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Deciphering Cognitive Processes in Creative Problem Solving: A Computational Approach

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Abstract: We propose a critical review of the research literature regarding creativity, which is required for creative problem-solving during a learning task, aiming to study this process from a triple perspective combining the neurosciences, the learning sciences, and creativity research through the framework of the seven Cs of creativity: creators, creating, collaborations, contexts, creations, consumption, and curricula. We also revisit and review the multi-disciplinary terminology and discuss the main conceptual dualities characterizing creativity. Our major contribution is at the level of brain processes in creative problem solving (CPS), providing a bridge into the learning sciences and creativity research to better understand the neurosciences of creativity during CPS tasks. This fundamental research review can shed light on the inner mechanisms of creativity and provide a more informed understanding of creative problem-solving as a dynamic process thanks to a computational model of creativity.

Key-words: ill-defined problem solving, creative problem solving, cognitive neuroscience, computational model of creativity.

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Décrypter les processus cognitifs dans la résolution créative de problèmes : une approche computationnelle

Résumé : Nous proposons une revue critique de la littérature de recherche concernant la créativité, qui est nécessaire à la résolution créative de problèmes lors d'une tâche d'apprentissage. Nous visons à étudier ce processus dans une triple perspective combinant les neurosciences, les sciences de l'apprentissage et la recherche sur la créativité à travers le cadre des sept ``C'' de la créativité : créateurs, création, collaborations, contextes, créations, consommation et computations. Nous revisitons et révisons également la terminologie multidisciplinaire et discutons des principales dualités conceptuelles caractérisant la créativité. Notre contribution majeure se situe au niveau des processus cérébraux dans la résolution créative de problèmes (CPS), offrant un pont vers les sciences de l'apprentissage et la recherche sur la créativité pour mieux comprendre les neurosciences de la créativité lors des tâches de CPS. Cette revue de recherche fondamentale peut mettre en lumière les mécanismes internes de la créativité et fournir une compréhension plus éclairée de la résolution créative de problèmes en tant que processus dynamique grâce à un modèle informatique de la créativité.

Mots clés : résolution de problèmes ouverts, résolution créative de problèmes, neurosciences cognitives, modèle computationnel de la créativité.

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1. Introduction

Creativity, a phenomenon whereby something new and valuable is formed by a subject in a specific sociocultural context, plays a critical role in specific phases of learning activities. Here, we aim to analyze creativity in the precise context of ill-defined problem-solving tasks, which are part of ecological learning activities. Creativity has already been studied in the learning sciences (Leroy et al., 2021; Jeffrey & Craft, 2004; Long & Wang, 2022; Runco & Chand, 1995) and in other related disciplines, such as psychology (Boden, 1998; Lubart, 2017), cognitive neuroscience (Bunge, 2004), and computer science (Oltețeanu, 2020), as well as philosophy (Gaut, 2010). The framework of the seven Cs of creativity proposed by Lubart (2017) proposes a macro perspective of the different factors that are related to creative activities: creators, creating, collaborations, contexts, creations, consumption, and curricula. In this study, we focus on three of the seven Cs, including the C related to the person (creator), the creative process (creating) and the context in which the creation is developed, including the task. In this study, we examine individual tasks; therefore, we do not consider collaborations, the final creation (the product of the creative process), consumption (the social adoption of the creation), or curricula (including the educational program supporting creativity). We focus primarily on "personal" creativity as defined by Boden (1998) as opposed to "historical" creativity, which can be found in culturally significant accomplishments and is also referred to as "Big-C creativity" (Kaufman & Beghetto, 2009).

The focus on the creative process (creating), the person (creator), and the creative problem-solving (CPS) task (context) aims to support a better understanding of these dimensions at the level of the cognitive process engaged in the task.

For this objective, we review the studies of cognitive and computational neuroscience, computer science, and learning science (Boden, 2009; Dietrich, 2004; Tubb & Dixon, 2014). Additionally, we consider Oltețeanu's analysis of computational creativity from 2020 and the more detailed cognitive neuroscience mechanisms discussed by Alexandre and Dietrich in 2020.

As pointed out by Kupers et al. (2019), current creativity studies need to overcome the macroanalysis of creativity to better characterize creativity as a dynamic process to be assessed at the micro level. We aim to achieve this objective by contributing to a better understanding of creativity within ill-defined CPS tasks, including complex problem-solving, through a multi-disciplinary approach using computational and neuro-cognitive formalisms. This approach allows us to propose a multi-factor theoretical description of such cognitive human activities. Based on this, we aim to operationalize a computational framework for creative processes during CPS learning tasks. We focus on an ill-defined CPS task performed by a unique learner, and sociocultural perspectives have to be considered even in this case.

To make computational modeling implementable through a computing mechanism, we first define a geometric formulation of a CPS task as a dynamic process within a problem space. We then consider the different types of cognitive processes unfolding as the learner progresses through the CPS task and focus on the different dual concepts used to characterize creativity. To this end, we start by reviewing creativity studies in the learning sciences, ranging from sociocultural approaches to the cognitive science

perspective. We then detail how the brain, described following a systemic approach to memory systems in interaction, works in creative problem solving (CPS). This study allows us to relate creative processes to computational mechanisms, focusing on the data representation level, which is often implicit in computational studies. After a synthetic presentation of the existing computational approaches, we propose an integrated framework that benefits from the aforementioned multi-disciplinary perspective.

