RIVISTA INTERNAZIONALE DI FILOSOFIA E PSICOLOGIA
DOI: 10.4453/rifp.2022.0001
ISSN 2039-4667; E-ISSN 2239-2629
Vol. 13 (2022), n. 1, pp. 1-18

RICERCHE

Creativity as an information-based process

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Ricevuto: 1 febbraio 2021; accettato: 8 novembre 2021

Abstract Creativity, mostly ignored in Western philosophy due to its supposed mysteriousness, has recently become a respected research topic in psychology, neuroscience, and artificial intelligence. We discuss how in science the approach has mainly been to describe creativity as an information-based process, coherently with a computational view of the human mind started with the cognitive revolution. This view has produced progressively convincing models of creativity, up to current artificial neural network systems, vaguely inspired by biological neural processing, but already competing with human creativity in several fields. These successes suggest that creativity might not be an exclusively human function, but actually a way of functioning of any natural or artificial system implementing the creative process. We conclude by acknowledging that the information-based view of creativity has tremendous explanatory and generative power, but we propose a thought experiment to start discussing how it actually leaves out the experiential side of being creative.
KEYWORDS: Creative Cognition; Cognitive Neuroscience; Computational Creativity; Generative Algorithms; Cognitive Science

Riassunto *La creatività come processo basato sull'informazione* – La creatività, spesso ignorata dalla filosofia occidentale per la sua presunta oscurità, in tempi recenti è diventata un rispettabile oggetto di ricerca per la psicologia, la neuroscienza e l'intelligenza artificiale. Vogliamo illustrare il modo in cui lo sguardo scientifico sia rivolto prevalentemente a considerare la creatività come processo *information-based*, coerentemente con la prospettiva computazionale sulla mente umana aperta dalla rivoluzione cognitiva. Questa prospettiva ha prodotto modelli della creatività sempre più convincenti, fino agli attuali sistemi di reti neurali artificiali, vagamente inspirati al processamento biologico neurale, ma già competitivi rispetto alla creatività umana in molti ambiti. Questi successi suggeriscono che la creatività possa non essere una funzione esclusivamente umana ma in effetti un modo di funzionare di un sistema naturale o artificiale capace di implementare il processo creativo. In conclusione, pur riconoscendo come il considerare la creatività come processo *information-based* possieda grande potere esplicativo e generativo, proporremo un esperimento mentale per aprire una discussione sul come questa prospettiva non copra in effetti il lato esperienziale dell'essere creativo.
PAROLE CHIAVE: Cognizione creativa; Neuroscienza cognitiva; Creatività computazionale; Algoritmi generativi; Scienza cognitiva

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1 Introduction

IT IS OFTEN SAID THAT the quintessence of humanity, as well as the fountainhead of human civilizations, is our ability to be creative. Works of art, science, technology, even social organizations are all the product of our ability to think and make things that are new (i.e., original and previously unseen) and valuable (i.e., good, useful, beautiful, etc).[1] Creative thinking has also been shown to play a crucial role in everyday problem solving.[2] Thus, it is not surprising that creative capacities have been acknowledged as one of the most important skills of the 21st century.[3] Despite the significance of this ability to human progress, we still seek a critical grasp of what creativity is and how it works.

Specifically, can creativity be described as a function of the human mind, as modern cognitive approaches do for perception, movement, or memory? In addition, if it can be described as a process, does it have to be an inherently human process, requiring life and self-consciousness (however we define those terms)? Alternatively, can we conceive of creativity as a *modus operandi* that could be found also in non-human systems, such as an information processing system (e.g., a computer, or a network of computers)? Is the evolution of the species on Earth the product of a fundamentally creative process that can explain their breathtaking and beautiful variety? Perhaps there is even an impersonal creative force pushing the entire Universe, which brings to the generation of the infinite types of planets, stars, galaxies (only to mention the visible objects) that populate the Cosmos as we know it?

In this article, we show how the view that creativity is an information-based process that can emerge in natural and artificial systems is the dominant one in Westernized societies. The current models of creativity revolve around the idea that creations emerge from fundamentally repeating patterns and processes, which have some resemblance in the competition/cooperation relationship between a disruptive principle (which brings novelty) and an ordering principle (which evaluates). Progressively, creativity has come to be viewed as a not uniquely human or human-like (like in a creator god or a demiurge) capacity, but as a process that can emerge out of any system, be it brain networks, artificial neural networks, or DNA interacting with changing environments.[4]

We first describe creativity as an information-based process from the point of view of cognitive science. We then discuss some of the aspects linked to the measurability of creativity, which is a necessary condition to test the scientific hypotheses and models. We then move on to illustrate the most updated neuroscientific hypotheses and a description of the core features of the brain networks involved in creative thinking. We then describe some of the most recent computational approaches in *Artificial Intelligence* (AI), and how they are deeply revolutionizing the field of creative computation, with an effect also in the world of Arts. This progress in scientific and technological understanding is slowly bringing us – as a society – to the view that a creative algorithm is not an oxymoron, but instead as a functional procedure. We discuss some of the societal, ethical and philosophical consequences of these advancements in the understanding of creativity as an information-based system process. At the end of the article, while we acknowledge that this information-based view of creativity has been very successful in industrialized society, we propose a thought experiment to start discussing how it actually leaves out the experiential and first-person aspects of being creative.

2 The creative process: from a source of divine inspiration to the object of scientific research

Interestingly enough, the rational investigation of creativity as a process that can be described is a very recent enterprise, while in the past it remained untouchable and sacred. In ancient Greece, Plato in *The Republic* wrote that poetry is made not by knowledge, but instead by divine inspiration by the Muses, thus somehow externalizing the power of poets. On the contrary, Aristotle in his *Poetics* underlined the various rational means by which the poets reach their goal of emphatically inducing emotions in the audience through their verses. After centuries in which creativity has been mostly ignored, with some exceptions in the Renaissance, we jump to the XVIII century in Germany, when Immanuel Kant described in his *Critique of the power of judgment* the conditions for creativity of geniuses via imagination, which – in line with Plato – he still interpreted as an obscure process that cannot be taught and does not follow rules, thus remaining fundamentally mysterious, even though he highlights its role in the formation of meaning.

A few years afterward, Arthur Schopenhauer, still writing about geniuses in his *The world as will and representation*, acknowledged their need for technical abilities, but he underlined that important increases beyond the ordinary were possible thanks to a disposition for madness. Of the few Western philosophers who did attempt to describe the creative process, a rather powerful depiction can be found in Friedrich Nietzsche. In his *The birth of tragedy*, he saw creativity as arising through the workings of two conflicting divine forces: the Apollonian and the Dionysian. The Apollonian is rationality, intellect and sobriety, while the Dionysian is irrationality, vitality and passion, even to the point of deriving these properties by substance-induced intoxication (from wine, for example). The first represents the forces of Order, the second the forces of Chaos. He thought that creativity came out of the meeting and the balance of the two, as magnificently depicted through in the tragedies of ancient Greece.[5]

Scientific research on creativity has emerged only as a relatively recent field of interest in psychology and neuroscience, after the cognitive revolution in the 1950s. In the cognitive approach that emerged in those years, and very much alive today, human beings interact with the "real world" only through the processing of information mediated by sensory input, and the study of cognition consists in building information-based models and systems that attempt to describe all mental functions as the product of information processing, that structures, interprets and storages data in neural a well as artificial systems. The cognitive revolution bridged the gap between the physical world and the mental world with a theory that explains the mind in terms of information, computation and feedback which are implemented in physical systems.[6]

This revolution began to deeply change the view of creativity, starting to rip off the halo of mystery around creativity, and on the contrary, igniting scientific research on this elusive concept. Creativity research has been, since the start, mostly divided into the contextualized evaluation of creative ideas (or artefacts) after their generation on one side, and the research on the creative process itself on the other. The rational attempt to describe creativity as a cognitive process, and to find empirical evidence in psychological and neuroscientific experiments, paves the way to the idea that also computing machines can be creative, while leaving aside the issue of whether subjectivity is a necessary condition for creativity. The question of whether a computer can really be creative remains open, as well as whether it even makes sense to say that an automatic and pre-programmed system can produce new ideas, original prototypes, novel artefacts, or even works of art.[7]

To answer these questions, computational creativity has become an emerging branch of AI that places information processing at the center of the creative process. Computational creativity investigates automatic systems that produce novel artefacts including poetry, visual arts, architectural projects, business and financial service designs, and progressively more objects or ideas that we would consider creative.[8]

To better clarify what it means that creativity can be described as an information-based process, we can refer to the well-known three levels of description of the neuroscientist David Marr.[9] To describe the process of vision, together with Tomaso Poggio, he put forward the idea that any information processing systems can be analyzed at three distinct levels:

1. A computational level: what does the information system do. At this level, we answer the questions of what problems it solves, and why it does these things.
2. An algorithmic level: how does the information system do what it does. At this level, we answer questions like what representations does the system use, or what processes does it employ to construct and manipulate the representations.
3. A physical level (also called implementational): at this level, we ask how the information system is physically realised.

Among the limitations of this distinction, it is useful in differentiating the various levels of analyses, avoiding possible confusions. If we apply this distinction to creativity, we see that we can ask three different types of questions:

A. The computational level of creativity: what does a creative process do?
B. The algorithmic level of creativity: how does an information system do to create?
C. The physical level of creativity: how is the creative information processing system physically actually implemented?

The first question concerns a general description of creativity, and it can be discussed within human cognition, but it should be general enough to be applied to any information processing system, independently of whether it is a human brain, a rule-based computational system, an artificial neural network, or more in general, any region of the universe (mechanical, electrical, chemical, biological, etc.), which takes a sequence of enumerated symbols or states (information) and is capable of processing it (transforming) into another form.

The second question concerns the actual algorithmic ways in which the system is creative, and thus it can be a description of the specific processing of the interaction between human brain networks, or instead, a definition of an artificial neural network and so on that performs the computational aspects of creativity.

The third question concerns the actual physical implementation, and therefore how the creative algorithm is implemented with actual biological neurons, or how the artificial neural network is processed in the electronic circuits of a computer.

In the next sections we discuss some of the different information-based descriptions of creativity, and support the idea that they are all pointing to the same basic underlying process, described at different levels (as defined by Marr). In particular, we describe cognitive theories (section 3) that answer the question of *what* creativity does (Marr's level A); but these theories are not specific or detailed enough to give an explicit description of *how* the human cognitive system is creative. To find such a fine grain description of the creative process we must refer instead to the computational models (section 5), which answer the question at the algorithmic level (Marr's level B). In these cases, the models have digital/electronic implementations (Marr's level C), whereas elements of biological implementations (still Marr's level C) are discussed when we illustrate some of the most influential brain network models (section 4).

3 Creativity as a cognitive process

A definition of creativity can be found in cognitive psychology, where it is conceived as the ability to produce novel (i.e. original, unusual) and good (i.e. valuable, effective, useful, beautiful) ideas or artefacts.[10] While this perspective is concerned with the identification of creative products, the core issue in the scientific study of creativity is the question of how creative ideas are generated.[11] Indeed, creative ideas require complex thinking processes, hence refer to the multiple and dynamic processes occurring during creative thought. Although several scholars, through history, have provided a range of frameworks that aim to explain creativity in more explicit process-based ways, currently there is no unified definition of the creative process.

