Creativity, Cognitive Mechanisms, and Logic

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Abstract. Creativity is usually not considered to be a major issue in current AI and AGI research. In this paper, we consider creativity as an important means to distinguish human-level intelligence from other forms of intelligence (be it natural or artificial). We claim that creativity can be reduced in many interesting cases to cognitive mechanisms like analogy-making and concept blending. These mechanisms can best be modeled using (non-classical) logical approaches. The paper argues for the usage of logical approaches for the modeling of manifestations of creativity in order to step further towards the goal of building an artificial general intelligence.
Keywords: Logic, Creativity, Analogy, Concept Blending, Cognitive Mechanisms.

1 Introduction

During the last decades many cognitive abilities of humans have been modeled with computational approaches trying to formally describe such abilities, to develop algorithmic solutions for concrete implementations, and to build robust systems that are of practical use in application domains. Whereas in the beginnings of AI as a scientific discipline the focus was mainly based on higher cognitive abilities, like reasoning, solving puzzles, playing chess, or proving mathematical statements, this has been changed during the last decades: in recent years, many researchers in AI focus more on lower cognitive abilities, such as perception tasks modeled by techniques of computer vision, motor abilities in robotic applications, text understanding tasks requiring the whole breadth of human-like world knowledge etc.

Due to the undeniable success of these endeavors, the following question can be raised: what is a cognitive ability that makes human cognition unique in comparison to animal cognition on the one hand and artificial cognition on the other? At the beginning of AI most researchers would probably have said "higher cognitive abilities" (see the above examples), because only humans are able to reason in abstract domains. In current (classical) AI research, many researchers would, on the contrary, (perhaps) say that all in all still "lower cognitive abilities" like performing motor actions in a real-world environment, perceiving natural (context-dependent) scenes, the ability to integrate multi-modal types of sensory input, or the social capabilities of humans are the basis for all cognition as a whole and therefore also the key features for human-level intelligence. Finally, an AGI researcher would probably stress the combination and integration of both aspects of cognition: a successful model of artificial general intelligence should be able to integrate higher and lower types of cognition in one architecture.

Besides these possibilities, there is nevertheless an important cognitive ability that seems to be usable as a rather clear feature to distinguish human intelligence from all other forms of animal or artificial intelligence: *creativity*. Although we ascribe creativity to many human actions, we would hardly say that a certain animal shows creative behavior or a machine solves a problem creatively. Even in the case of IBM's Watson, probably the most advanced massive knowledge-based system that exists so far, most people would not ascribe general creative abilities to it. At most certain particular solutions of the system seem to be creative, because they are extremely hard to achieve for humans.

This conceptual paper discusses some aspects of creativity, as well as the possibility to explain creativity with cognitive principles and to subsequently model creativity with logical means. The underlying main idea is not to model creativity directly with classical logic, but to reduce many forms of creativity to cognitive mechanisms like analogy-making and concept blending. Such mechanisms in turn can be modeled with (non-)classical logical formalisms.

The paper has the following structure: In Section 2, we sketch some forms and manifestations of creativity. Section 3 discusses the possibility to describe creative acts by cognitive mechanisms, such as analogy-making and concept blending. It is explained that this cannot only be done for examples of creativity from highly structured domains but for a broad variety of different domains. Section 4 proposes the logical framework Heuristic-Driven Theory Projection (HDTP) for analogy-making and concept blending in order to model creativity. Section 5 concludes the paper.

2 Forms of Creativity

Creativity describes a general cognitive capacity that is in different degrees involved in any process of generating an invention or innovation.[1] The concepts invention and innovation describe properties of concrete products, services, or ideas. From a more engineering- and business-oriented perspective, an invention is usually considered as the manifestation of the creative mental act, resulting in a new artifact (prototype), a new type of service, a new concept, or even the mental concretization of a conception. An innovation requires standardly the acceptance of the invention by the market, where market is not exclusively restricted to business aspects. We are considering in this paper creativity as a cognitive ability, but we have to refer to inventions, innovations, new concepts, new findings etc. in order exemplify creativity in a concrete setting.

Creativity appears in various forms and characteristics. Creativity can be found in science, in art, in business processes, and in daily life, i.e. creative acts can occur in highly structured and clearly defined domains (like in mathematics), in less structured domains (like business processes), or even in relatively

[1] The following distinction is based on [5].

Examples for creative acts		
Domain	**Areas**	**Examples**
Science	Mathematics	Argand's geometric interpretation of complex numbers [3]
	Linguistics	Chomsky's recursive analysis of natural language syntax [6]
	Physics	Einstein's theories of special and general relativity
Art	Music	Invention of twelve-tone music by Arnold Schönberg
	Poetry	The invention of a novel (as a genre of poetry)
	Visual arts	Usage of iconographic and symbolic elements in paintings (Eyck)
Other	Daily life	Fixing a household problem
	Business	Nested doll principle for product design

Table 1. Some domains, areas, and examples of manifestations of creativity are mentioned. Clearly, the table is not considered to give a complete overview of domains in which creative inventions of humans can occur.

unstructured domains (like a marketing department of a company having, for instance, the task to design a new advertisement for a certain product).