We hypothesize that solving such an ill-defined problem requires creativity, in a sense that we will define precisely in the following, and we will show that this corresponds to what is considered creativity in cognitive and computational neuroscience, computer science, and learning science studies (Boden, 2009; Dietrich, 2004; Tubb & Dixon, 2014). We also consider the review of computational creativity by Olteteanu (2020) and the more specific cognitive neuroscience mechanisms described by Authors (2020) and Dietrich (2004).

Here, we mainly consider “personal” creativity in the sense of Boden (1998) rather than “historical” creativity found in culturally significant achievements, also called Big-C creativity (Kaufman & Beghetto, 2009).

2. From Creative Pedagogy to the Pedagogy of Creativity

In education, creativity is summoned at two levels. On the one hand, a creative approach to disciplinary learning at both the teacher and student level is of great benefit, for instance, to optimize student engagement or to widen the ways to learn better (Leroy et al., 2021). On the other hand, creativity on its own is one of the most important 21st-century skills and is thus a competence in itself (Engeness, 2020).

Creativity in Learning Science: A Brief Overview and General Positioning

Kupers et al. (2019) defined creativity as an iterative process of interrelations between the child, the task, and the social environment, with “constraints” and “emergences”. It is based on Rhodes’s (1961) 4 Ps of creativity, as reviewed, for example, by Tang and Gruszka (2017)—person, product, process, and press organized in a hierarchical way—and considers that they are interrelated to create “constraints” in the top-down direction and “emergences” in the bottom-up direction. We agree with such a general view but will have to anchor it in recent knowledge about cognitive processes, as proposed in the next section.

Further clarification in the framework proposed by Kupers et al. (2019) concerns the different levels of creativity (the micro-level within a task, in a dynamic view on an evolving and measurable “creative act” (behaviors and strategies); the macro-level considering “creative personalities” in a static way) and how they can be evaluated (e.g., by assessment or personality questionnaires), whether the study is static (measurement at a given time) or dynamic (measurement of the evolution of creativity over time), and whether the proposed intervention is unidirectional (simple evaluation of its effect on creativity) or takes place within a causality process (examining the chain of causes and effects over time). Here, our geometric formulation of CPS is rather micro, dynamic, and causal, therefore being complementary to what is generally studied, according to Kupers et al. (2019) for children or Thurlings et al. (2015) at the level of teachers’ innovative behaviors and pedagogical innovation. Depending on the domain and the task, creativity has been evaluated through different psychometric measures, such as the Torrance Tests of Creative Thinking (TTCT) (Torrance, 1990; Kim, 2006), but also self-reported and subjective measures. Depending on the “divergent thinking (DT) test, task content domain, intellectual giftedness, and country of study” the results could show some differences in DT development (Said-Metwaly et al., 2021) but also convergent results with fluid reasoning assessment (Silvia, 2015). On subjective creativity assessment, the study of Long and Wang (2022) points out the influence of the judges’ expertise level but also the focus on novelty as the main criteria for assessing creativity.

Not only should creativity assessment be domain- and task-specific, but creativity training should also consider not only cognitive but also situational factors within a certain domain and task. Mansfield et al.

(1978) highlighted the fact that studies of the effectiveness of creativity training methods generally suffer from methodological weaknesses, for example, the Hawthorne effect (the fact that individuals modify aspects of their behavior in response to their awareness of being observed). Regarding creativity training, they observed that only considering divergent thinking as a creativity process yields biased results, whereas it is a complete process influenced by cognitive, motivational, personality, and situational factors.

While cognitive neuroscience advances the understanding of how the brain functions in creative tasks (Daikoku et al., 2021), education and psychology researchers undertaking creative studies have developed a diversity of approaches in which we can find studies at the cognitive level (Hao et al., 2016; Lubart & Sternberg, 1995; Radel et al., 2015); the behavioral level (Nemiro et al., 2017); the small-group level (Cassone et al., 2020; Kelly & Karau, 1999; Paulus, 2000; Sarmiento & Stahl, 2008); the localization (Bradley, 2012); and the organizational level (Selkrig & Keamy, 2017). Learning scientists have focused more often on situated learning tasks in ecological contexts of education in some cases to analyze the creative process (Savic, 2016), consider the emergence of the creative process at the individual, small-group, or classroom level (Mathisen & Einarsen, 2004; Stinkeste et al., 2021), and observe differences with respect to culture, personality, and recognized values (Basantia, 2017; Lubart, 1999), as represented in Figure 1. These approaches also lead to applications in pedagogy, as reported by Ni et al. (2014), in which the theoretical approach successfully helped students improve their divergent thinking.