3.1 Psychological studies

A pioneering theory of creativity as a process was proposed by Graham Wallas.[12] The author suggested that creativity is an iterative thought process of generation and evaluation of solutions. In his model, Wallas included four phases: namely, *preparation* (identification of the creative goal), *incubation* (taking a break from the problem, as a way to sort out inappropriate strategies and thinking patterns), *illumination* or insight (a sudden realization of how a problem might be solved) and *verification* (check whether the idea has value). Notably, Wallas' model includes a remarkable differentiation between unconscious (spontaneous or unintentional) creativity, occurring during the incubation and illumination stages, and conscious (deliberate or intentional) creativity, occurring during the preparation and verification stages. Even though Wallas' four-stage model still holds significance, a recent reformulation of the model moves away from the notion of a fixed sequence of activities, suggesting the need to specify in much greater detail the sub-processes involved in the creative process. A broader and well-established model of creativity has been introduced by Joy Paul Guilford in 1956, which distinguishes two different operations of thought: divergent and convergent thinking. Divergent thinking, often referred to as associate thought, serves to explore multiple potential solutions to an ill-defined open-ended problem (i.e., a problem that does not have a clear goal and an expected solution). Thus, it contributes to a wide, highly variable and original range of alternative solutions. Convergent thinking, or analytical thought, on the other hand, leads to the realization of new solutions by identifying a single unique and appropriate solution to a close-ended problem (i.e., a problem that has a clear and expected solution). Precisely, Guilford assumed a major role of divergent thinking in creative cognition,[13] breaking it down into three main sub-processes: *fluency* (being able to come up with multiple solutions to a given problem); *flexibility* (the ability to consider a variety of alternatives simultaneously); and *originality* (being able to produce ideas that differ from others). Although Guilford's model of creativity is not without criticism, it also seems to have been established by scholars as one of the most influential, broadly known also as dual-process models of creativity.[14]

In line with Guilford's theory,another well-known definition of the creative process was proposed by Paul Torrance over 50 years ago, who described creativity as «a process of becoming sensitive to problems, deficiencies, gaps in knowledge, disharmonies; identifying the difficulty; searching for solutions, or formulating hypotheses about the deficiencies: testing and retesting these hypotheses, and possibly modifying and retesting them, and finally communicating the results».[15] In addition to these principles, Torrance[16] identified four necessary components of the creative process: *originality* (uniqueness of the resulting product), *fluency* (the quantity of meaningful and relevant ideas in response to a given problem), *flexibility* (the ability to overcome functional fixedness), *elaboration* (add details to the idea).

Other theories relevant to creativity at the functional levels come from evolutionary psychology. Indeed, given that the process of creative thinking appears to evolve in time, it can be explained by applying Darwinian logic. Among these models is the *blind-variation and selective-retention model* (BVSR) of creativity proposed by Donald T. Campbell.[17] The idea behind this model is that humans generate new solutions by alternating variation and selection: the first phase entails the abundance of ideational variation, ensuring that several creative ideas are developed; the second phase comprises the refinement of the chosen solution. The BVSR has been described as a superordinate process of creativity, showing a major theoretical overlap with Guilford's model. In that regard, divergent thinking constitutes one of the processes that contribute to blind ideational combinations. On the other hand, convergent thinking is assimilated to the concept of selective-retention, which is crucial, for example, in creative problem solving to either know exactly what constitutes a solution and internally select representations that most fit to the external world.[18]

Since the pioneering work of Campbell, the BVSR model of creativity continued to develop over decades.[19] However, a commonly discussed problem derived from the conceptualization of Campbell is that he did not give a clear description of what it means to be “blind” for the variation stage. This was due to the fact that Campbell recognized that there are multiple mechanisms behind BV, thus he deliberately avoided identifying its nature. For example, while the term “blind” has referred to a lack of prior knowledge about an idea’s value,[20] to date it is also discussed in the literature as a variation in degrees of sightedness,[21] highlighting the role of cognitive control in the creative process. Yet, the lack of a precise definition, makes it impossible to understand whether or how BV supports the creative process. Notably, this discussion seems to be of paramount importance today for the *Reinforcement Learning* (RL) community, where the *Exploration/Exploitation* trade-off in decision making is mostly studied, and where the *Exploration* policy issue may be compared to Campbell’s BV.

Along these lines, associative theories of creativity emphasize the crucial role of memory in creative thought, with elements of knowledge representing its building blocks. By definition, generating something creative implies moving beyond memory, since mere recall would never be thought of as truly creative. Nevertheless, new solutions do not come completely *ex nihilo*, but they are assumed to emerge from variation and recombination of accessible knowledge.[22] Sarnoff Mednick’s[24] offered an interpretation in terms of unique associations between concepts, stimuli and responses correlated in unusual ways. The author defined the creative process as: «the forming of associative elements into new combinations which either meet specific requirements or are in some way useful. The more mutually remote the elements of the new combination, the more creative the process or solution».[23] Yet, for the sake of efficacy in everyday contexts, our mind/brain is tuned to keep common associations available,[24] hindering original ways of thinking.

Additionally, Margaret Boden[25] provided a general cognitivist theory, whose mathematical formalization was proposed by Geraint Wiggins,[26] in which he distinguished between different creative processes: to create novel combination of familiar ideas, to explore the potential of conceptual spaces and transform them, thus allowing for previously impossible ideas to be generated. As we will see later, these models of creativity based on associative theories have now found great empirical support.[27]

In recent years, researchers have proposed representations of the creative process within the framework of complex systems. Liane Gabora[28] proposed a novel theory of creativity, referred to as *honing theory*. Her theory aimed to understand how ideas develop over time, considering the mind/brain as a self-organizing complex system that interacts constantly while adapting to the environment to reduce *psychological entropy*. Indeed, as humans, we are psychologically tuned to experience uncertainty in the form of anxiety. This feeling is referred to as psychological entropy. Its standard definition was framed in terms of anxiety-provoking uncertainty,[29] and Gabora referred to it as the driving force for the process of creativity, as progressively replacing anxiety with arousal and embracing it in a positive manner.[30] Indeed, psychological entropy has been proposed to guide the creative process in monitoring progress, until it is sufficiently restructured, and then the arousal dissipates. Creative restructuring can thus eliminate dissonance and unify previously conflicting results. Thus, creative cognition could be encouraged through momentarily defocusing attention and switching to a more associative way of thinking.[31]

Finally, Jürgen Schmidhuber[32] formalized a theory of creativity based on information-processing and predictive coding notions and related to the concept of intrinsic motivation, defined as «an inherent tendency to seek out novelty, [...] to explore and to learn».[33] General exploratory behaviour, curiosity, and playfulness are caused by such intrinsic motivation. Therefore, the process of creativity is focused on maximizing this intrinsic reward in order to actively create behaviour, which in turn allows prediction. Intrinsic motivation drives goal-directed reasoning of the agents. In his view of creativity, Schmidhuber thinks that no theory of consciousness is necessary. He considers consciousness as a sort of by-product of the problem solving and data-compression procedure. Thus, he uses all the terms “motivation”, “curiosity”, “playfulness”, etc., thinking that the actual subjective component of these phenomenological states comes as a side effect of the computations[34] (see the last section of this article for a discussion on the subjective aspects).

All the above-described models have increased our understanding of how the individual creative processes might happen. Among all models, the most commonly accepted view nowadays remains the dual-process models of creativity,[35] which interpret the creative process as an interplay between a more spontaneous (divergent) and controlled (convergent) mode of thinking. Crucially, we have also seen how recent models conceptualize creative thinking in the framework of adaptive behaviour and predictive coding, also highlighting the major role of subjective experience and context.[36] The overall picture however remains very fragmented. Given the complexity of creative cognition, a major issue remains related to the difficulty of identifying, formalizing and disentangling the cognitive subprocesses underlying the creative thought.

3.2 How to measure creativity

The cognitive approach has investigated creativity mainly as an information-based process, with the advantage of starting to tackle it scientifically and trying to overcome its mysteriousness coming from past views. Some of its subjective components have been considered, but fundamentally put aside as by-products. An important consequence of this approach has been that researchers have finally started to address the fundamental problem of how to measure creativity, even though it does remain a major challenge. Indeed, choosing an instrument to measure creativity and whether it has adequate psychometric properties are all decisions that must be made by creativity researchers, as well as how to create ideal testing conditions to maximize creativity scores, and whether to evaluate creativity as domain-general or domain-specific.

The complex issue of creativity measurement has a comprehensive and thriving history of research,[37] revolving around the problem of reliability (producing consistent outcomes) and validity (measurement accuracy). Most approaches to evaluating creativity usually distinguish between the already mentioned convergent and divergent thinking processes. On the one hand, the *Remote Associates Test* (RAT)[38] is a widely used test for measuring convergent thinking processes (the use of deductive reasoning to solve a close-ended problem). The RAT tests the ability to make associations: the participant is asked, given three words, to come up with a fourth word associated with all three of them. For example, given the three words: "cream, skate and water" the correct answer, that relates to all of the previous, could be "ice". Even though the RAT is shown to be reliable, its validity is questionable.[39]

On the other hand, divergent thinking tasks are largely obtained from the foundational *Torrance Creative Thinking Test*,[40] which allows the formation of associative hierarchies.

Similarly, Guilford's *Alternative Uses Test* (AUT)[41] represents one of the most employed tasks for divergent thought. It requires participants to name as many and unusual/original uses of an everyday object. For example, one the most common verbal prompt used for the AUT is the "brick". Given some interval of time (usually 2-3 min) participants should provide different responses referring to the alternative use of a "brick", such as "build a school" or "use it as a pot" or even "use it as a weapon". Following this example, the use of bricks to construct a building could be considered less original when compared to pots with flowers.

A question that remains is how researchers assess the creative extent from divergent thinking tasks. Throughout its history, creativity has mostly been studied as an entirely divergent thinking process, and several indicators that attempt to quantify this specific aspect have been adopted; for example, *ideational fluency* (number of given solutions), *originality* (novelty or unusualness of the answer), *flexibility* (i.e. the number of different semantic categories of ideas) and *elaboration* (precision and details).

A notable criticism of this form of evaluation is that fluency might act as a contaminating factor for originality ratings, thus favoring quantity over quality of ideas, although a validated approach exists to avoid this confound factor.[42] Other notable criticisms regard the subjective scoring of a given creative idea. Indeed, a gold standard in most of the research are methods based on human judgment (a panel of judges or experts), such as in the *Creative Assessment Technique* (CAT),[43] which measures the originality, novelty or the overall creativity of the generated products on a Likert-scale. The application of the CAQ or Torrence scoring to the AUT have shown consistent evidence of validity with several studies reporting moderate to large correlations between AUT performance and real-world creative achievement in the arts and sciences.[44]

However, although the AUT appears to provide a good indication of a person's ability to come up with new and original ideas, it's not entirely clear what makes one idea more creative than another due to the complexity of individual opinions and rater's experiences. Nevertheless, since the CAT relies on subjective judgments based on norms that are generally not precisely described, its effectiveness can only be measured in part by the agreement among raters.