We summarize different types of creativity in Table 1. Taking into account the various domains in which creativity can occur it seems to be hard to specify a domain, in which creativity does not play a role. Rather certain aspects of creativity can appear in nearly all environments and situations. This is one reason why the specification of common properties and features of creativity is a non-trivial task. For example, some attempts have been made to specify certain phases in the creative process (cf. [23]). Unfortunately, such phases, as for example a "preparation phase", are quite general and hard to specify in detail. It is doubtful whether any interesting consequences for a computational model can be derived from such properties.

3 Creativity and Cognition

There seems to be an opposition between creativity and logical frameworks. Certain creative insights, inventions, and findings do seem to be creative, precisely because the inventor did not apply a deterministic, strictly regimented form of formal reasoning (the prototypical example being classical logical reasoning), but departed from the strict corset of logic. Therefore, often a natural clash and opposition between logical modeling and creativity seem to be perceived. We think that this claim should be rejected. On the contrary, we advocate that the natural way to start is to model creativity with logical means, at least in highly structured domains like science, business applications, or classical problem solving tasks. The reason for this is based on the hypothesis that creativity is to a large extent based on certain cognitive mechanisms like analogy-making and concept blending. But now, due to the fact that analogy-making and concept blending is essentially the identification and association of structural commonalities, in turn a natural way to model these mechanisms are logic-based frameworks.

 

Fig. 1. Two design examples (one from the engineering domain and one from product design) that are based on the same principle, namely the nested doll principle. Objects are contained in similar other objects in order to satisfy certain constraints.

Although creativity seems to be an omnipresent aspect of human cognition (compare Table 1), not much is known about its psychological foundation, the neurobiological basis, or the cognitive mechanisms underlying creative acts. One reason might be that examples for creativity cover rather different domains, where completely different mechanisms could play important roles. Nevertheless, we hypothesize that many classical examples for creativity can be reduced to two important cognitive mechanisms, namely analogy-making on the one hand and concept blending on the other. We mention some examples in order to make this hypothesis more plausible:

- Conceptually, the usage of analogy-making is rather clear in cases where one is using a general principle in a new domain, e.g. the nested doll principle in design processes (compare Figure 1): creativity can be considered as a transfer of a structure from one domain (e.g. the structure of a planetary gearing, namely gears that revolve about a central gear) to another domain (e.g. the design of nesting bowls containing each other). This transfer of structural properties is best described as an analogy.
- In science, analogies and blend spaces do appear quite regularly. For example, in [10] it is shown how analogies can be used to learn a rudimentary number concept and how concept blending can be used to compute new mathematical structures. Furthermore, in [16] it is shown that concept blending can lead to a geometric interpretation of complex numbers, inspired by the historically important findings of Argand mentioned above in Table 1.
- Also the interpretation of certain visual inputs can easily be described by analogy-making (visual metaphor). Figure 2 gives an example, depicting an advertisement. In order to understand this advertisement a mapping between tongue and sock as well as a transfer of properties of socks need to be performed.

The number of examples, which show that analogy-making and concept blending can be used to explain manifestations of creativity, are numerous. If

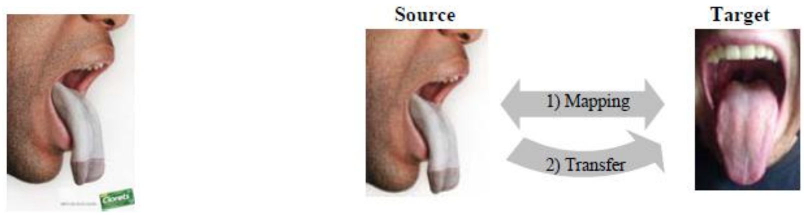

Fig. 2. Advertisement on the left side depicting an association between a tongue and a sock. In order to understand this advertisement (as a marketing tool for hard candy) the establishment of a mapping between tongue and sock is necessary. Then, hard candy can be used as a means against breadth odor. In [21], a formal modeling is specified.

it is true that several characteristics of creativity can be modeled by analogies and concept blending, a computational approach towards creativity can naturally be based on an algorithmic theory of analogy and concept blending. Due to the fact that analogy-making is the identification of structural commonalities and concept blending is the (partial) merger of structures, the natural way for an algorithmic approach is to use logic as the methodological basis. Whereas for concept blending, a symbolic approach for modeling is quite undisputed, the situation in analogy-making is more complicated. Concerning the modeling of analogies, also several neurally inspired and hybrid models have been proposed. Nevertheless, when having a closer look, it turns out that the most important subsymbolic aspects of such models are activation spreading properties or synchronization issues in a (localist) network, whereas the basic computational units of the network still are quite often symbolic (or quasi-symbolic) entities (cf. [12] or [13] for two of the best known neurally inspired analogy models). Additionally, logic-based models of analogy-making have a wider application domain in comparison to neurally inspired or hybrid models. Therefore, in total, it seems a natural choice to apply logical means in modeling these two cognitive mechanisms.