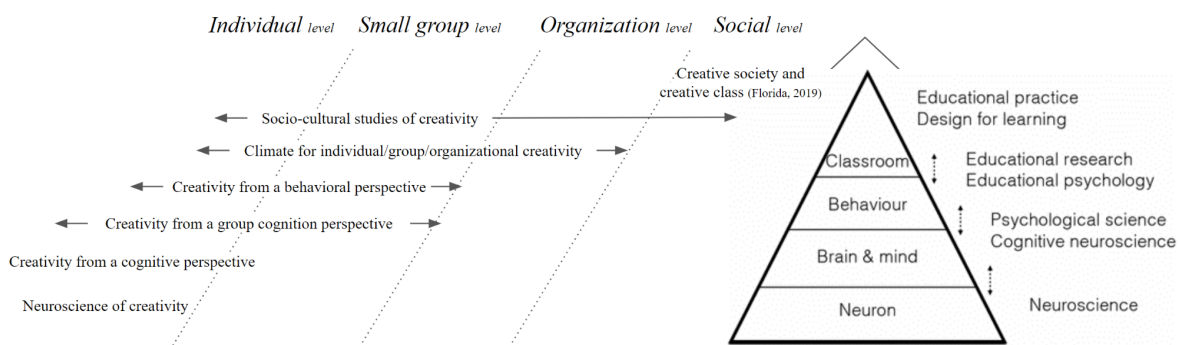


FIGURE 1: Different Levels of Analysis of Creativity in the Learning Sciences, adapted from Lodge et al. (2017).

These different levels of analysis of creativity create diversity not only in conceptual but also in methodological models in the study of this phenomenon in education, as illustrated in Figure 4. To advance in the consideration of a multilevel approach to creativity, we consider a pluralistic epistemological approach (Turkle & Papert, 1992) in the study of creativity in domain-specific tasks, thus being restrained to an activity-oriented approach (Albero & Guérin, 2014; Authors), and we focus on ill-defined problem-solving tasks engaging one learner. This allows us, as stated in the introduction, to consider a behavioral time sequence in which divergent and convergent thinking processes appear at different moments. In CPS, the divergent and convergent thinking processes appear in successive steps during the CPS task (Byron, 2012).

Despite this specificity, we acknowledge that studying human creativity also requires the consideration of a sociocultural perspective to analyze how knowledge is shaped by prior experiences, the cultural context, and the activity system in which the subjects are developing their creative processes, as briefly reviewed below.

2. Creativity in Problem Solving: Dual Notions

In this study, we focus on CPS, corresponding to problem-solving tasks in which the subject (creator) requires to engage in creative processes (creating), to disambiguate different stages of the CPS process: from the problem posing to the problem-solving enaction within a specific task and sociocultural context (Engeström, 2015), corresponding to the context (Lubart, 2017), mediated by the subject's body and actions but also by all the different types of analogical or digital artifacts engaged in the development of a creative performance or product (Leroy et al., 2021).

The Divergent versus Convergent Thinking Phases

Creative problem solving is decomposed into multiple cycles of alternating divergent and convergent thinking phases (Dietrich & Haider, 2017; Guilford, 1967; Hennessey & Amabile, 2010), the former in which new ideas or responses are generated, and the latter in which the appropriateness of these solutions is evaluated. As developed in more detail by Amabile (1996), these two phases are preceded by a preparation phase, resulting in a three-step process. In what the author referred to as the componential model, this process is surrounded by two more steps: starting with the problem presentation and ending with the creative outcome, as illustrated in Figure 2. Let us propose an adaptation of this componential approach and explain why we propose to revisit it.

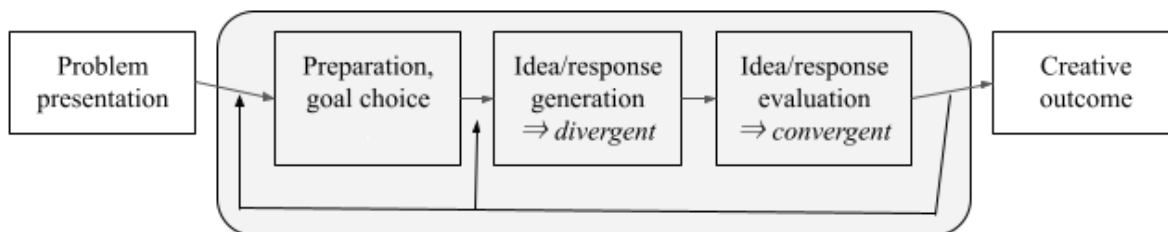


FIGURE 2: General Schema of Creative Problem-Solving Steps, Adapted to Our Approach from the Componential Model Proposed by Amabile (1996).

In Amabile's (1996) study, the problem presentation corresponds to the task identification, driven by internal or external stimuli. The outcome corresponds to observing the expected achievement, considering that there is no reasonable response, or deciding that some progress has been made and looping back to one of the previous steps. This recurrent process has already been mentioned in the componential approach, yet we consider it here to be a primary property. It was evoked as follows by Amabile (1996): "As tasks become more complex, the application of this outline to the production of creative responses to those tasks also becomes increasingly more complex. Work on any given task or problem may involve a long series of loops through the process until success in a final product is achieved" (p. 97). Furthermore, we consider that the problem presentation and creative outcome steps are external to the creative cognitive process itself, as made explicit, for instance, by Romero et al. (2019) for the CreaCube task. We thus consider that the creative process is a recurrent process between the three internal steps, as illustrated in Figure 2. Let us now describe these three internal steps in more detail.

According to Amabile (1996), the preparation step involves building up or reactivating relevant knowledge, policies, or heuristics, and we consider that this should be completed by choosing a goal or subgoal to attain. The idea generation step corresponds to the divergent phase, that is, the search in the memory and the immediate environment of possibilities, while the idea evaluation step refers to the convergent phase, that is, the response test against the available knowledge and criteria.