Interestingly, using the RAT and AUT task as an example, it would appear that the dichotomy of divergent vs. convergent oriented tasks offers an easy solution to isolate components of creative cognition (novelty and usefulness). However, this aspect is not without criticism.[45] Each creativity task seems to account only at a particular aspect of the creative construct based on the assumption that this narrow aspect of creativity is representative of the entire construct.[46] Indeed, the ecological validity and domain specificity (according to the domain of knowledge: art, science, sport and so on) of these tasks are rather limited.[47] Creative cognition can be best reflected in alternative and naturalistic tasks that are embodied in real-world contexts.[48] A few examples are already present in the literature, such as artistic and drawing tasks, story writing and musical improvisation.

Notably, recent advances in the assessment of creative potential have allowed researchers to solve at least in part probing techniques for automated scoring of creative quality.[49] For instance, a method to score originality or uniqueness of the creative performance was formalized by Wallach and Kogan in 1965.[50] The method requires researchers to compile all the responses of the divergent thinking task, such as the AUT, and assign each response a 0 (for responses given by two or more participants) or a 1 (for truly unique responses). A variant of this method involved the count of frequencies among responses given by all the samples in a study. Given a frequency threshold (e.g., Responses given by the 10% of the sample), researchers assign for each response a 0 (if the response falls under the threshold), otherwise 1. This procedure has been criticized since the uniqueness scores are heavily influenced by sample size; as the sample size increases, the number of creative responses decreases. More reliable methods for assessing creativity are making their way today.[51] They are particularly suited for verbal tasks, such as the AUT, and more ecologically valid tasks such as the word-association task. Those methods exploit models of natural language processing in order to measure the semantic distance between a target word and its response, which could serve as an objective measure of divergent thinking.[52]

However, the issue of creativity measurement is still ongoing and is even more relevant if we consider how it relates to cognitive neuroscience, given that additional methodological limitations are imposed by neurophysiological evaluations.[53] Indeed, a further step in the study of the science of creativity has taken the direction of studying its neural bases, almost exclusively in humans, with very few animal exceptions that we do not discuss here.[54]

4 Creativity as a brain process

Neuroscience research on creativity has followed a quite different route from cognitive theories, mostly because the approach has been bottom-up, that is to say a collection of attempts to adjust the empirical findings. Some of the first studies can be traced back to Colin Martindale's studies (1975). Since then, the number of neuroscientific publications on this topic has gradually grown until the end of 2000, and about 70% of them have been published since 2010, up to about 850 articles. Such growth has been facilitated by progress in psychometric and behavioral creativity research that accompany the neuroscience studies and by the rapidly increased availability of modern brain imaging methods.

Neuroscientific research devoted to the study of divergent processes has been extensively exploited using electroencephalography (EEG) to examine the functional significance of brain dynamics associated with the generative process as a function of the level of originality of the ideas produced. One robust and widely replicated finding concerns the increase in alpha power frequency range (8 to 12 Hz) during divergent thinking tasks. Changes in alpha power are typically calculated in terms of *Task-Related Potential* (TRP). Since the pioneering work of Martindale and Mines, creativity has been consistently associated with increased alpha power by several other studies. During the AUT, alpha synchronization has been consistently identified in association with the production of highly original ideas, compared to those with low levels of originality, as well as in highly creative participants compared to less creative ones. Particularly, researchers reported that alpha power in the frontal cortex might reflect the involvement of a more convergent and goal-directed thought. Posterior parietal alpha bands, on the other hand, appear to reflect a more divergent cognitive process, with internally directed attentional mechanisms. Other interesting findings from EEG research emphasise how idea generation is not to be considered an isolated phase in the creative process, but instead appears to operate dynamically in joint action with other components, such as the idea evaluation phase. Hao and collaborators, for example, have shown that reiteration between the idea generation and idea evaluation phases facilitates the development of creative ideas.

In addition to EEG research, brain activation associated with creative thinking has been extensively investigated through functional magnetic resonance (fMRI). Although these investigations are quite recent, they have outnumbered EEG, providing a deep contribution to the overall research on creative cognition. A recent attempt to summarize the current state of knowledge on the neurophysiological basis of creativity comes from Anna Abraham, who distinguished between global- and local-based explanations. The local explanation highlights specific brain regions involved in creative cognition. The prefrontal cortex seems to play major and distinct contributions, as an integrator of the output of several cognitive processes. Lesions in the prefrontal cortex have been related to decreased creative capacities, along with reduced fluency and originality in creative ideation tasks. Global explanations of creative cognition, on the other hand, are supported by systems neuroscience, which corroborates the view of creativity as a cognitive process supported by dynamic interactions within and between large-scale brain networks. Far from being a single unique process, these explanations focused on the notion that creativity relies on a series of multiple and simultaneously operating processes, which emerge from large-scale neural assemblies working in synchrony during the ideation.

Recent studies reported a consistent pattern of functional connectivity during the creative performance, characterized by the interactions between two major large-scale brain networks; namely the *Executive Control* (ECN) and *Default Mode* (DMN) networks:

- The ECN consists of lateral nodes of the dorsolateral prefrontal cortex and posterior parietal regions. This network supports cognitive control processes, abstract thinking, and planning, including the capacity to enable the relational

integration, retention and inhibition of mental representations involved in externally-goal directed attention.
- The DMN includes regions of the prefrontal cortex and temporal lobe, the posterior cingulate cortex, the medial temporal lobes, the precuneus and the temporo-parietal junction. In contrast to the ECN, the DMN is found to be active in the absence of current external stimuli and thus during self-referential or spontaneous thought, such as mind-wandering, episodic and semantic memory, as well as divergent thinking and mental simulation.

These two large-scale brain networks have often been considered as antagonistic, as much as the putative cognitive processes needed to support them, namely divergent and convergent thinking. These perspectives contribute to the ongoing debate between a more spontaneous (divergent) and controlled (convergent) mode of thinking, also known as the dual-process models of creativity. Crucially, the ECN and the DMN seem to exhibit increased functional coupling during different creative activities such as creative idea generation, artistic visual ideation, musical improvisation, literary generation. This perspective was corroborated by a meta-analysis of functional imaging findings on creativity by Gonen-Yaacovi and colleagues, who identified a set of frontal and parieto-temporal regions activated during tasks that engage creative thinking. Moreover, a review by Beaty and colleagues elaborated on the creative network dynamics and demonstrated that the executive and default mode networks can reliably predict the creative thinking ability of individuals.

In addition, studies that implemented analysis of dynamic changes in functional connectivity patterns found that ECN and DMN's switching rate predicts the performance of higher-order cognitive functions, and particularly creative cognition. Creative ideation seems to be related to the temporal variability of resting-state functional brain networks at 3 different scales (the regional level; the network level: within networks and between networks; and the whole-brain level) to a verbal score. In line with these findings, Shi and colleagues examined the associations between brain entropy, a measure of the level of brain activity disorder, and divergent thinking. They found that divergent thinking positively correlated with regional brain entropy in the left dorsal anterior cingulate cortex and left dorsolateral prefrontal cortex, suggesting that spontaneous processes underpinning divergent thinking are characterized by high disordered activity in specific brain areas. All the above findings have shown that variations in brain-network connectivity provide a reliable biomarker of creative thinking ability. Overall, the neuroimaging investigation of creative cognition suggests that creativity is a complex and heterogeneous phenomenon, which encompasses more ordinary cognitive processes such as memory, attention executive function, as well as the interaction between them.

5 Creativity as a computational process

Machine learning is a subset of the more general field of AI, and it allows artificial systems to learn how to perform some tasks without being explicitly programmed.[55] Recent tremendous advancement in the field of machine learning is starting to realize systems that seem to capture the general computational description of creativity that current processors can implement very efficiently. Some of these creative architectures appear to share some similarities with the algorithmic descriptions of biological neural network models discussed in the previous section. Hence, computational models can provide an excellent mechanistic testbed for detailed cognitive and brain models of creative cognition.

The general question is: how can a computer be creative? As a first step to address this issue, cognitive endeavor is mainly concerned with central processes that can be translated in computational terms. This includes the extent to which information is structured and accessed by different types of memory systems, and the related processes or operations that are applied in such systems, such as retrieving and evaluating various sources of information. In that sense, once the memory systems and the operation applied to them are known, we may be able to circumscribe the creative process in a computational sense.[56]

5.1 Evolutionary computation

Since the 1970s, one of the main approaches in computer science to attempt to implement creative processes has been in trying to imitate the process of the evolution of biological species. The field is called evolutionary computation, and it is proving to be quite useful in addressing design and engineering problems tasks. The different algorithms include genetic algorithms, evolution strategies and programming, and finally genetic programming. In recent years, this area of research is entering a new phase, mainly due to the progress in hardware solutions, which can process massive amounts of information at an unprecedented rate. Such solutions allow the opening up of new possibilities for autonomous machines to adapt to a variety of environments. The core algorithmic description of evolutionary processing is as follows. First, there is an initialization process that starts the search for a solution within a population of randomly generated solutions. Then there is a loop that evaluates the current generation of solutions, selecting some to act as the basis for the next generation, and then creating new solutions through variation (mutation). The selection is therefore grounded on a *fitness function*, which is specific to the problem to be solved by the evolutionary algorithm, that will find solutions that optimize the fitness values, or at least approximate them. The algorithm repeatedly checks whether termination criteria specified by the programmer are met — such as reaching a desired level of fitness, or not having any improvement in fitness for several generations.

At a more general level, we can say that evolutionary computation is based on the idea of progressively iterating population improvement through the interplay between random events and a selection guided by a fitness function. Therefore, a general computational description (in Marr's terms) is that these algorithms work by cycling the interplay between generative components (the randomness and the mutations), and a selective component until a satisfactory threshold is reached. This interplay shares some similarities with a computational description of creativity as an interplay between a random (novel, chaotic, etc.) process and an evaluative (useful, ordering, etc.) process, as seen under many forms (convergent/divergent thinking or Campbell's BVSR model) in the previous descriptions of creativity in other domains. This description is the basic process of creativity that we see instantiated also in other very successful artificial creative systems that we are going to list below.