4 A Logical Framework for Modeling Creativity

4.1 HDTP and Analogy Making

In what follows, we will use *Heuristic-Driven Theory Projection* (HDTP) [20] as the underlying modeling framework. HDTP is a mathematically sound framework for analogy making, together with the corresponding implementation of an analogy engine for computing analogical relations between two logical theories, representing two domains (domain theories are represented in HDTP as sets of axioms formulated in a many-sorted, first-order logic language). HDTP applies restricted higher-order anti-unification [14] to find generalizations of formulas and to subsequently propose analogical relations between source and target domain (cf. Figure 3), that can later be used as basis for an analogy-based transfer of knowledge between the two domains (see [1, 10, 16, 20] for more details about HDTP and an expanded elaboration of recent application domains).

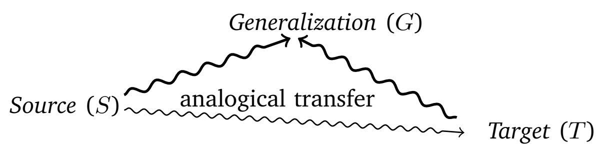

Fig. 3. HDTP's overall approach to creating analogies (cf. [20]).

Analogical transfer results in *structure enrichment* of the target side, which usually corresponds to the addition of new axioms to the target theory, but may also involve the addition of new first-order symbols. There are application cases in which two conceptual spaces (in our case the input theories source and target) need not to be (partially) mapped onto each other, but partially merged in order to create a new conceptual space. In such cases, HDTP uses the computed generalization, the given source and target theories, and the analogical relation between source and target to compute a new conceptual space which is called a blend space.

4.2 Concept Blending and HDTP

Concept blending (CB) has been proposed as a powerful mechanism that facilitates the creation of new concepts by a constrained integration[2] of available knowledge. CB operates by merging two input knowledge domains to form a new domain that crucially depends on and is constrained by structural commonalities between the original input domains. The new domain is called the blend, maintaining partial structures from both input domains and presumably adding an emergent structure of its own.

In cognitive models, three (not necessarily ordered) steps usually are assumed to take place in order to generate a blend. The first step is the composition (or fusion) step, which pairs selective constituents from the input spaces into the blend. In the second step, the completion (or emergence), a pattern in the blend is filled when structure projection matches long-term memory information. The actual functioning of the blend comes in the third step, the elaboration step, in which a performance of cognitive work within the blend is simulated according to its logic (cf. [8, 19]).

Figure 4 illustrates the four-space model of CB, in which two concepts, SOURCE and TARGET, represent two input spaces (the mental spaces). Common

[2] Whence, CB is sometimes referred to as 'conceptual integration'.

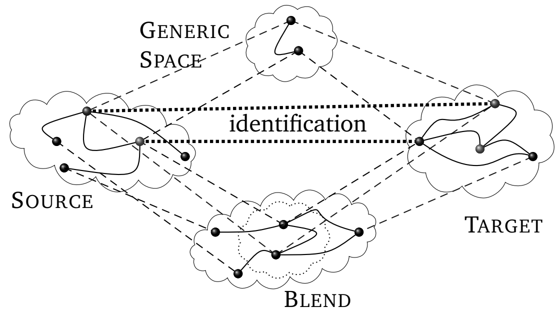

Fig. 4. The four-space model of CB: common parts of the SOURCE and TARGET concepts are identified, defining a GENERIC SPACE and a BLEND. The connecting curves within a concept reflect an internal structure.

parts of the input spaces are matched by identifying their structural commonalities, where the matched parts may be seen as constituting a GENERIC SPACE. The BLEND space has an emergent structure that arises from the blending process and consists of some matched and possibly some of the unmatched parts of the input spaces (cf. Figure 4). One of the famous blending examples is Goguen's HOUSEBOAT and BOATHOUSE blends, which result, among others, from blending the two input spaces representing the words HOUSE and BOAT (cf. [9]).

Only few accounts have been proposed formalizing CB or its principles in the first place, and those that have been proposed are unfortunately not broad enough to suit generic computational accounts of CB (cf. [2, 9, 19, 22]). CB itself noticeably still suffers from the lack of a formally precise model integrating its many aspects. The well-known optimality principles of CB, for instance, raise a challenge for developing such formalizations: these principles are the guideline pressures that are assumed to derive the generation of a feasible blend and distinguish good blends from bad ones [8, 18].