More precisely, during the initial preparatory phase, a goal or subgoal is fixed, an estimation of the present state is performed, and state-space knowledge requirements (i.e., constraints) are considered. Given these elements, a task is chosen, and an action sequence or action combination to realize this task is decided. The primary goal is engagement in the task, which is the first inner response to the outer problem presentation step.

Creative elements are generated during the divergent phase: new ideas are generated in a way that may require the most obvious responses to be inhibited (which is referred to as “outside-the-box thinking”). Existing assumptions are questioned, and unexplored possible solutions are considered. This approach includes estimating the partially observable current situation, that is, which state we are in, and identifying the available resources and the possible actions to reach the goal, that is, what the possible path toward the chosen goal or subgoal is.

Ideas elaborated in the divergent phase are evaluated during the convergent thinking phase, and then the internal representation and potentially the chosen goal are reviewed or refined (up to the creative outcome), as during the initial preparation phase, yielding an iterative process.

Amabile (1996) also considered creativity in context regarding task-intrinsic and task-extrinsic motivation, which are involved when engaging in the task during the problem presentation outer step and during the divergent thinking phase. Following Liu et al. (2016), we consider that motivation is strongly involved during the preparation step, including goal setting, but also during the evaluation step. The componential approach also identifies domain-relevant skills versus transversal creative abilities, the former being mainly involved during preparation and evaluation and the latter during generation.

The Importance of the Initial or Preparation Phase

The preparation phase is also called the initial phase by Boden (2004), in which the initial goal and state have to be re-evaluated in the subsequent convergent phase. In the present study, we model serendipity as an iterative process in the phase of preparation or in the reformulation phase after one divergent and convergent iteration. Serendipity is an unplanned, unintended, but fortunate discovery. Serendipity does not occur by pure “chance,” instead requiring (i) preparation, (ii) a search step (as formalized by Wiggins, 2014), with (iii) the ability to change and adapt the behavior, including the initial objective, (iv) drawing unexpected links in the wide sense (thinking out of the box), with (v) an interaction with some stochastic mechanisms, and (vi) the ability to recognize what is relevant (or to filter out what is not) to (vii) take action before (viii) evaluating the obtained result. Here, steps (ii) to (v) correspond to the divergent phase, while steps (vi) to (viii) correspond to the convergent phase.

When engaged in creative problem solving, a subject will formulate and choose an answer to the question, “What is the problem?” By doing so, the situation must be perceived and understood, and the

problem to be solved must be identified and expressed. This is a crucial step that we propose to formalize, as shown in Figure 3, inspired by Freksa (2015) and Oltețeanu (2020) for the conceptualization phase and, for example, Cassone et al. (2020) for the instantiation phase.

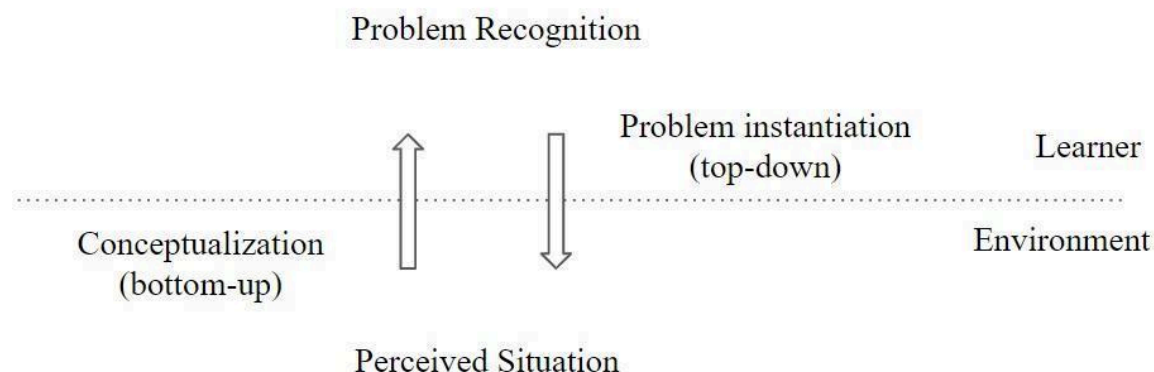


FIGURE 3: Interaction between the environment and the learner during the preparation phase in CPS.

We formalize this interaction in terms of bottom-up conceptualization, that is, building an internal representation of the external situation to raise the problem issue, and top-down instantiation of the problem, that is, setting a goal for the next step.

Regarding our geometrical definition, this includes estimating the current state (of the environment and the learner) and determining the goal or subgoal. These tasks may require some creativity in the sense that defining and deciding on the goal may itself require a divergent search phase and a convergent evaluation phase. In that case, it simply means that the first subgoal might be to better understand the final goal (e.g., better understand what “build a vehicle” could mean in a puzzle-style task such as CreaCube) without needing to invoke any “meta” mechanisms. This also allows us to solve the apparent paradox of searching to reach a goal without knowing precisely what that goal is. Furthermore, in line with an iterative approach, before each new divergent search, we consider that a new preparation phase is possible to revisit the current state estimation and goal specification in relation to the problem-solving regulation process.