Soon it is expected that we will see many applications where human creativity is augmented by evolutionary computation in the search of complex solutions, mainly in the field of industry and technology, healthcare, agriculture, finance and commerce.[57]

5.2 Single vs. dual computational models of creativity

In previous sections, the two components of creativity (novelty and usefulness) were suggested to emerge in humans due to a loop of divergent (flexible, internally focused attention) and convergent (controlled, or externally focused attention) thinking. This view was further corroborated in recent neurocognitive studies, which delineated brain mechanisms underpinning these two modes of thinking. In light of these results, recent computational models simulating creative cognition have implemented divergent and convergent processes. In a recent review, Mekern and colleagues[58] summarized these models distinguishing between single and dual computational models of creativity, and they suggested a unitary approach that accounts for the distinction between processes underlying creative cognition. Among the single models, divergent thinking has been studied using a network science approach,[59] and modelled as spreading activity in artificial neural networks.[60] Several works provided empirical evidence that differences in the organization of the semantic memory networks influence the extent of divergent thinking, both in adults[61] and in children.[62] Particularly, the semantic networks of highly creative individuals were characterized by small-world network topography, which was interpreted by the authors as enabling more efficient retrieval strategies when connecting remote associations. The flexible properties of this semantic network structure were corroborated by a study that probed the robustness of the network with response to targeted attacks within a percolation theory framework.[63] Another recent approach is based on computational models implemented within a theoretical framework named CreaCogs,[64] which simulated performance on both the AUT and the RAT. Specifically, performance on the AUT relies on the *object replacement and object composition* (OROC) model, which is focused on the spread of search. Through the CreaCogs-OROC insight problems (well-defined problem space with stimuli that are sufficiently obvious to enable the sudden realization of the solution) might, at least theoretically, be solved. This system organized memory into three different layers (from the subsymbolic level to a problem-solution template level), each grounded in the subordinate layer, allowing to solve the creative problem by simply taking similar problems and already existing solutions, and substituting or decomposing them. In a similar vein, performance on the RAT was achieved following a more convergent search process. Indeed, the ComRAT is able to identify a word that was associated with each of the stimuli words by employing a winner-takes-all approach in the divergent spreading activity over an associative network. This was also observed in a biological feasible spiking neuron whose performance on the RAT mirrored those of humans.[65] It is worth mentioning that for a cognitive model, being able to be creative does not directly mean that it is being creative in the same way as people. Still, simulating human behavior could be of great importance in gaining insight into the creative process.

A recent proposed cognitive architecture based on the framework of predictive coding (systems motivated by a principle of efficiency in information processing) is the *Information Dynamics of Thinking* (IDyOT).[66] The IdyOT has been programmed with distinct representations of sequence in time and semantic memory in a deeply hierarchical fashion, as described by Wiggins. Implemented in a similar vein to the well-known Baars' *Global Workspace Theory*,[67] the IDyOT represents a statistical learning model to create new predictions and compete for attention in a global workspace, therefore it also accounts for cognitive processing "in terms of a pre-conscious predictive loop".[68] Bringing back the role of consciousness and attention, this cognitive architecture is structured in different parts directly inspired by Wallas' ideas, and it is also related to the notion of curiosity and compression expressed by Schmidhuber as a fundamental motivation for cognitive process.

With the above brief excursion, we have started to see how artificial neural networks, thanks to their ability to incorporate context meaning and to build associations, may model creative thinking.

5.3 Generative adversarial networks

Among the generative models, there are the so-called *Generative Adversarial Networks* (GANs), which are a class of artificial neural networks that have gained considerable popularity in the past few years[69] (for similar approaches see also).[70] *Generative deep learning* refers to a collection of network-based machine learning methods particularly successful. They can be understood as stochastic recipes that support the generation of new data maintaining a similar internal structure to training data.[71] In order to create new data, generative models need a huge number of training data (e.g., images, sounds, sentences, etc.). A key feature of these systems is that their number of parameters is significantly smaller than the amount of data in which they are trained. With such configuration, the models are therefore required to learn (detect and internalize) the essence of the data effectively in order to generate it.

GANs operate with two reciprocal and separate neural networks, namely one that acts as a generator and another that acts as a discriminator. While the generator takes as input a vector of random numbers and converts it into the form of data that is of interest to mimic (for example images of faces, or landscapes or songs), the discriminator takes as input a set of data, either real (from a repository, for example from the web) or generated by the generator, and it returns as output a probability that those data are real and not generated (real faces, true landscapes, real songs, and so on). Hence, the discriminator aims to distinguish between data generated by the generator and the real-world data. Both the generator and discriminator implement a so-called min-max game between one another (minimizing the maximum risk).[72] As a result, on the one hand, the discriminator learns to increase the likelihood of distinguishing the real data from the fake data produced by the generator; on the other hand, the generator learns to increase the likelihood that it will be able to fool the discriminator. Following this cycle, the efficiency of the discriminator increases the performance of the outputs of the generators.[73] The results are a generation of new data, which are fake, in the sense of not directly taken from real data (i.e., a repository), but on the other end they are so valuable as to be indistinguishable from a real thing. Therefore, being this data new and valuable, they are as close as you can get to a creation.

6 Consequence of creativity as an information-based process

Whether it is GANs, or some hybrid system capable of implementing a creative process with other machine learning devices, the human creativity ecosystem is most likely just at the dawn of a profound transformation. The consequences of the development of AI algorithms for creativity are beginning to be pervasive, and probably will be increasingly so. The consequences are affecting, on the one hand, the scenario of the products generated using creative artificial neural networks, and on the other hand, also the way in which human beings can be creative, with a series of influences also on arts, sciences and industry, expanding what it means to be human and the conceptual limits of our relationship with the world.

In arts, besides a few timid experiments using basic AI systems until a few years ago, very recently there has been a rapid increase of interest in algorithms to generate artistic products. In 2018 at the Chriestie's auction house, a portrait entitled *Portrait of Edmond de Belamy* was sold in the international market, but it was signed by the collective of artists Obvious who declared that they used an AI system based on GANs. The initial estimate, prior to the auction, was $7,000, but it then sold for $432,000, marking a historic transition in the attribution of value to creative products generated by automated systems.

The potentiality of adopting AI creative systems, and GANs in particular, has been embraced by other artists such as Obvious, the most famous of which is the German artist Mario Klingemann. His work has been exhibited from the Museum of Modern Art in New York, to the Centre Pompidou in Paris and the Photographers' Gallery in London. He uses the expression *neurography* to indicate the process he adopts to set up his artistic installations (e.g., one of the most famous is *Memories of Passerby*). He trains his artificial neural networks using a variety of sources, online and offline (e.g., photographs from electron-microscopes in one of his installations), and then he lets his set up to generate thousands of images per day. In his view, automated systems can be really creative, or even more creative than humans, who instead have limited access to information, and tend to behave "more automatically and habitually". He claims that machines can give humans the capacity to open up new ways of appreciating a form of creativity that is more advanced than ours. For a discussion on the aesthetics of artificial neural networks.[74]

While until now GANs have proved useful and the most convincing systems in generating images and visual art, currently there are several attempts to use them in several other domains, even though they are not as successful yet. There are several technical issues to be solved for example with generating texts, but several companies and research institutes are working to overcome them with the complementary use of other machine learning methods.[75] Several types of computational devices are progressively used for generating poetry, stories, metaphors, analogic reasoning, and even jokes.[76] Recent years have also seen rapid growth in the number of programs capable of composing music, and most of these solutions, such as Flow Machine or Aiva, are very successful with the public.[77] Given the appreciation, questions of quality do not seem to be the main problems, which are instead philosophical (are these pieces real works of art?), or commercial (who owns the copyright?).

These technological advancements are just a part of the more general societal transformations linked to the understanding of creativity as an information-based process. A recent business intelligence report released by HTF MI entitled *Global Computational Creativity Market Size, Status and Forecast 2019-2025* covered a detailed analysis of the expected adoption of automatic creative systems by manufacturers in a great variety of business segments and technology-based companies (such as IBM, Google, Microsoft, Adobe, Amazon, Autodesk, Jukedesk, etc). The survey analysis covered the expected use of computer science “to imitate, study, and stimulate human imagination”. North America held the largest market share in 2019, both in terms of services (for example, to designers) and solutions (various products), but now also Asia is expected to grow extremely fast in the years to come, with the backup of increased government spending on AI technology. The computational creativity market is expected to hit around 3 billion USD by 2028.

We are just at the beginning of a business and technology-driven societal transformation, and it is hard to predict how these new services and products will transform the general perception of creativity. On one hand, these changes can be perceived as AI giving people extremely powerful tools that can help them exhibit superhuman capacities. On the other side, they will bring human beings to the problem of dealing with AI systems that we can perceive as unbeatable. This has already happened in many other specific domains, ranging from simple arithmetic (very few individuals still do mental arithmetic, given that we can use calculators on our smartphones), to precision in design or manufacturing, to playing chess, in driving a car, in making complex choices in business, government and economy, and so ultimately also in the creative process.

In the past, what we have seen in specific fields or activities that have been superseded by AI systems, after an initial human reaction of non-acceptance or anger at this superiority in automatic performance, later on, people realize that machines are not against the human way. A progressive adaptation of this type has occurred, for example, in the limited terrain of the game of chess. At the moment, chess is not a "solved" game, that is, it is not yet mathematically proven that there is always a strategy that if executed by a perfect player leads him to certain victory, or at least to a draw if the opponent is also perfect, as it happened for example for the checkers. This is due to the still too high number of possible combinations for this game compared to the current computing potential. Nonetheless, the level of play of current AI systems has surpassed the level of play of the greatest international masters numerous times. The impact of AI on chess was first of flattening, to the detriment of the charm, mystery and dynamism linked to the difficulty of the game, but then there was an acceptance of this new tool, which was also included in the amateur level and in the experience of the player who can use these systems to improve progressively. Once assimilated, automatic systems are perceived as expanding the emotional and experiential components linked to the activities.

If we think in terms of the superiority of humans or machines, we are clearly destined to succumb. But this is a meaningless comparison, as automatic systems are not human, and they are, with all probability, not conscious, or at least not as conscious as human beings are. Similarly, none of us would compare the human body’s speed when running to that of cars, airplanes or artificial satellites in orbit. This is not a meaningful comparison to make. Observing a machine that "surpasses" us in perception, reasoning and creativity can induce a sense of inability in us, but these are functions that cannot be compared. As our human body has value because it is human, and machines are simply supporters of everyday human life and activities, in symbiosis with our body, something similar happens with our mental functions when they are surpassed by computational devices.

Emerging technologies change the way we live by opening us to new ways of acting. Creative machines are not and will not compete with our abilities, with all probability they will be perceived as a vehicle that can allow human consciousness to transport humans to places of knowledge where it would be difficult or impossible to go without their support.

7 Final considerations on the role of the first-person experience in human creativity

These societal transformations mostly driven by AI technology advancements are affecting the view of creativity. Creativity is becoming more and more perceived as an information-based process, and not, as in the past views, as some inexplicable or divine event that cannot be guided in any way, that is only possible in mad geniuses or particularly talented individuals. As everybody today can do rapid and complex calculations in a matter of seconds using digital calculators, should we expect that anyone will be able to be creative in generating works of art, or industrial innovations, or governmental policies just pressing a few buttons? With all probability, the answer is affirmative, because as we have seen, this is already happening now in a variety of creative fields, for example in the visual arts. But, in more philosophical terms, are we in the presence of creativity? Some would argue negatively.