In fact, CB has already shown its importance as a substantial part of cognition and a means of constructing new conceptions. It has been extensively used in the literature in attempts at expressing and explaining cognitive phenomena, such as the invention of new concepts, the meaning of natural language metaphors, as well as its usefulness in expansion, reorganization, and creation of mathematical thoughts and theories ([1, 2, 8, 9, 10]).

The ideas of CB are very much related to the properties of a creative process, since a creative process can result in new insights as a result of a ladder-ascending procedure that steps through "background knowledge", and subsequently increasingly refines the insights to spell-out an innovation (cf. Section 2). Undoubtedly, creative agents must have (enough) background knowledge before a creative process can take place, still mere knowledge most likely is not sufficient: For example, simply having knowledge about Maxwell's equations, the principles of semi-conductors, and the principles of graph theory al-

$$\begin{tikzcd}
& G \arrow[dl] \arrow[dr] \arrow[dd] & \\
S \arrow[rr, dotted, "m"] \arrow[dr, dashed] & & T \arrow[dl, dashed] \\
& B &
\end{tikzcd}$$

Fig. 5. HDTP's view of concept blending. S and T are source and target input theories. m represents the analogical relation between S and T and G is the generalization computed by anti-unifying S and T. The dashed arrows $S \rightarrow B$ and $T \rightarrow B$ describe the injections of facts and rules from source and target to the blend space. Due to the fact that the input theories may contain inconsistent information, the injections are partial in general.

most surely by itself is not enough in order to devise the ideas of very-large-scale integration (i.e., the creation of integrated circuits by combining thousands of transistors into one single chip). We claim that this is exactly where CB comes into play.

HDTP now provides a framework for a CB-based computation of novel concepts given a source and target domain: Assume two input theories S and T are given. The computation of an analogical relation between S and T by HDTP outputs (besides other things) a shared generalization G of S and T by the anti-unification process. This generalized theory G functions in the further process as the generic space in CB mentioned above. The construction of the blend space is computed by first, collecting the associated facts and rules from S and T generated by the analogical relation between S and T and second, by projecting unmatched facts and rules from both domains into the blend space. This second step can result in clashes and inconsistencies. Furthermore, the coverage of the blend space concerning S and T can be more or less maximal. Taking additionally into account that for every given S and T HDTP can compute different analogical relations, there can be many possible blend spaces for a given input. Figure 5 depicts diagrammatically the overall structure of concept blending using HDTP.

HDTP has successfully been used to compute concept blends in complex domains like mathematics. In [10], Lakoff and Núñez's mathematical grounding metaphors [15] are modeled that are intended to explain how children can learn a rudimentary concept of numbers based on simple real-world actions in their environment. These metaphors and the emergence of an abstract number concept can be explained by analogy-making and concept blending. In [16], the invention of a geometrical interpretation of complex numbers (i.e., the complex plane) was computationally modeled by concept blending. This example shows that even for rather formal and complex theories the creative generation of a new concept can be computed using a logical approach.

5 Conclusions

In particular for AGI systems, creative problem solving abilities and the finding of novel solutions in unknown situations seems to be crucial. We consider creativity as a crucial step towards building a general form of AI. From a cognitive perspective creativity can often be reduced to cognitive mechanisms such as analogy-making and concept blending, which in turn can neatly be modeled using logic-based approaches. Therefore, the apparent tension between creative abilities of agents and a logical basis for their modeling disappears.

In fact, we are not the first ones to investigate into the computational modeling of creativity as a cognitive capacity. Going back already to work by Newell, Shaw and Simon [17], researchers in AI and related fields over the decades repeatedly have addressed different issues and aspects of creative thought. The results of these investigations range from contributions on the more conceptual side (as, e.g., Boden's theory of P- and H-creativity [4]), to concrete implementations of allegedly "creative systems" (as, e.g., The Painting Fool [7]). And also in the computational analogy-making domain there already is relevant work on the relation between creativity and analogy, most prominently exemplified by Hofstadter's contributions related to the Copycat system [11]. Still, on the one hand, work on issues of creativity within human-style intelligent systems this far has not gained wide attention in an AGI context. On the other hand, even within the more general setting of computational creativity research, only very few approaches try to integrate models of different cognitive capacities into a system aiming for general creativity capacities, instead of limiting the focus to modeling one specific kind of creative act.

This paper sketches the necessity to tackle the hard problem of creativity in AGI systems. Although the described HDTP framework has been applied to show that the computation of interesting blend spaces can be achieved in certain rather complex (but highly specific) domains, no generalizations of such specific examples exist so far. This remains a task for future work, besides a further formally sound and complete characterization of concept blending on a syntactic and semantic level.

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