Computational Creativity

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Synonyms

Innovation, ingenuity, ideation.

Definition

Computational creativity is the capacity to find solutions that are both novel and appropriate using computational means.

Characteristics

Understanding brain processes behind creativity and modeling them using computational means is one of the grand challenges for systems biology. Computational creativity is a new field, inspired by cognitive psychology and neuroscience. In many respects human-level intelligence is far beyond what artificial intelligence can provide now, especially in regard to the high-level functions, involving thinking, reasoning, planning and the use of language. Intuition, insight, imagery and creativity are important aspects of all these functions. Computational models show great promise both in elucidating mechanisms behind such high-level mental functions, and in applications requiring intelligence (Duch 2007).

Creativity, defined by Sternberg (1998) as "the capacity to create a solution that is both novel and appropriate", has often been understood in a narrow sense, with focus on big discoveries, inventions and creation of novel theories, arts and music, but it also permeates everyday activity, thinking, understanding language, providing flexible solutions to everyday problems (R. Richards, in Runco & Pritzke, 2005, pp. 683-688). Creativity research has been mostly in the domain of philosophers, educators and psychologists, with many research results published in two specialized journals: **Creativity Research Journal** and **Journal of Creative Behavior**. The "Encyclopedia of creativity" (Runco & Pritzke, 2005), written by 167 experts does not contain any testable neurological or computational models of creativity. MIT Encyclopedia of Cognitive Sciences (Wilson & Keil, 1999) devotes only a single page to creativity (it has about 1100 pages), does not mention intuition at all, but devotes 6 articles to logic, appearing in the index almost 100 times. Logic has never been too successful in modeling real thinking processes that rely on intuition and creativity. The interest in research on computational and neuroscience approaches to creativity is thus quite recent.

Creativity from psychological and neuroscientific perspective

D.T. Campbell (1960) described creativity as a two-stage process of blind-variation and selective-retention (BVSR). This idea is the basis of combinatorial models of creative thinking (Simonton, 2010). It is also the basis of evolutionary biological processes, where the mechanisms of blind variations operate on many levels, with selective retention due to the increased fitness in a given context. Viruses, bacteria and other living organisms exhibit creativity solving collectively the problem of survival. However, BVSR idea is more general as it does not have to rely on specific Darwinian mechanism. It has applications in such diverse fields as immunology, psychiatry, neuroscience, cognitive sciences, memetics, linguistics, anthropology, philosophy and computer science (Simonton, 2010). Blind variation is never random: it is structured by specific interactions of basic elements, from molecular to social, determining probabilities of arising combinations.

Psychological research on creativity has been focused on empirical research with gifted children, distinguishing creativity from general intelligence, testing fluency, flexibility, and originality of thought in both visual and verbal domains (Runco & Pritzke, 2005). Successful intelligence theory separates creative and cognitive components of intelligence (Sternberg 1998), with creativity implying not only high quality but also novelty. Creativity is not reducible to cognitive thinking skills. The four basic stages of problem solving according to the widely used *Gestalt model* involve preparation, incubation (that may be followed by a period of frustration), illumination (insight) and verification of solution, including communication. These stages, not necessarily in the same sequences, were identified in creative problem solving by individuals and small groups of people.

M. Boden (1991) defined creativity as “a matter of using one’s computational resources to explore, and sometimes to break out of, familiar conceptual spaces.” Concepts are patterns of brain activations (Pulvermüller 2003, Duch et al. 2007) and exploration of conceptual spaces may be linked to transitions between brain activations. Processing remote, loose associations between ideas is at the foundation of associative basis of creativity (Mednick, 1962; Simonton, 2010). Exploratory creativity is incremental and combinatorial in nature, usually restricted to personal discoveries (novel only for one person), binding diverse activity of brain areas in a new way. “Transformational creativity” leads to ideas that are new for the whole humanity, big paradigm shifts (Boden, 1991). It is not clear whether brain mechanisms behind transformational creativity are really different, requiring change of the rules that are used to define conceptual spaces, or is it rather due to the linking of many brain patterns that form new, higher-level complex representing observations in a more coherent way.