This article has aimed to integrate some of the key steps in the evolution of the idea that creativity can be described as an information-based process. We started from the very first philosophical views attempting to describe creativity as an interaction between order and chaos, then we moved to cognitive models and the methods to measure creativity, to the most recent neuroscientific studies on the creative brain and finally to the great advancements in creative AI technologies that are so radically changing the way we understand creativity in art, industry, economy and so on. But when we talk about human functions, such as creativity, we can also consider an experiential component concerning the subjectivity of the agent of these functions.[78] This experiential aspect is clearly secondary or neglected completely in all these information-based recipes for creativity, where the subject producing the creative ideas is nowhere to be found.

In the information-theoretic approach, it is not a matter of verifying whether creativity has the property of being an experience in a conscious mind. When we view creativity in the experiential sense, then it becomes a human property, as long as we do not have scientific verifications of naturalistic and physicalist explanations of what first-person experience and subjectivity are in terms of special arrangements of information, as theorized for example in *Integrated Information Theory*.[79]

In ordinary language, we might switch from one meaning of creativity (as an information-based process) to the other meaning (as a subjective experience), thus mostly confusing the views. For example, when we say that nature is creative in showing all the beautiful and different colors of the flowers, we might mean it as an information-based process if we think in evolutionary terms, or as the creation of a conscious god if we are creationists. Otherwise, in less religious terms, when we say that to understand a work of art we need to be creative, as in Tröndle and Tschacher,[80] we are using the term mostly in the experiential sense, where the phenomenological first-person perspective is required.

The evolution of the idea of creativity as an information-based process is fundamentally neutral to the theme of subjectivity, in the sense that it is not considered a necessary condition. But what if actually what all these AI systems are doing is not really implementing a creative process, but just a simulation of it, as when a digital vocal assistant synthesized voice simulates a tone, and we do not really think that it is feeling those emotions. And simulating creativity is a very different simulation from that of performing a mathematical calculation, where no particular emotion is involved and the first person experience of calculating is irrelevant. Thus, what is the role of the experiential component in being creative? What is the role of wonder in becoming creative,[81] or the role of feeling bored,[82] just to name some of the human experiences that are linked to *being* creative, against a more functional and utilitaristic view of creativity as a process? What is the role of being curious or motivated to be creative?

The philosopher Bence Nanay, for example, claims that an idea is felt as creative only if a person that produces it also experiences it as something that appeared impossible to her before.[83] He claims that the right analysis for the concept of creativity cannot be of the functional or computational aspects, but it should be about the experiences. Also other authors claim that creativity should not be defined as a disposition to produce valuable ideas, and instead, they underline a more phenomenological approach in terms of the imagination.[84]

Are we in the presence of two, perhaps incompatible, descriptions of the same process, one that is information-based and the other that is experience-based? After all, even the process of walking can be described in two apparently separate terms, namely as an information-based algorithm (e.g., a humanoid robot walking in a forest), or as a first-person experience (e.g., being a person who walks in a forest). Afterall, Marr's levels of description illustrated earlier in the paper (computational, algorithmic, and implementational), which he formulated relative to the process of vision, do not leave any space for a subjective and qualitative description of vision. He did not include a level 4 consisting in the description of the *experience* of seeing (colors, or shapes, or faces, etc), and thus like this:

4. An experiential level (also called subjective): at this level, we ask how is *to be* the information system which, referred to creativity, could be formulated as:

D. The experiential level of creativity: how is it *to be* the creative information processing system?

We are not going to directly address these ancient, deep, and controversial philosophical questions in this article,[85] but we want to end by proposing a novel thought experiment that could help to at least frame the problem. This thought experiment is a variation of what was proposed by the philosopher Frank Jackson in his so-called *Mary the super-scientist* experiment, where in his case it concerned physicalism in conscious vision.[86]

Let us imagine that in a not so distant future there is a person named *Mario the super-artist*, whose brain is structured in a way that makes it impossible for him to be really creative (for example, the connections between his DMN and his ECN have been cut since birth, assuming that this biological connection turns out to be necessary and sufficient for being creative). Additionally, he is a great expert on the information-based process of creativity, because he spent many years studying it, up to the point of knowing perfectly well the most updated algorithm for implementing creativity (as, for example, in a very advanced evolution of a GAN). Mario is recognized worldwide as a great artist, but in reality, his work consists in collecting digital images of his life with a webcam mounted on his head, and then performing several calculations on them by hand, working pixel by pixel while following the creative procedure. Several art critics, as well as the general public, unbeknownst of his methodology, are very appreciative of his work, and thus his images are sold at very high prices and exhibited in top museums around the world. With time he has become very fast and efficient in implementing the creative procedure, and he is satisfied with the money that he earns. Is Mario creative or not?

Let us remember that the images are entirely worked by him, and they are the product of his knowledge of the recipe for creativity, and so he is not even using other electronic devices. Clearly, his work is not the product of his creativity or insight, because he is not capable of performing it, but nonetheless, his knowledge of the creative process allows him to produce images that are judged new, beautiful, and of great value.

One day, Mario undergoes a brain surgery that restores the malfunctioning connections in his brain, and he becomes fully capable of being creative and of having direct experience of it. Mario continues to work on his digital images, but now that his brain is capable of being creative of its own, he decides to not follow the creative procedure anymore and to just work on the digital images of his life as it pleases him and with his enjoyment. He actually enters in a mental state of great immersion when he works on his images, an ecstatic state of flow that he had never experienced before.[87] But, unexpectedly, the quality of his images decreases considerably compared to when he used the algorithms, and both the art critics and the general public stop appreciating his works and performances. Has Mario lost or gained creativity after the brain surgery?

Notes

[1] Cf. M.I. Stein, *Creativity and culture*; M.A. Runco, G.J. Jaeger, *The standard definition of creativity*.
[2] Cf. G. Wallas, *The art of thought*.
[3] Cfr. L. Donovan, T.D. Green, C. Mason, *Examining the 21st century classroom*; S.M. Ritter, N. Mostert, *Enhancement of creative thinking skills using a cognitive-based creativity training*.
[4] Cfr. R.A. Finke, *Imagery, creativity, and emergent structure*; M. Tegmark, *Consciousness as a state of matter*.
[5] Cfr. F. Nietzsche, *Nietzsche: The birth of tragedy and other writings*.
[6] Cfr. G.A. Miller, *The cognitive revolution: A historical perspective*.
[7] Cfr. A.M. Noll, *The digital computer as a creative medium*.
[8] Cf. S. Colton, G.A. Wiggins, *Computational creativity: The final frontier?*.
[9] Cf. D. Marr, T. Poggio, *A computational theory of human stereo vision*.
[10] I.M. Stein, *Creativity and culture*; M.A. Runco, G. Jaeger, *The standard definition of creativity*.
[11] Cf. P. Langley, H.A. Simon, G.L. Bradshaw, J.M. Zytkow, *Scientific discovery: Computational explorations of the creative processes*.
[12] Cf. G. Wallas, *The art of thought*.
[13] Cf. J.P. Guilford, *The structure of intellect*.
[14] Cf. P.T. Sowden, A. Pringle, L. Gabora, *The shifting sands of creative thinking*; D.K. Simonton, *On praising convergent thinking*; N. Barr, *Intuition, reason, and creativity: An integrative dual-process perspective*; J.S.B. Evans, *Dual-processing accounts of reasoning, judgment, and social cognition*; A.P. Allen, K.E. Thomas, *A dual process account of creative thinking*.
[15] Cf. E.P. Torrance, *Scientific views of creativity and factors affecting its growth*.
[16] Cf. E.P. Torrance, *Norms-technical manual: Torrance tests of creative thinking*.
[17] Cf. D.T. Campbell, *Blind variation and selective retentions in creative thought as in other knowledge processes*.
[18] Cf. D.K. Simonton, *On praising convergent thinking*.
[19] Cf., e.g., D.K. Simonton, *Creativity as blind variation and selective retention*; O. Vartanian, *Decision junctures in the creative process*.
[20] Cf. D.K. Simonton, *Creativity, automaticity, irrationality, fortuity, fantasy, and other contingencies*.
[21] Cf. A. Dietrich, *Where in the brain is creativity: A brief account of a wild-goose chase*; M.E. Kronfeldner, *Darwinian "blind" hypothesis formation revisited*.
[22] Cf. D.T. Campbell, *Blind variation and selective retentions in creative thought as in other knowledge processes*.
[23] Cf. S. Mednick, *The associative basis of the creative process*.
[24] Cf. D. Kahneman, *Thinking, fast and slow*.
[25] Cf. M.A. Boden, *The creative mind: Myths and mechanisms*.
[26] Cf. G.A. Wiggins, *Searching for computational creativity*.
[27] Cf. Y.N. Kenett, M. Faust, *A semantic network cartography of the creative mind*.
[28] Cf. L. Gabora, *Honing theory: A complex systems framework for creativity*.
[29] Cf. J.B. Hirsh, R.A. Mar, J.B. Peterson, *Psychological entropy*.
[30] Cf. L. Gabora, *A possible role for entropy in creative cognition*.
[31] Cf. L. Gabora, *Honing theory*.
[32] Cf. J. Schmidhuber, *Formal theory of creativity, fun, and intrinsic motivation (1990-2010)*.
[33] Cf. R.M. Ryan, E.L. Deci, *Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being*.

