to the recognition that, despite recent advances, challenges persist in the quality and applicability of existing text-to-image models. Meta's method integrates various features into the classical autoregressive paradigm in order to address these challenges effectively. Firstly, Meta introduces a control mechanism, scene layout, which complements textual input, improving structural consistency

and quality while enabling scene editing. The utilisation of a scene composed of semantic segmentation groups provides additional global context and conditioning cues during image generation. This is achieved by explicitly guiding the model towards generating images that align better with human preferences, particularly focusing on aspects such as faces and salient objects. text editing with anchor scenes, and overcoming out-of-distribution text prompts. Secondly, the tokenisation process is refined by incorporating domain-specific knowledge over crucial image regions, such as faces and salient objects. This enhances the overall representation of the token space and improves generation quality and alignment with textual input. A CFG mechanism is introduced to raise generation quality without relying on post-generation filtering. This allows the model to leverage implicit feedback during training, resulting in improved image fidelity and text alignment.

**Styledrop** The synthesis of image styles that utilise specific design patterns, textures, or materials is impeded by the challenges of natural language ambiguity and the presence of out-of-distribution effects. Styledrop [95] uses a transformer-based model for text-to-image generation, specifically leveraging Muse, [96] a transformer model capable of modelling discrete visual token sequences. This architectural approach offers a distinct advantage over diffusion models such as Imagen and Stable Diffusion, particularly in the context of learning fine-grained styles from single images. It involves taking a representation of the caption through the Muse model and fine-tuning it with a specific style, drawing from one or more images as a reference. Adapter tuning is the technique utilized in Styledrop to style-tune the text-to-image transformer. The process entails creating a text input based on a style reference image. This input comprises content and style text descriptors, which have been designed to promote content-style disentanglement, a crucial factor in achieving compositional image synthesis. Styledrop employs an

iterative training framework to raise model performance over successive iterations. This framework involves training a new adapter on images sampled from a previously trained adapter. This iterative approach enables the model to gradually enhance its comprehension of the relationships between style and content, resulting in improved synthesis outcomes. A CFG mechanism is employed to refine the generation process, thereby obviating the necessity for external classifiers or post-processing techniques. This further improves image quality and coherence.

## 4 Discussion

### Differences and analogies

**Structural differences** AI is based on the premise that the mind can be viewed as a computational device. This approach limits the study of the human mind to cognition, excluding emotions, motivations, and irrationality, which are also involved in the process as we have already discussed. Studies reveal that mood states significantly influence creativity. Positive-activating moods, such as happiness, and negative moods, such as sadness and depression, have a positive impact on the creative process. Conversely, relaxation, anger, and anxiety have a negative influence [97]–[99]. In addition, machine learning (ML) algorithms rely on their ability to represent numbers with a high degree of resolution and accuracy. This is difficult or impossible with biological neurons. Moreover, the more accuracy needed, the slower a neuron-based system will run [100]. Any biological brain implementing the numerical precision required by ML would be too slow to be useful. Although, Neurons operate at a much slower pace compared to electronic signals, firing at a maximum rate of about 250 Hz, leading to limitations in processing speed. This structural difference highlights the working process dissimilarities. The maximum number of values which can be represented by neuron firing is between 10 and 100 unique values. ML algorithms require much more precision than this be-

cause the underlying concept of gradient descent presumes a continuous gradient surface. In addition, dendrites have the ability to perform XOR operations [101], which perceptrons [102] cannot. Therefore, numerical comparisons between neurons are not valid. Studies have shown that to accurately emulate the behaviour of a human neuron, it requires approximately 5-7 convolutional neural network layers [103]. This implies that a single neuron in our body can be compared to an entire network. Interestingly, when the upper bounds of dendrites is not thresholded, the number of layers decreases to one.

**Training process** In the context of the training process, the artificial neural network is able to emulate the philosophy of deliberate practice [23] and the incorporation of feedback, as exemplified by the backpropagation mechanism. However, the absence of a tangible layer structure in a biological system precludes the existence of a mechanism that could be employed to dictate the weight of any specific synapse. Consequently, in order to reduce the weight of a synapse in our brain, the target must fire shortly before the source. In order to effect any meaningful change in a synapse weight, a number of repetitions must be performed. Additionally, the connections in the brain are not organised in the orderly layers as artificial neural networks [104], which requires some modification to the basic perceptron algorithm. This may prevent backpropagation from working at all. Artist learning by doing an image and then receiving feedback is more similar to Gans' process than diffusion models. The diffusion model process of reverse from an initial paint to the white canvas, which is the most similar thing to the initial noise, is never done. Furthermore, as has been demonstrated, the quality of the training data affects the quality of the output. It can be reasonably assumed that the quality of the prompt entered into these models also influences their ability to produce images. This is arguably true even for humans.

**Memory** In human cognitive frameworks, knowledge representation is typically manifested by conceptualising entities as objects with attributes, encapsulating a hierarchical structure that reflects real-world semantics. In artificial neural networks, particularly in our context of text-to-image processing, the intrinsic meaning associated with a word or concept is replaced by its correlation with visual representations. Clip functionality seems to mirror well-enough the human ability to associate words with our mental representations of them, in fact is used in most of the state of the art diffusion models architectures. Although, CLIP embedding itself does not explicitly bind attributes to objects [85], this produces limitations in the replication of attributes pertaining to subjects in the output. This absence emphasises the lack of semantic memory structured like ours. Furthermore, the Parti autoregressive solution incorporates the meaning of an image into the encoder process. It employs cross-attention, a mechanism that enables the model to focus on pertinent information from the encoder while processing another sequence for the decoder. In particular, the text encoder embeddings are utilised as conditioning for the image decoder, which predicts one image token after another. This approach facilitates the handling of image coherence and long prompts, provided that the number of tokens is adjusted in accordance with the aforementioned discussion. CM3Leon, instead, employs a decoder transformer to comprehend the meaning of both modalities. This approach enables not only text-to-image but also image-to-text. This method bears resemblance to the human capacity to convert one to the other. In fact, the transformer decoder accepts either text or image as input, with the vocabulary being merged. The mask system allows for the selection of which modality is input and which is output. Although the CM3Leon architecture is similar, it does not represent a perfect reverse process of the human brain’s flow.