Dual Processes in Interaction during Creative Problem Solving

Beyond the previously well-accepted dichotomy between divergent and convergent phases, authors have made a distinction between other dual modes in interaction, sometimes called implicit versus explicit or spontaneous versus deliberate, to be put in relation to (but not conflatable with) stimulus-based versus goal-directed creative behavior, which is likely to be influenced by the dual processing model of the fast-thinking versus slow-thinking view of Kahneman (2011). The general idea is to differentiate explicit CPS, which can be reported and consciously organized, experimented with, and analyzed, from implicit CPS, which may have the same level of efficiency but is carried out automatically from the expression of the problem with no access to its constituents or its motivations. Cognitive science researchers have agreed on such distinctions, but when considering details, their descriptions have differed (Zander et al., 2016).

With the research objective of developing a computational model accounting for human learning, we need to dissect these notions precisely up to their computational meaning at the implementation level. On the one hand, as summarized by Tubb and Dixon (2014) and detailed in Table 1, there is the idea that these complementary dual processes can all be related to each other. Such a view is not far from the Taoist concepts of yin and yang, as discussed in Deborah Frisch’s commentary in the study by Stanovich and West (2000). We consider this to be an interesting integrated view but believe that it should be taken as an inspired outline; while (i) the two systems can act conjointly and interact, (ii) some qualities may also be related to the other system; for instance, we may consciously (thus explicitly) partially control our implicit

system, as discussed in Stanovich and West's (2000) study. On the other hand, as summarized in Table 2, other dual aspects are to be taken into account that cannot be projected onto the S1/S2 dual axis, thus showing that the cognitive processes involved in complex, ill-defined CPS are multi-dimensional.

TABLE 1: The S1/S2 System as Summarized by Tubb and Dixon (2014), following Stanovich and West (2000), with Supplements from Garcez and Lamb (2020) and the Authors.

System 1/implicit	System 2/explicit
spontaneous mode	deliberate mode
associative reasoning	rule-based reasoning
parallel processing	sequential processing
holistic dialectical reasoning, involving understanding a system as a whole, considering its large-scale patterns, and reacting to them	analytic reasoning, thinking about system parts and how they work together to produce larger-scale effects
automatic processing	controlled processing
machine learning numeric processing implementation	machine learning symbolic processing implementation
short-term reactions	long-term planning
relatively undemanding	cognitively demanding
with large associative memory	with limited working memory capacity
acquisition through biology and experience	acquisition through cultural and formal tuition
- slow learning ⁵ : requires a certain amount of examples to extract pattern regularities and adapt internal parameters accordingly - fast retrieval thanks to the acquisition of automatisms	- faster learning (a few explicit examples can be enough) - slower retrieval
phylogenetically evolved first	evolved recently

⁵ There also exist few-shot, when not one-shot or zero-shot learning S1-related mechanisms, when the system is pre-trained and superficially adapted to new incoming samples.

TABLE 2: Other Dual Notions Encountered in CPS.

Divergent/ convergent thinking	As discussed earlier, these are two temporally separated phases in creativity, in fact forming a triad with the preparation phase, as analyzed by Amabile (1996).
Fast thinking (S1)/slow thinking (S2)	As shown in Table 1 and discussed by Tubb and Dixon (2014) and Augello et al. (2015). They considered that the divergent process decomposes into exploratory versus reflective mechanisms, respectively, with regard to the S1 versus the S2 system, and the convergent process decomposes into tacit versus analytic mechanisms, respectively.
Emotional/cognitive	According to Dietrich (2004), the emotional versus cognitive knowledge domain is crossed with the spontaneous versus deliberate (thus S1 versus S2) domain to produce four basic types of creativity at the cognitive neuroscience level.
Semantic/syntactic	In the study by Alexandre (2020), the standard S1/S2 distinction was discussed at the neuro-cognitive level, with different perspectives making the difference between semantic and syntactic aspects. Furthermore, semantic value was related to emotional valuation.
Exploration/ exploitation	This polysemic notion has a precise definition ⁶ in reinforcement learning and has been related to divergent versus convergent processes by several authors, as reviewed by Quillien (2019); to the best of our understanding, it has a different meaning. The divergent process in implicit (S1) mode was also named exploration ⁷ by Tubb and Dixon (2014) and subsequent authors, and this seems to be yet another concept.
Model free/model based	In problem solving involving reinforcement learning, as discussed by, for example, Collins and Cockburn (2020), learning and decision

⁶ In a nutshell, exploitation corresponds to continuing to act in accordance with the optimal policy, given the present knowledge about the problem, and exploration involves trying something new without a guarantee of a better reward but with the aim of increasing the knowledge about the problem environment.

⁷ The concept of “exploration” is thus not to be understood in the exploration/exploitation duality in reinforcement learning at this stage. In fact, it has a contradictory usage in the study by Dietrich (2004), in which the word is not used but deliberate divergent thinking is described as an internal exploration, and Tubb and Dixon’s (2014) schema considers only exploration as an implicit divergent process.