[34] Cf. J. SCHMIDHUBER, *Philosophers & futurists, catch up! Response to The Singularity*.
[35] Cf. J.P. GUILFORD, *Creativity: Yesterday, today and tomorrow*.
[36] Cf. D.T. CAMPBELL, *Blind variation and selective retentions in creative thought*; L. GABORA, *Honing theory*; J. SCHMIDHUBER, *Formal theory of creativity, fun, and intrinsic motivation*.
[37] Cf. J.A. PLUCKER, M.A. RUNCO, *The death of creativity measurement has been greatly exaggerated*.
[38] Cf. S.A. MEDNICK, M. MEDNICK, *Remote associates test*.
[39] Cf. M.A. RUNCO, S.R. PRITZKER, *Encyclopedia of creativity*.
[40] Cf. D.K. SIMONTON, *On praising convergent thinking*.
[41] Cf. J.P. GUILFORD, *The nature of human intelligence*.
[42] Cf. B. FORTHMANN, C. SZARDENINGS, H. HOLLING, *Understanding the confounding effect of fluency in divergent thinking scores*; P.J. SILVIA, B.P. WINTERSTEIN, J.T. WILLSE, C.M. BARONA, J.T. CRAM, K.I. HESS, J.L. MARTINEZ, C.A. RICHARD, *Assessing creativity with divergent thinking tasks*.
[43] Cf. J.A. PLUCKER, M.C. MAKEL, *Assessment of creativity*. In: J.C. KAUFMAN, R.J. STERNBERG (eds.), *The Cambridge handbook of creativity*.
[44] S.H. CARSON, J.B. PETERSON, D.M. HIGGINS, *Reliability, validity, and factor structure of the creative achievement questionnaire*; M. BENEDEK, E. JAUK, M. SOMMER, M. ARENDASY, A.C. NEUBAUER, *Intelligence, creativity, and cognitive control*; J.A. PLUCKER, J.S. RENZULLI, *Psychometric approaches to the study of human creativity*.
[45] For an extensive discussion, cf. A. DIETRICH, *Where in the brain is creativity*; L. GABORA, *Reframing convergent and divergent thought for the 21st century*.
[46] Cf. S. SAID-METWALY, W. VAN DEN NOORTGATE, E. KYNDT, *Methodological issues in measuring creativity*.
[47] Cf. L. ZENG, R.W. PROCTOR, G. SALVENDY, *Can traditional divergent thinking tests be trusted in measuring and predicting real-world creativity?*.
[48] M. BOCCIA, L. PICCARDI, L. PALERMO, R. NORI, M. PALMIERO, *Where do bright ideas occur in our brain?*.
[49] Cf. S. ACAR, M.A. RUNCO, *Assessing associative distance among ideas elicited by tests of divergent thinking*; C.M. ZEDELIUS, C. MILLS, J.M. SCHOOLER, *Beyond subjective judgments*; R.E. BEATY, D.R. JOHNSON, *Automating creativity assessment with SemDis*; J.A. OLSON, J. NAHAS, D. CHMOULEVITCH, S.J. CROPPER, M.E. WEBB, *Naming unrelated words predicts creativity*.
[50] Cf. M.A. WALLACH, N. KOGAN, *Modes of thinking in young children*.
[51] Cf. R.E. BEATY, D.R. JOHNSON, *Automating creativity assessment with SemDis*; Y.N. KENETT, *What can quantitative measures of semantic distance tell us about creativity?*; D.J.P. HEINEN, D.R. JOHNSON, *Semantic distance*.
[52] Cf. R.E. BEATY, D.R. JOHNSON, *Automating creativity assessment with SemDis*; J.A. OLSON, J. NAHAS, D. CHMOULEVITCH, S.J. CROPPER, M.E. WEBB, *Naming unrelated words predicts creativity*.
[53] Cf. A. DIETRICH, *Where in the brain is creativity*; A. ABRAHAM, *The promises and perils of the neuroscience of creativity*; K. SAWYER, *The cognitive neuroscience of creativity*.
[54] Cf. W.J. O'HEARN, A.B. KAUFMAN, J.C. KAUFMAN, *Animal creativity and innovation: An integrated look at the field*.
[55] Cf. E. ALPAYDIN, *Machine learning: The new AI*.
[56] Cf. V. MEKERN, B. HOMMEL, Z. SJOERDS, *Computational models of creativity*.
[57] Cf. A.E. EIBEN, J. SMITH, *From evolutionary computation to the evolution of things*.
[58] Cf. V. MEKERN, B. HOMMEL, Z. SJOERDS, *Computational models of creativity*.
[59] Cf. Y.N. KENETT, M. FAUST, *A semantic network cartography of the creative mind*.
[60] Cf. P.T. SOWDEN, A. PRINGLE, L. GABORA, *The shifting sands of creative thinking*.
[61] Cf. N.Y. KENETT, D. ANAKI, M. FAUST, *Investigating the structure of semantic networks in low and high creative persons*.
[62] Cf. C. RASTELLI, A. GRECO, C. FINOCCHIARO, *Revealing the role of divergent thinking and fluid intelligence in children's semantic memory organization*.
[63] Cf. Y.N. KENETT, O. LEVY, D.Y. KENETT, H.E. STANLEY, M. FAUST, S. HAVLIN, *Flexibility of thought in high creative individuals represented by percolation analysis*.
[64] Cf. A.-M. OLTETEANU, Z. FALOMIR, C. FREKSA, *Artificial cognitive systems that can answer human creativity tests*.
[65] Cf. I. KAJIĆ, J. GOSMANN, T.C. STEWART, T. WENNEKERS, C. ELIASMITH, A SPIKING, *Neuron model of word associations for the remote associates test*.
[66] Cf. G.A. WIGGINS, *Searching for computational creativity*; G.A. WIGGINS, *Creativity, information, and consciousness: The information dynamics of thinking*.
[67] Cf. B.J. BAARS, *A cognitive theory of consciousness*.
[68] Cf. G.A. WIGGINS, *Creativity, information, and consciousness*.
[69] Cf. I.J. GOODFELLOW, J. POUGET-ABADIE, M. MIRZA, B. XU, D. WARDE-FARLEY, S. OZAIR, A. COURVILLE, Y. BENGIO, *Generative adversarial networks*; J. SCHMIDHUBER, *Generative adversarial networks are special cases of artificial curiosity (1990) and also closely related to predictability minimization (1991)*.
[70] Cf. D.P. KINGMA, M. WELLING, *Auto-encoding variational Bayes*.
[71] Cf. S.J. GERSHMAN, *The generative adversarial brain*.
[72] Cf. V. DUMOULIN, I. BELGHAZI, B. POOLE, O. MASTROPIETRO, A. LAMB, M. ARJOVSKY, A. COURVILLE, *Adversarially learned inference*.
[73] Cf. I.J. GOODFELLOW, J. POUGET-ABADIE, M. MIRZA, B. XU, D. WARDE-FARLEY, S. OZAIR, A. COURVILLE, Y. BENGIO, *Generative adversarial networks*.
[74] Cf., for example, A. BARALE, *Arte e intelligenza artificiale: Be My GAN*; A. HERTZMANN, *Aesthetics of Neural Network Art*.
[75] Cf. S. RAJESWAR, S. SUBRAMANIAN, F. DUTIL, C. PAL, A. COURVILLE, *Adversarial generation of natural language*.
[76] Cf. R. CARTER, *Language and creativity: The art of common talk*; L.-C. YANG, S.Y. CHOU, Y.-H. YANG, *MidiNet: A convolutional generative adversarial network for symbolic-domain music generation*.
[77] Cf. D. HERREMANS, C.-H. CHUAN, E. CHEW, *A functional taxonomy of music generation systems*.
[78] Cf. T. NAGEL, *What is it like to be a bat?*.
[79] Cf. M. TEGMARK, *Consciousness as a state of matter*; G. TONONI, M. BOLY, M. MASSIMINI, C. KOCH, *Integrated information theory*.
[80] Cf. B.J. BAARS, *A cognitive theory of consciousness*.
[81] Cf. V.P. GLĂVEANU, *Creativity and wonder*.
[82] Cf. A. ELPIDOROU, *The good of boredom*.
[83] Cf. B. NANAY, *An experiential account of creativity*.
[84] Cf. A. HILLS, A. BIRD, *Against creativity*.
[85] Cf. W.R. UTTAL, *Dualism: The original sin of cognitivism*.

[86] Cf. F. JACKSON, *What Mary didn't know*.
[87] Cf. A. HERTZMANN, *Aesthetics of neural network art*.

Literature

ABRAHAM, A. (2013). *The promises and perils of the neuroscience of creativity*. In: «Frontiers in Human Neuroscience», vol. VII, Art.Nr. 246 – doi: 10.3389/fnhum.2013.00246.

ABRAHAM, A. (2016). *The imaginative mind*. In: «Human Brain Mapping», vol. XXXVII, n. 11, pp. 4197-4211.

ABRAHAM, A. (2018). *The neuroscience of creativity*, Cambridge University Press, Cam-bridge.

ABRAHAM, A., BEUDT, S., OTT, D.V.M., YVES VON CRAMON, D. (2012). *Creative cognition and the brain: Dissociations between frontal, parietal-temporal and basal ganglia groups*. In: «Brain Research», n. 1482, pp. 55-70.

ACAR, S., RUNCO, M.A. (2014). *Assessing associative distance among ideas elicited by tests of divergent thinking*. In: «Creative Research Journal», vol. XXVI, n. 2, pp. 229-238.

ALLEN, A.P., THOMAS, K.E. (2011). *A dual process account of creative thinking*. In: «Journal of Creative Research», vol. XXIII, n. 2, pp. 109-118.

ALPAYDIN, E. (2016). *Machine learning: The new AI*, MIT Press, Cambridge (MA).

BAARS, B.J. (1995). *A cognitive theory of consciousness*, Cambridge University Press, Cambridge.

BARALE, A. (2020). *Arte e intelligenza artificiale: Be My GAN*, Jaca Book, Milan.

BARR, N. (2018). *Intuition, reason, and creativity: An integrative dual-process perspective*. In: G. PENNYCOOK (ed.), *The new reflectionism in cognitive psychology. Why reason matters*, Routledge, London/New York, pp. 99-124.

BEATY, R.E., BENEDEK, M., BARRY KAUFMAN, S., SILVIA, P.J. (2015). *Default and executive network coupling supports creative idea production*. In: «Scientific Reports», vol. V, n. 1, Art.Nr. 10964 – doi: 10.1038/srep10964.

BEATY, R.E., CHRISTENSEN, A.P., BENEDEK, M., SILVIA, P.J., SCHACTER, D.L. (2017). *Creative constraints: Brain activity and network dynamics underlying semantic interference during idea production*. In: «Neuroimage», vol. CXLVIII, pp. 189-196.

BEATY, R.E., JOHNSON, D.R. (2021). *Automating creativity assessment with SemDis: An open platform for computing semantic distance*. In: «Behavior Research Methods», vol. LIII, n. 2, pp. 1-24.

BEATY, R.E., SELI, P., SCHACTER, D.L. (2019). *Network neuroscience of creative cognition: Mapping cognitive mechanisms and individual differences in the creative brain*. In: «Current Opinions in Behavioral Sciences», vol. XXVII, pp. 22-30.

BENEDEK, M. (2018). *The neuroscience of creative idea generation*. In: Z. KAPOULA, E. VOLLE, J. RENOULT, M. ANDREATTA (eds.), *Exploring transdisciplinarity in art and sciences*, Springer, Cham, pp. 31-48.

BENEDEK, M., CHRISTENSEN, A.P., FINK, A., BEATY, R.E. (2019). *Creativity assessment in neuroscience research*. In: «Psychology of Aesthetics, Creativity, and Arts», vol. XIII, n. 2, pp. 218-226.

BENEDEK, M., FINK, A. (2019). *Toward a neurocognitive framework of creative cognition: The role of memory, attention, and cognitive control*. In: «Current Opinions in Behavioral Sciences», vol. XXVII, pp. 116-122.

BENEDEK, M., JAUK, E., SOMMER, M., ARENDASY, M., NEUBAUER, A.C. (2014). *Intelligence, creativity, and cognitive control: The common and differential involvement of executive functions in intelligence and creativity*. In: «Intelligence», vol. XLVI, pp. 73-83.

BOCCIA, M., PICCARDI, L., PALERMO, L., NORI, R., PALMIERO, M. (2015). *Where do bright ideas occur in our brain? Meta-analytic evidence from neuroimaging studies of domain-specific creativity*. In: «Frontiers in Psychology», vol. VI, Art.Nr. 1195 – doi: 10.3389/fpsyg.2015.01195.

BODEN, M.A. (2004). *The creative mind: Myths and mechanisms*, Routledge, London/ New York, 2nd edition.

CAMPBELL, D.T. (1960). *Blind variation and selective retentions in creative thought as in other knowledge processes*. In: «Psychological Review», vol. LXVII, n. 6, pp. 380-400.