Despite the limitation of the current knowledge of the neural processes that give rise to the cognitive processes in the brain it is possible to propose a testable, neurocognitive model of creative processes. Although direct brain imaging of creative thinking has not yet been done, the “Aha!” phenomenon, or *insight experience* (Sternberg & Davidson, 1995) during problem solving, understanding a joke or a metaphor, has been studied using functional MRI and EEG techniques. Brain states during insight are contrasted with analytical problem solving that does not require insight (Kounios and Jung-Beeman, 2009). Although the insight experience is sudden it is a culmination of a series of brain processes. Few seconds before the insight alpha burst is seen in the right occipital cortex, and about 300 ms before the feeling of insight a burst of gamma activity is observed in the right hemisphere anterior superior temporal gyrus. Alpha activity helps to decrease activation of irrelevant cortex after the information stating the verbal problem has been taken in, while gamma burst reflects connection of distantly related patterns. Right brain hemisphere is able to create more abstract associations based on meanings, avoiding close associations that the left hemisphere is routinely processing. The same neural structures are probably involved in creative thinking. This shows the need for multiple levels of representations of concepts that help to constraint search for solutions of problems requiring creativity.

Intuition is also a concept difficult to grasp (Lieberman, 2000; Myers, 2002), but plays an important role in mathematics, science and general decision making. It has been defined as “knowing without being able to explain how we know”. Intuition relies on implicit learning, gaining tacit knowledge without being aware of learning. Insight into structural relations is usually not present, only fast judgment or response based on probability estimation. Social intuition is the basis of nonverbal communication, and can be seen as the phenomenological and behavioral correlate of knowledge gained through implicit learning (Lieberman, 2000).

Measurement of intuition is based on several tests and inventories (for example the Myers-Briggs Type Inventory, or Accumulated Clues Task), but there is little correlation between them, so the concept of intuition is not well defined from operational point of view. Significant correlations were found between the Rational-Experiential Inventory (REI) intuition scale and some measures of creativity (Raidl & Lubart, 2001). Such tests reflect rather complex cognitive processes, and it is not clear which brain processes are behind these measures.

From computational point of view it is much easier to create predictive models of data then to provide explanations (Duch, 2007). In particular it is difficult to explain decisions made by neural networks or similarity-based systems. Using such systems for learning from partial observations can constrain search for solutions, avoiding combinatorial explosion that is the main problem in AI, making the reasoning process feasible.

Creativity from computational perspective

Psychology and neuroscience agree that creativity is a product of ordinary cognitive processes. The lack of understanding of detailed mechanisms involved in creative activity made the development of creative computing rather difficult. The need for everyday creativity has been almost completely neglected by the artificial intelligence research community and may be credited for failures of many AI programs. Early attempts to model intuition, insight and inspiration from the AI point of view have been summarized by H. Simon (1995). His work has mostly been directed at understanding historical discoveries of scientific laws, as well as search for new scientific knowledge of this kind in astronomy, physics, chemistry and biology. Simon made no attempts to connect search-based AI approaches to processes in the brain. Research in automatic genetic programming (Koza et al. 2003) can be credited with useful patentable inventions in automated synthesis of antennas, analog electrical circuits, controllers, metabolic pathways, genetic networks and other areas. While these inventions have been mostly optimized versions of known designs genetic programming is capable of creative problem solving, but a real bottleneck is to find a good way to represent knowledge domain in which genetic processes will operate. Other approaches to insight include the “small world” network model of Schilling (2005) and the work on fluid concepts and creative analogies (Hofstadter, 1995), with some applications to design.

Direct attempt to model creative processes in the brain is still not feasible, but inspirations from the BVSR models may be used in a number of ways. Results of experimental and theoretical research are summarized in 3 points:

1) **Space**: creativity involves neural processes that are realized in the space of quasi-stable neural activities, leading to patterns of activity that reflect relations between concepts in some domain.
2) **Blind variation**: priming by concepts that represent the problem leads to distributed fluctuating neural activity constrained by the strength of associations between patterns of neural activity coding concepts; this process is responsible for imagination, flexible formation of transient novel associations.
3) **Selective retention**: filtering of interesting results, discovering partial solutions that may be useful to reach goals, amplifying or forming new associations; in biological systems this may involve emotional arousal.