	<p>making may involve a predictive mechanism of the environment either explicitly or implicitly (with or without a model). When considering a creative process, these aspects interact with other dimensions mentioned here, as discussed by the authors.</p>
Stimulus driven/ goal directed	<p>Alexandre (2021) considered a systemic approach, distinguishing two different neuro-cognitive modalities, as discussed in the conclusion of section 3, relating to the attention to external versus internal goals (Ede et al., 2020).</p> <p>This is also related to top-down versus bottom-up processes, which are a relevant but polysemic notion, as clarified in the text.</p>
Flexibility/ persistence	<p>Zhang et al. (2020), following Nijstad et al. (2010), drew a link between divergent thinking and cognitive flexibility, promoting “loose thinking” and creative thought as a process introducing more positive mood states, as opposed to convergent thinking, which is associated with cognitive persistence, for instance narrowing the focus of attention and increasing the top-down control.</p> <p>As discussed by Collins and Koechlin (2012), flexibility is related to a form of exploration (as detailed above) when referring to the choice of task sets and related actions when attempting to complete a task, while the persistence of using a given task set is related to exploitation, the link with the corresponding reinforcement learning mechanisms being made by the authors at the implementation level.</p>
Default mode network (DMN)/ central executive network (CEN)	<p>As reviewed by Alexandre (2020) and Dietrich and Haider (2017), the DMN network is involved in the spontaneous bottom-up processing mode of creativity, while the CEN network is used in creativity that emanates from the explicit system, a deliberate top-down mode.</p>
Insight/intuition	<p>Furthermore, insight and intuition are two</p>

	notions that cannot be reduced to other dualities and are made more explicit in the text.
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Insight versus intuition

Here, a distinction is made between the spontaneous emergence of an idea, as a “bounce” effect of the creative approach, and a deliberate search for new ideas, including questioning existing beliefs or knowledge about the problem to solve. This insight phenomenon corresponds to a well-identified sensation, and it is worth noticing that it also occurs in an ill-defined situation, even if it is not easy to put into words.

As far as the spontaneous aspect is concerned, a distinction is made between “insight” (the aha effect), which is sudden and unexpected apprehension of the solution, and intuition, which is mainly characterized by reaching, more gradually, a solution with neither an explicit representation nor a clear explanation of how it emerged (Zander et al., 2016). The distinction is worked out in depth, with Zhang et al. (2016) observing that insight is related to the emergence of “what” could be the solution after a restructuring of mental processes, whereas—in experimental paradigms—intuition is more related to the spontaneous selection of a solution among alternatives with an emerging perception of coherence (Zander et al., 2016). As pointed out by Zhang et al. (2016), the involved neural networks are similar, with the one related to insight working totally in a spontaneous mode and the one related to intuition being more in an intermediate mode between spontaneous and deliberate.

Taking a step further and considering the link with metacognition, Metcalfe and Wiebe (1987) examined the difference in metacognitive judgment processes between insight and non-insight problem solving by using metacognitive judgments such as “feeling or knowing” ratings of perceived closeness to the solutions (warmth ratings). Their results of higher warmth ratings during non-insight problem solving than during insight problem solving supported the view that the sudden realization of the solution is the distinguishing characteristic of insight problem solving.

As far as deliberate aspects of divergent thinking are concerned, the previously quoted authors have mainly considered two roles: search and reflection, that is, a generative and a regulating effect. On the one hand, creativity can be driven by a deliberate internal or external search, interacting with memories, ideas, or objects of the environment; this is exploratory in a sense. This is another process yielding creativity, different (but not independent) from the others described here, as formalized by Ritchie (2012) after Wiggins (2006). On the other hand, creativity is triggered by “intention,” and the deliberate system regulates the spontaneous process. This involves judgment along both cognitive and emotional dimensions (Dietrich, 2004), with emotion allowing the comparison of different signals using a common currency (Levy & Glimcher, 2012). At this stage, a rather subtle difference is to be made between regulation and evaluation: during the divergent phase, the role of the deliberate system is not to evaluate the result of the spontaneous generation process but rather to regulate the way in which the generation process is performed (Tubb & Dixon, 2014). Intuition is a continuous process, while insight is perceived as a one-shot process.

These four processes of insight, intuition, search, and regulation are not exhaustive regarding both spontaneous and deliberate divergent thinking, but they are illustrative of how creativity is mainly explained by interactions between cognitive subsystems rather than their nominal behaviors.

To understand these dual notions better, we will review, first regarding learning science and then cognitive neuroscience, how these dual notions form a multi-dimensional framework to describe and analyze creativity processes. Considering these elements, we will then develop a computational specification of creativity as a functionality emerging from the interaction between specific processes acting in dedicated modes.

3. Creativity as Production Processes

Alternative Possible State Generation

At the computational level, to implement idea generation, that is, the divergent thinking process (DT), and evaluation, that is, the convergent thinking process (CT), there is a need to represent the different ideas generated during the creating process. This model supports the computation of different types of differences between the intermediates produced in the CPS process. Dietrich and Haider (2017) discussed several computational mechanisms of divergent thinking, such as evolutionary algorithms and Bayesian-based prediction, that could implement some of these modalities, while Han et al. (2018) proposed analogy reasoning, and Oltețeanu (2020) developed a recent framework proposal after analyzing the main existing systems. As previously mentioned, when introducing these computational considerations, associative thinking is a key process in divergent thinking. More precisely, bisociation, defined by Dubitzky et al. (2012) as the association of two concepts from different domains perceived simultaneously, allows the generation of novel ideas. This can be achieved in several ways. For instance, in a partial match between two concepts, conceptual blending (Fauconnier & Turner, 2003) consists of selectively projecting some features into a “blended space,” resulting in the emergence of a new structure and new meaning. In our geometric formalism, projection would be an adequate model of this mechanism. Another example is analogy reasoning, as defined previously, which requires the transfer of a relationship from one domain to another, thus corresponding more to a geometric translation. In a nutshell, at the geometric level, divergent thinking requires us not only to interpolate but also to extrapolate new concepts from existing ones. Let us describe these opportunities by considering two non-exclusive examples, as illustrated in Fig. 4.