**Drawing process** Diffusion models in general can be said to emulate the principle of the human process of sketching and refining the result. In particular, the DALL-E method appears to be the most natural emulation of the human brain among all the state-of-the-art architectures. The text-encoding converts natural language into a (possible) graphical representation of it, which aligns with the associative thinking well. Subsequently, the prior applies modifications to this vector in order to enhance diversity and, consequently, creativity. This aligns with the initial stage of the creativity process, the problem framing, which improves the potential for creative outcomes. Indeed, the phenomenon has been observed in studies of creativity in art students, who have been found to produce more creative work when they take the time to modify the spatial representation of their objects [105]. Therefore, diffusion models exhibit similarities with the human brain, yet also exhibit critical differences in terms of the dimensions sampled. While the UNet pooling technique can be useful for understanding the meaning of an image, the latent space sampling approach is a computational-saving trick and is therefore not feasible for humans. Additionally, most models have a fixed width and height of the image, which humans can adapt according to their imagination about the representation.

## Evaluation metrics

**FID** In the term usefulness on the creativity definition we implicitly say that the image should be meaningful. Hallucinations or random noise have novelty but definitely not usefulness. FID is a measure of similarity between two datasets of images, it is used in evaluating the quality of generated images, how they match the real images in terms of visual quality and diversity. FID is calculated by computing the Fréchet distance [106] between two Gaussians fitted to feature representations of the Inception network. However, it has been demonstrated that FID may differ from the evaluations of human raters, particularly in

significant cases. Human raters are obviously the most valuable evaluators in this context. Therefore, relying solely on FID as a measurement may not be suitable.

**CMMD** Instead of estimating the Frechet distance, Google researchers propose using an alternative new metric called CMMD [107]. This metric is based on richer CLIP embeddings and the maximum mean discrepancy distance with the Gaussian RBF kernel. It is an unbiased estimator that does not make any assumptions on the probability distribution of the embeddings and is sample efficient. Image Reward simulate the commissioning of an image to an artist by integrating human preference feedback to enhance text-to-image models. After the generation phase, humans vote on four parameters: Overall satisfaction, adherence to the prompt, aesthetics, and meta-feedbacks. ImageReward [108] is a general-purpose text-to-image human preference reward model that encodes human preferences in the diffusion process. It outperforms existing scoring models and metrics in human evaluation, making it a promising automatic metric for evaluating text-to-image synthesis. Text-image scoring methods such as CLIP or BLIP can assess whether an image generated by e.g. Stable Diffusion matches a text prompt. However, these methods do not always match human preferences and perceptions. ImageReward has been trained with 137,000 human scores of AI images and is expected to provide significantly better image syntheses. It introduces Reward Feedback Learning (ReFL) to tune diffusion models with respect to human preference scorers. This information about the quality in the final denoising steps allows direct feedback learning on diffusion models that do not provide a probability for their generations.

## Conclusion

The need to increase the refinement of the input does not detract from the fact that for all intents and purposes, despite being a mathemat-

ical calculation, the AI is able to synthesize an image that differs from the commissioning author's imagination. This is for all intents and purposes assessable as creativity. Nonetheless, hybrid architectures emphasise the importance of a holistic approach to evaluating the end result. As previously stated, the quality of the prompt exerts a significant influence on the final result. However, the definition of prompt quality is specific to the model in question. For this reason, human creativity is not expressed in the conventional manner; rather, it is manifested in the selection of an appropriate word selection for a given model and an understanding of the system's training data and configuration parameters. These factors are crucial for the generation of high-fidelity images [109]. The art of prompt engineering is a learned skill, as it is not immediately apparent how to write effective prompts and which keywords make good prompt modifiers [110]. The outcome of this debate depends on how we define and conceive creativity. If we adhere to the definition of novelty and usefulness, AI models can be considered creative. Nevertheless, the existence of these hybrid architectures highlights the lack of inherent creativity in machines, which require more initial information to produce something more creative. This text emphasises the collaborative nature of creative processes. The analysis of AI-generated images is evaluated in relation to the creativity of the initial prompt, thereby highlighting the symbiotic relationship between human input and machine output. The text-to-image process extends beyond algorithmic execution to embody a collaborative endeavour akin to commissioned artwork. The machine performs mathematical calculations, which is also done heuristically by humans. However, if we consider heuristics as the defining characteristic of human creativity, then machines can also be considered creative since they have different ways of arriving at the final output. It is important to acknowledge that machines are primarily calculators, but the hypothesis that they are not creative is incomplete. Despite the objective aim of text-to-image mod-

els to produce accurate visual representations of the input text, focusing on fidelity to the description rather than subjective interpretation, it is possible for these models to produce such images, without prompt, if activated by humans. In this context, we do not search for subjectiveness inside this picture because we are aware that it does not exist, and therefore it feels like mere randomness. In extent, we can argue that the two are different and then should exist the term Artificial creativity [111] that recognize the originality and effectiveness but also the differences with the human creativity. As the Google Researchers in the Parti paper posited: "Like a paint brush, these models are a kind of tool that on their own do not produce art—instead people use these tools to develop concepts and push their creative vision forward".

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