CARSON, S.H., PETERSON, J.B., HIGGINS, D.M. (2005). *Reliability, validity, and factor structure of the creative achievement questionnaire*. In: «Creativity Research Journal», vol. XVII, n. 1, pp. 37-50.

CARTER, R. (2016). *Language and creativity: The art of common talk*, Routledge, London/New York, 2nd edition.

CHRYSIKOU, E.G. (2019). *Creativity in and out of (cognitive) control*. In: «Current Opinion in Behavioral Sciences», vol. XXVII, pp. 94-99.

COLTON, S., WIGGINS, G.A. (2012). *Computational creativity: The final frontier?*. In: «Frontiers in Artificial Intelligence and Applications», n. 242, 2012, pp 21-26.

DE PISAPIA, N., BACCI, F., PARROTT, D., MELCHER, D. (2016). *Brain networks for visual creativity: A functional connectivity study of planning a visual artwork*. In: «Scientific Reports», vol. VI, n. 1, Art.Nr. 39185 – doi: 10.1038/srep39185.

DIETRICH, A. (2019). *Where in the brain is creativity: A brief account of a wild-goose chase*. In: «Current Opinions in Behavioral Sciences», vol. XXVII, pp. 36-39.

DIETRICH, A., KANSO, R. (2010). *A review of EEG, ERP, and neuroimaging studies of creativity and insight*. In: «Psychological Bulletin», vol. CXXXVI, n. 5, pp. 822-848.

DONOVAN, L., GREEN, T.D., MASON, C. (2014). *Examining the 21st century classroom: Developing an innovation configuration map*. In: «Journal of education and Computational Research», vol. L, n. 2, pp. 161-178.

DUMOULIN, V., BELGHAZI, I., POOLE, B., MASTROPIETRO, O., LAMB, A., ARJOVSKY, M., COURVILLE, A. (2017). *Adversarially learned inference*, ArXiv160600704.

EIBEN, A.E., SMITH, J. (2015). *From evolutionary computation to the evolution of things*. In: «Nature», vol. DXXI, n. 7553, pp. 476-482.

ELPIDOROU, A. (2018). *The good of boredom*. In: «Philosophical Psychology», vol. XXXI, n. 3, pp. 323-351.

ERHARD, K., KESSLER, F., NEUMANN, N., ORTHEIL, H.-J., LOTZE, M. (2014). *Professional training in creative writing is associated with enhanced fronto-striatal activity in a literary text continuation task*. In: «NeuroImage», vol. C, pp. 15-23.

EVANS, J.S.B. (2008). *Dual-processing accounts of reasoning, judgment, and social cognition*. In: «Annual Review of Psychology», vol. LIX, pp. 255-278.

FINK, A., BENEDEK, M. (2014). *EEG alpha power and creative ideation*. In: «Neuroscience and Biobehavioral

Review», vol. XLIV, n. 100, pp. 111-123.

FINK, A., BENEDEK, M., GRABNER, R., STAUDT, B., NEUBAUER, A. (2007). *Creativity meets neuroscience: Experimental tasks for the neuroscientific study of creative thinking*. In: «Methods», vol. XLII, n. 1, pp. 68-76.

FINK, A., ROMINGER, C., BENEDEK, M., PERCHTOLD, C.M., PAPOUSEK, I., WEISS, E.M., SEIDEL, A., MEMMERT, D. (2018). *EEG alpha activity during imagining creative moves in soccer decision-making situations*. In: «Neuropsychologia», vol. CXIV, pp. 118-124.

FINKE, R.A. (1996). *Imagery, creativity, and emergent structure*. In: «Consciousness and Cognition», vol. V, n. 3, pp. 381-393.

FORTHMANN, B., SZARDENINGS, C., HOLLING, H. (2020). *Understanding the confounding effect of fluency in divergent thinking scores: Revisiting average scores to quantify artifactual correlation*. In: «Psychology of Aesthetics, Creativity, and Arts», vol. XIV, n. 1, pp. 94-112.

GABORA, L. (2016). *A possible role for entropy in creative cognition*. In: *Proceedings of the 3rd International. Electronic Conference on Entropy and its Applications* – doi: 10.3390/ecea-3-E001.

GABORA, L. (2017). *Honing theory: A complex systems framework for creativity*. In: «Nonlinear Dynamics, Psychology, and Life Sciences», vol. XXI, n. 1, pp. 35-88.

GABORA, L. (2019). *Reframing convergent and divergent thought for the 21st century*. In: A. GOEL, C. SEIFERT, C. FRESKA (eds.), *Proceedings of 41st Annual Meeting of the Cognitive Science Society*, The Cognitive Science Society Press, Austin (TX), pp. 1794-1800.

GERSHMAN, S.J. (2019). *The generative adversarial brain*. In: «Frontiers in Artificial Intelligence», vol. II, Art.Nr. 18 – doi: 10.3389/frai.2019.00018

GLĂVEANU, V.P. (2019). *Creativity and wonder*. In: «Journal of Creative Behavior», vol. LIII, n. 2, pp. 171-177.

GOLLAND, Y., BENTIN, S., GELBARD, H., BENJAMINI, Y., HELLER, R. NIR, Y., HASSON, U., MALACH, R. (2007). *Extrinsic and intrinsic systems in the posterior cortex of the human brain revealed during natural sensory stimulation*. In: «Cerebral Cortex», vol. XVII, n. 4, pp. 766-777.

GONEN-YAACOVI, G., DE SOUZA, L.C., LEVY, R., URBANSKI, M., JOSSE, G., VOLLE, E. (2013). *Rostral and caudal prefrontal contribution to creativity: A meta-analysis of functional imaging data*. In: «Frontiers in Human Neuroscience», vol. VII, Art.Nr. 465 - 10.3389/fnhum.2013.00465.

GOODFELLOW, I.J., POUGET-ABADIE, J., MIRZA, M., XU, B., WARDE-FARLEY, D., OZAIR, S., COURVILLE, A., BENGIO, Y. (2014). *Generative adversarial networks*, ArXiv14062661.

GUILFORD, J.P. (1956). *The structure of intellect*. In: «Psychological Bulletin», vol. LIII, n. 4, pp. 267-293.

GUILFORD, J.P. (1967). *Creativity: Yesterday, today and tomorrow*. In: «Journal of Creative Behavior», vol. I, n. 1 pp. 3-14.

GUILFORD, J.P. (1967). *The nature of human intelligence*, McGraw-Hill, New York.

HAO, N., KU, Y., LIU, M., HU, Y., BODNER, M., GRABNER, R.H., FINK, A. (2016). *Reflection enhances creativity: Beneficial effects of idea evaluation on idea generation*. In: «Brain and Cognition», vol. CIII, n. 1, pp. 30-37.

HEINEN, D.J.P., JOHNSON, D.R. (2018). *Semantic distance: An automated measure of creativity that is novel and appropriate*. In: «Psychology of Aesthetics, Creativity, and Arts», vol. XII, n. 2, pp. 144-156.

HERREMANS, D., CHUAN, C.-H., CHEW, E. (2017). *A functional taxonomy of music generation systems*. In: «ACM Computing Survey», vol. L, n. 5, pp. 1-30.

HERTZMANN, A. (2019). *Aesthetics of neural network art, ArXiv Prepr. ArXiv190305696.*

HILLS, A., BIRD, A. (2019). *Against creativity*. In: «Philosophy and Phenomenological Research», vol. XCIX, n. 3, pp. 694-713.

HIRSH, J.B., MAR, R.A., PETERSON, J.B. (2012). *Psychological entropy: A framework for understanding uncertainty-related anxiety*. In: «Psychological Review», vol. CXIX, n. 2, p. 304-320.

HOWARD-JONES, P.A., BLAKEMORE, S.-J., SAMUEL, E.A., SUMMERS, I.R., CLAXTON, G. (2005). *Semantic divergence and creative story generation: An FMRI investigation*. In: «Cognitive Brain Research», vol. XXV, n. 1, pp. 240-250.

JACKSON, F. (1986). *What Mary didn't know*. In: «The Journal of Philosophy», vol. LXXXIII, n. 5, pp. 291-295.

JUNG, R.E. (2013). *The structure of creative cognition in the human brain*. In: «Frontiers in Human Neuroscience», vol. VII, Art.Nr. 330 – doi: 10.3389/fnhum.2013.00330.

KAHNEMAN, D. (2011). *Thinking, fast and slow*, Ferrar, Straus and Giroux, New York.

KAJIĆ, I., GOSMANN, J., STEWART, T.C., WENNEKERS, T., ELIASMITH, C., SPIKING, A. (2017). *Neuron model of word associations for the remote associates test*. In: «Frontiers in Psychology», vol. VIII, Art.Nr. 99 – doi: 10.3389/fpsyg.2017.00099.

KENETT, N.Y., ANAKI, D., FAUST, M. (2014). *Investigating the structure of semantic networks in low and high creative persons*. In: «Frontiers in Human Neuroscience», vol. VIII, Art.Nr.407 – doi 10.3389/fnhum.2014.00407.

KENETT, Y.N. (2019). *What can quantitative measures of semantic distance tell us about creativity?*. In: «Current Opinions in Behavioral Sciences», vol. XXVII, pp. 11-16.

KENETT, Y.N., FAUST, M. (2019). *A semantic network cartography of the creative mind*. In: «Trends in Cognitive Sciences», vol. XXIII, n. 4, pp. 271-274.

KENETT, Y.N., LEVY, O., KENETT, D.Y., STANLEY, H.E., FAUST, M., HAVLIN, S. (2018). *Flexibility of thought in high creative individuals represented by percolation analysis*. In: «Proceedings of the National Academy of Sciences», vol. CXV, n. 5, pp. 867-872.

KINGMA, D.P., WELLING, M. (2014). *Auto-encoding variational Bayes*, ArXiv13126114.

KOESTLER, A. (1964). *The act of creation*, Arkana, New York.

KRONFELDNER, M.E. (2010). *Darwinian "blind" hypothesis formation revisited*. In: «Synthese», vol. CLXXV, n. 2, pp. 193-218.

LANGLEY, P., SIMON, H.A., BRADSHAW, G.L., ZYTKOW, J.M. (1987). *Scientific discovery: Computational explorations of the creative processes*, MIT Press, Cambridge (MA).

LI, J., ZHANG, D., LIANG, A., LIANG, B., WANG, Z., CAI, Y., GAO, M., GAO, Z., CHANG, S., JIAO, B., HUANG, R., LIU, M. (2017). *High transition frequencies of dynamic functional connectivity states in the creative* *brain*. In: «Scientific Reports», vol. VII, n. 1, Art. Nr. 46072.

MARR, D., POGGIO, T. (1979). *A computational theory of human stereo vision*. In: «Proceedings of the Royal Society of London – Biological Sciences B», vol. CCIV, n. 1156, pp. 301-328.

MEDNICK, S. (1962). *The associative basis of the creative process*. In: «Psychological Review», vol. LXIX, n. 3, pp. 220-232.

MEDNICK, S.A., MEDNICK, M. (1971). *Remote associates test: Examiner's manual*, Mifflin, Houghton.