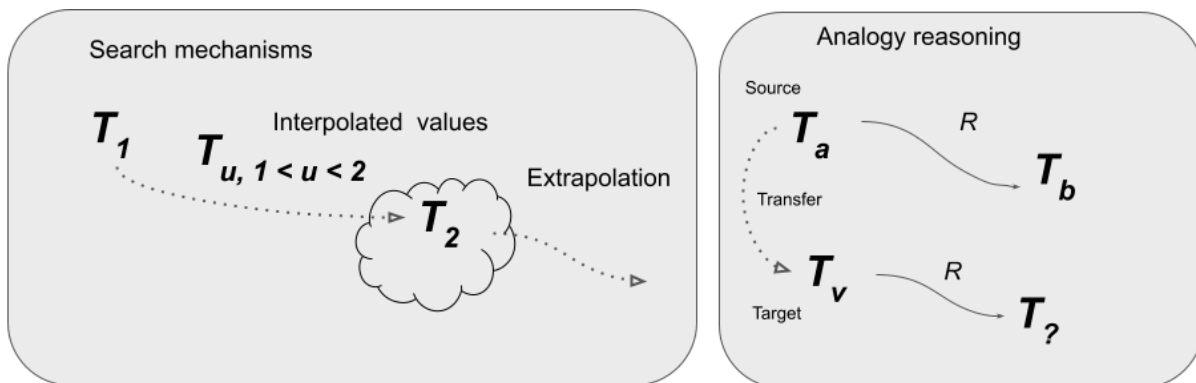


FIGURE 4: A schematic representation of two idea generation mechanisms. Left: Exploratory search in the sense of Ritchie (2012) and Wiggins (2006). Right: Reasoning by analogy. See the text for details.

Search Mechanisms

As established by Ritchie (2012) and G. A. Wiggins (2006), generating new creative concepts can be considered a search process. For instance, we may wish not only to interpolate but also to extrapolate another state, only constrained by a certain requirement. For instance, we may invent not only a “penguinemu” (a penguin (T_1 in Fig. 4) morphing towards an emu (T_2 in Fig. 4)) but also a “nonpenguinemu” (a morphing of a penguin beyond the emu interpolation trajectory). In such an extrapolation mechanism, we

basically consider the editing sequence from T1 to T2 and reapply it to T2. This corresponds to the exploration scheme of Ritchie (2012). Extrapolation can also be temporal, considering, for instance, the yesterday state and the today state, whatever this means, and reapplying the editing sequence to the today state allows us to extrapolate what the tomorrow state could be under the assumption that the evolution will be the same. Interpolation is also related to a geometric projection. For instance, we may wish to invent a “flying penguin,” that is, starting from a penguin (T1 in Fig. 4) and projecting it onto the region (the region around T2 in Fig. 4) of flying objects without considering a unique prototype of a bird but several prototypes of birds or only the capability to fly. We could also add some randomness to explore alternatives in interpolation and extrapolation in exploration schemes.

Reasoning by Analogy

Following the definition of analogy reasoning proposed by Han et al. (2018), for example, a reasoning of the form “Robin is to Batman what Sancho is to Don Quixote”, we can use the editing sequence from Robin to Batman in the source context and reapply it to Sancho in the target context to generate analogy features that could apply to Don Quixote. The mapping from Robin to Sancho, that is, from the source to the target domain, forms a commutative diagram with the source and target relations. Proportional analogy reasoning thus translates a known relation between two concepts in a source context or domain into a target domain given an “analogy” between concepts. The capacity to transform the representations is discussed by Runco and Chand (1995) as part of the ideation process, which is confronted with the limits of retrieving declarative and procedural knowledge from long-term memory while transforming this representation into novel ideas that can be influenced by chance and socio-cultural permutations as described by the change-configuration model (Simonton, 1988). Torrance (1995) considers the insights to be important moments in the ideation process. Insights are often triggered by exposure to new stimuli, allowing, in certain cases, sudden shifts in thinking that allow individuals to generate novel ideas. Sweller (2009) discusses “randomness as the genesis principle” from a cognitive load perspective to explain the novelty of ideas. According to Sweller, this principle can be learned and supported by strategies such as brainstorming. Idea generation techniques such as brainstorming are also considered in the Generating Ideas stage of the Creative Problem Solving Framework (Treffinger, 1995; Treffinger et al., 2003).

As developed by Dietrich and Haide (2017), creativity can emerge from both deliberate top-down processes and spontaneous bottom-up mechanisms, the former being biased by prior information and the latter being less constrained and more related to serendipity mechanisms. The previous three geometrical mechanisms can be interpreted in several ways, such as:

- Enumerate other alternatives, including those not directly applicable;
- Randomly draw alternatives to sample a set that is not easily enumerable;
- Attempt to disassemble or find other combinations of a particular element, for example, concrete object pieces or action steps;
- Perform reasoning by analogy, that is, use opportunistic heuristics to infer new relations between elements.
- Perform reasoning by extrapolation or prediction, using the episodic memory capability to generate putative episodes from memorized ones.

To summarize, as developed by Ritchie (2012), who formalized the computation proposal of Wiggins (2006), creativity is mainly a search process within a geometrical problem space that we have proposed to implement here, through several concrete mechanisms, within our geometric formalization.