The blind variation process may require some structuring to be effective. Brainstorming, free associations, random stimulation or lateral thinking have not been very successful in generation of creative ideas in advertising and product innovation (Goldenberg et al. 2002). Structured approaches, based on higher-order rules and templates, led to excellent results. Computer generated ideas based on templates were rated significantly higher both for creativity and originality than the non-template human ideas. The associative processes may in this case have been guided by general rules. Connectionist models for generation of ideas within the brainstorming context can successfully predict factors that enhance brainstorming productivity. The model of Iyere et al. (2009) is perhaps most sophisticated, with features, concepts and cognitive control components as separate neural layers. Ideas emerge in a multi-level, modular semantic space from itinerant attractor dynamics shaped by context, synaptic learning and ongoing evaluative feedback. This model generates novel ideas by multi-level dynamical search in various contexts, capturing the interplay between semantic representations, working memory, attentional selection, and reinforcement signals. The model is quite useful in elucidation of the mechanisms of creativity and could find interesting associations for various “outing and vacation” contexts.

The simplest domain in which creativity is frequently manifested and can be studied in experiments as well as computational models is the invention and understanding of neologisms. Poems by Lewis Carroll are full of neologisms, but novel words are also in great demand for products, sites or company names. In languages with rich morphological and phonological compositionality (latin, slavic and other families) out-of-vocabulary words appear fairly often in conversation. In most cases morphology of these words gives sufficient information to understand their meaning. Given keywords or a short description from which keywords are extracted primes the brain at the phonetic and semantic level. The structure of the language is internalized in the neural space. Priming leads to blind variation at the level of word constituents (syllables, morphemes), creating a large number of transient resonant configurations of neural cell assemblies that remain unconscious. This process explores the space of possibilities that agree with internalized constraints on the statistical probabilities of phonological structure (phonotactics of the language) and morphological structure. Imagery processes are approximated in a better way by taking keywords, finding their synonyms to increase the pool of words, breaking words into syllables and morphemes, and combining the fragments in all possible ways. Words that share properties with many other words (that is patterns that code them in the brain overlap strongly with patterns for other words) have a higher chance to win competition for access to awareness. Many variants of words are created around the same morphemes. The same word is used in many meanings because context creates specific brain activation pattern for this word. Creative brains spread activation to more words associated with initial keywords, produce more combinations, selecting the most interesting ones using phonological, affective and semantic filters.

In computational models these putative processes may be implemented in a large scale neural models, but even the simplest approximations give interesting results (Duch 2006; Duch & Pilichowski, 2007). The algorithm involves three major components:

1) An autoassociative memory (AM) structure, trained on a large lexicon to learn statistical properties at the morphological level, providing the model of a neural space and storing background knowledge that is modified (primed) by keywords.
2) Blind variation process (imagery), forming new strings from combinations of substrings found in keywords and their synonyms, with probabilistic constraints provided by the AM to select only lexically plausible strings.
3) Selective retention ranking the quality of the strings representing neologisms from phonological and semantic point of view.

Filters should estimate phonological plausibility and “semantic density,” or the number of potential associations with commonly known words, calculating the number of substrings in the lexical tokens that may serve as morphemes in each new candidate string. Many factors may be included here: general similarity between morphemes, personal biases, tweaking phonology for neologisms with interesting phonetics. Implementation of this algorithm led to generation of neologisms with highest ranks that have actually been used as a company or domain names in about 75% of cases. For example, starting from an extended list of keywords, *portal, imagination, creativity, journey, discovery, travel, time, space, infinite*, best neologisms included *creatival* (used by creatival.com), *creativery* (used by creativery.com). Novel neologisms (not found by the Google search engine), included *discoverity*, associated with discovery of something true (verity), and linked to many morphemes: *disc, disco, discover, verity, discovery, creativity, verity*, and through phonology to many others. Another interesting word found is *digventure*, with many associations to *dig* and *venture*.

These examples show that computational approaches to creativity can, at least in restricted domains, lead to results that are comparable with human ingenuity, and that blind variation selective retention ideas based on generalization of evolutionary processes may be as useful in cognitive science as they are in life sciences.

Cross-references

Artificial Intelligence
Computational Intelligence

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