MEKERN, V., HOMMEL, B., SJOERDS, Z. (2019). *Computational models of creativity: A review of single-process and multi-process recent approaches to demystify creative cognition*. In: «Current Opinions in Behavioral Sciences», vol. XXVII, pp. 47-54.

MILLER, G.A. (2003). *The cognitive revolution: A historical perspective*. In: «Trends in Cognitive Sciences», vol. VII, n. 3, pp. 141-144.

NAGEL, T. (1974). *What is it like to be a bat?*. In: «The Philosophical Review», vol. LXXXIII, n. 4, pp. 435-450.

NANAY, B. (2014). *An experiential account of creativity*. In: E. PAUL, S.B. KAUFMAN (eds.), *The philosophy of creativity*, pp. 17-35.

NIETZSCHE, F. (1999). *Nietzsche: The birth of tragedy and other writings*, edited by R. GEUSS, R. SPEIRS, Cambridge University Press, Cambridge (ed. or. *Die Geburt der Tragödie oder Griechentum und Pessimismus*, E.W. Fritzsch, Leipzig 1886).

NOLL, A.M. (1967). *The digital computer as a creative medium*. In: «IEEE Spectrum», vol. IV, n. 10, pp. 89-95.

O'HEARN, W.J., KAUFMAN, A.B., KAUFMAN, J.C. (2015). *Animal creativity and innovation: An integrated look at the field*. In: A.B. KAUFMAN, J.C. KAUFMAN (eds.), *Animal creativity and innovation*, Elsevier, Amsterdam/New York, pp. 501-505.

OLSON, J.A., NAHAS, J., CHMOULEVITCH, D., CROPPER, S.J., WEBB, M.E. (2021). *Naming unrelated words predicts creativity*. In: «Proceedings of the National Academy of Sciences», vol. CXVIII, n. 25, Art. Nr. 2022340118 – doi: 10.1073/pnas.2022340118.

OLTETEANU, A.M., FALOMIR, Z., FREKSA, C. (2018). *Artificial cognitive systems that can answer human creativity tests: An approach and two case studies*. In: «IEEE Transactions on Cognitive and Developmental Systems», vol. X, n. 2, pp. 469-475.

PINHO, A.L., DE MANZANO, O., FRANSSON, P., ERIKSSON, H., ULLEN, F. (2014). *Connecting to create: Expertise in musical improvisation is associated with increased functional connectivity between premotor and prefrontal areas*. In: «Journal of Neuroscience», vol. XXXIV, n. 18, pp. 6156-6163.

PLUCKER, J.A., MAKEL, M.C. (2010). *Assessment of creativity*. In: J.C. KAUFMAN, R.J. STERNBERG (eds.), *The Cambridge handbook of creativity*, Cambridge University Press, Cambridge, pp. 48-73.

PLUCKER, J.A., RENZULLI, J.S. (1999). *Psychometric approaches to the study of human creativity*. In: R.J. STERNBERG (ed.), *Handbook of creativity*, Cambridge University Press, Cambridge, pp. 35-61.

PLUCKER, J.A., RUNCO, M.A. (1998). *The death of creativity measurement has been greatly exaggerated: Current issues, recent advances, and future directions in creativity assessment*. In: «Roeper Review», vol. XXI, n. 1, pp. 36-39.

RAJESWAR, S., SUBRAMANIAN, S., DUTIL, F., PAL, C., COURVILLE, A. (2017). *Adversarial generation of natural language*, ArXiv170510929.

RASTELLI, C., GRECO, A., FINOCCHIARO, C. (2020). *Revealing the role of divergent thinking and fluid intelligence in children's semantic memory organization*. In: «Journal of Intelligence», vol. VIII, n. 4, Art.Nr.443 – doi: 10.3390/jintelligence8040043.

RITTER, S.M., MOSTERT, N. (2017). *Enhancement of creative thinking skills using a cognitive-based creativity training*. In: «Journal of Cognitive Enhancement», vol. I, n. 3, pp. 243-253.

RUNCO, M.A., JAEGER, G.J. (2012). *The standard definition of creativity*. In: «Creativity research Journal», vol. XXIV, 1, pp. 92-96.

RUNCO, M.A., PRITZKER, S.R. (2020). *Encyclopedia of creativity,* Academic Press, New York.

RYAN, R.M., DECI, E.L. (2000). *Self-determi-nation theory and the facilitation of intrinsic motivation, social development, and well-being*. In: «American Psychologist», vol. LV, n. 1, pp. 68-78.

SAID-METWALY, S., VAN DEN NOORTGATE, W., KYNDT, E. (2017). *Methodological issues in measuring creativity: A systematic literature review*. In: «Creativity Theories – Research - Applications», vol. IV, n. 2, pp. 276-301.

SAWYER, K. (2011). *The cognitive neuroscience of creativity: A critical Review*. In: «Creativity Research Journal», vol. XXIII, n. 2, pp. 137-154.

SCHMIDHUBER, J. (2010). *Formal theory of creativity, fun, and intrinsic motivation (1990-2010)*. In: «IEEE Transactions on Autonomous Mental Development», vol. II, n. 3, pp. 230-247.

SCHMIDHUBER, J. (2012). *Philosophers & futurists, catch up! Response to The Singularity*. In: «Journal of Consciousness Studies», vol. XIX, n. 1-2, pp. 173-182.

SCHMIDHUBER, J. (2020). *Generative adversarial networks are special cases of artificial curiosity (1990) and also closely related to predictability minimization (1991)*. In: «Neural Network», vol. CXXVII, 2020, pp. 58-66.

SCHWAB, D., BENEDEK, M., PAPOUSEK, I., WEISS, E.M., FINK, A. (2014). *The time-course of EEG alpha power changes in creative ideation*. In: «Frontiers in Human Neuroscience», vol. VIII, Art.Nr 310 – doi: 10.3389/fnhum.2014.00310.

SHI, L., BEATY, R.E., CHEN, Q., SUN, J., WEI, D., YANG, W., QIU, J. (2020). *Brain entropy is associated with divergent thinking*. In: «Cerebral Cortex», vol. XXX, n. 2, pp. 708-717.

SILVIA, P.J., WINTERSTEIN, B.P., WILLSE, J.T., BARONA, C.M., CRAM, J.T., HESS, K.I., MARTINEZ, J.L., RICHARD, C.A. (2008). *Assessing creativity with divergent thinking tasks: Exploring the reliability and validity of new subjective scoring methods*. In: «Psychology of Aesthetics, Creativity, and Arts», vol. II, n. 2, pp. 68-85.

SIMONTON, D.K. (1999). *Creativity as blind variation and selective retention: Is the creative process darwinian?*. In: «Psychological Inquiry», vol. 10, n. 4, pp. 309-328.

SIMONTON, D.K. (2015). *On praising convergent thinking: Creativity as blind variation and selective retention*. In: «Creative Research Journal», vol. XXVII, n. 3, pp. 262-270.

SIMONTON, D.K. (2016). *Creativity, automaticity, irra-*

tionality, fortuity, fantasy, and other contingencies: An eightfold response typology. In: «Review of General Psychology», vol. XX, n. 2, pp. 194-204.

SOWDEN, P.T., PRINGLE, A., GABORA, L. (2015). *The shifting sands of creative thinking: Connections to dual-process theory*. In: «Thinking and Reasoning», vol. XXI, n. 1, pp. 40-60.

STEIN, M.I. (1953). *Creativity and culture*. In: «Journal of Psychology», vol. XXXVI, n. 2, pp. 311-322.

STEVENS, C.E. JR, ZABELINA, D.L. (2019). *Creativity comes in waves: An EEG-focused exploration of the creative brain*. In: «Curent Opinions in Behavioral Sciences», vol. XXVII, pp. 154-162.

SUN, J., LIU, Z., ROLLS, E.T., CHEN, Q., YAO, Y., YANG, W., WEI, D., ZHANG, Q., ZHANG, J., FENG, J., QIU, J. (2019). *Verbal creativity correlates with the temporal variability of brain networks during the resting state*. In: «Cerebral Cortex», vol. XXIX, n. 3, pp. 1047-1058.

TEGMARK, M. (2015). *Consciousness as a state of matter*. In: «Chaos, Solitons, and Fractals», vol. LXXVI, pp. 238-270.

TONONI, G., BOLY, M., MASSIMINI, M., KOCH, C. (2016). *Integrated information theory: From consciousness to its physical substrate*. In: «Nature Review Neuroscience», vol. XVII, n. 7, pp. 450-461.

TORRANCE, E.P. (1965). *Scientific views of creativity and factors affecting its growth*. In: «Daedalus», vol. XCIV, n. 3, pp. 663-681.

TORRANCE, E.P. (1974). *Norms-technical manual: Torrance tests of creative thinking*, McGinn, Lexington.

UTTAL, W.R. (2013). *Dualism: The original sin of cognitivism*, Psychology Press, New York.

VARTANIAN, O. (2011). *Decision junctures in the creative process*. In: O. VARTANIAN, D.R. MANDEL (eds.), *Neuroscience of decision making*, Psychology Press, New York, pp. 311-327.

VARTANIAN, O., BEATTY, E.L., SMITH, I., FORBES, S., RICE, E., CROCKER, J. (2019). *Measurement matters: The relationship between methods of scoring the alternate uses task and brain activation*. In: «Current Opinions in Behavioral Sciences», vol. XXVII, pp. 109-115.

WALLACH, M.A., KOGAN, N. (1965). *Modes of thinking in young children. A study of the creativity-intelligence distinction*, Holt, Rinehart & Winston, New York.

WALLAS, G. (1926). *The art of thought*, Cape, London.

WANG, M., HAO, N., KU, Y., GRABNER, R.H., FINK, A. (2017). *Neural correlates of serial order effect in verbal divergent thinking*. In: «Neuropsychologia», vol. XCIX, pp. 92-100.

WIGGINS, G.A. (2006). *Searching for computational creativity*. In: «New Generation Computing», vol. XXIV, n. 3, pp. 209-222.

WIGGINS, G.A. (2020). *Creativity, information, and consciousness: The information dynamics of thinking*. In: «Physics of Life Reviews», vol. XXXIV-XXXV, pp. 1-39.

YANG, L.-C., CHOU, S.Y., YANG, Y.-H. (2017). *MidiNet: A convolutional generative adversarial network for symbolic-domain music generation*, ArXiv170310847.

ZABELINA, D.L., ANDREWS-HANNA, J.R. (2016). *Dynamic network interactions supporting internally-oriented cognition*. In: «Current Opinions in Neurobiology», vol. XL, pp. 86-93.

ZEDELIUS, C.M., MILLS, C., SCHOOLER, J.M. (2019). *Beyond subjective judgments: Predicting evaluations of creative writing from computational linguistic features*. In: «Behavior Research Methods», vol. LI, n. 2, pp. 879-894.

ZENG, L., PROCTOR, R.W., SALVENDY, G. (2011). *Can traditional divergent thinking tests be trusted in measuring and predicting real-world creativity?*. In: «Creativity Research Journal», vol. XXIII, n. 1, pp. 24-37.