The Need for Computational Regulatory Mechanisms

Creative intention and exploration are not enough; regulatory cognitive processes are also required in CPS. More precisely, not only do we need to deploy the different processes developed previously, but we also need to regulate these processes in the sense of being able to initiate and stop them, switch between them, and evaluate their outcome. Our proposal, as schematized in Figure 1, is to represent this CPS regulation process as a recurrent feedback loop.

Furthermore, as in operational computational approaches such as that by Collins and Koechlin (2012), the system must consider different task sets, that is, operational representations of behavioral strategies, including the goal, the prerequisites to be initiated, the expected outcomes, and the action sets to realize the task. These task sets are managed in parallel, with an estimation of their benefit, that is, the reward minus the cost in a simple case, and a thresholding mechanism to switch from one task to another. Here we consider each preparation, generation, and evaluation step of the internal creative process as a collection of task sets. We also consider that the regulation processes proposed by these authors correspond to preparation, generation, or generation regulation, enforced by selecting a task set in a corresponding category. Given a current task, for example, generation, there is a concurrent process between carrying on and stopping to switch to the evaluation stage, the result of which could be to consider success, failure, or starting another task.

In Collins and Koechlin's (2012) approach, each action set corresponds to a basic reinforcement learning numerical mechanism, and here we propose to consider the generalization to reinforcement symbolic learning in the sense defined by Mercier et al. (2021). The task set could be considered a set of strategies of the creator (Lubart, 2017) that are mobilized during the creating process depending on the emergent context of the CPS task.

According to Zhang et al. (2020), creative cognition in divergent and convergent thinking is modulated by metacontrol states. Divergent thinking and insight solutions are enhanced by flexibility and benefit from metacontrol biases toward flexibility, whereas convergent thinking seems to benefit from metacontrol biases toward persistence. Metacognition, here, is related to the selection of the goal and the decision on persistence or flexibility with respect to the choice of a task set. Drawing the link with the PROBE framework of Collins and Koechlin (2012), we may consider flexibility as an exploration process and persistence as an exploitation process, as introduced in our section on dual approaches, here reconsidered at the implementation level.

Conclusion

This study has analyzed creativity in ill-defined CPS tasks from a triple perspective: the research in neuroscience, the seven Cs framework of Lubart (2017), and the regulatory process in the learning sciences. We focused on a unique learner but also considered sociocultural perspectives (Engeström, 2015). Through this interdisciplinary perspective, the present work has considered these three different scientific communities to develop an operationalizable framework for modeling the CPS processes in ill-defined tasks. Part of this effort translates into developing the terminology introduced in Tables 1 and 2, which correspond to these dual notions corresponding to rather sophisticated complementary aspects of creativity. As a result, they may be used to shed light on the pedagogical aspect of creativity on two levels.

On the one hand, a better understanding of what happens in the brain beyond problem solving (Berthier, 2019) may also help when creative processes are engaged in ill-defined problem-solving tasks. We thus offer here some basic material to extend the previous work. It is also complementary to, for example, Herbert's (2010) work on how theoretical psychology can have a bearing on classroom practice; our add-on is that sharing cognitive neuroscience elements can also contribute to enlightening pedagogical practices.

On the other hand, we have a more prospective view related to computational thinking in the sense of Wing (2006), following Papert (1980). We hypothesized, as pointed out in the learning science section and discussed by Barnabé et al. (2020) and Menon et al. (2019), that there is a benefit to explicitly characterizing a

human learning process as a computational process, even if it is partially at a metaphoric level. Here, the basic idea is to “spatialize” the problem and its characteristics (ill-defined problem, alternative solutions, partial knowledge of the present state, etc.) to construct a meta-representation of the creative process. It helps to “learn how to learn” and is thus a concrete lever for meta-learning pedagogy. Nevertheless, the present work is only a preliminary step toward these ambitious applications, but it still proposes some basic material for further developments in learning science.

The present work had another ambition, which was to provide a computational specification that considers as much as possible the different elements reviewed at both the behavioral and cognitive levels, up to a concrete algorithmic implementation. What is referred to as a geometric model allowed us, instead of proposing yet another formalism, to summon the existing formalisms discussed previously and integrate them thanks to a well-defined generic data structure, thus making them interoperable. With respect to the other main existing computational frameworks reviewed by Oltețeanu (2020), including her own proposal, what has been developed has two characteristics. We concentrated on biologically plausible mechanisms, linked to our cognitive science review. We also made the choice of a minimal framework in the sense that we collected the minimal ingredients to propose effective divergent thinking processes with an architecture that is somehow much simpler and thus more falsifiable than other very sophisticated alternatives in order to better serve the objective of supporting the CPS modeling.

Through our study, we have contributed to a better understanding of creative problem-solving processes, which is important for improving educational interventions and activities based on the current state of the art developed in this study.

Finally, the proposed material is also a way to help create resources to demystify creativity and the link between natural and so-called artificial intelligence, as the authors undertook in large-audience science outreach articles (Authors). Teaching creativity can also contribute to developing critical thinking with respect to our beliefs regarding creativity, and such a science outreach approach starts by understanding what the right questions are when engaging in ill-defined CPS. To this end, we have advanced toward a multi-disciplinary approach to the study of CPS.

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