From Simple Machines to Eureka in Four Not-So-Easy Steps. Towards Creative Visuospatial Intelligence.

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Abstract This chapter builds an account of the cognitive abilities and mechanisms required to produce creative problem-solving and insight. Such mechanisms are identified in an essentialized set of human abilities: making visuospatial inferences, creatively solving problems involving object affordances, using experience with previously solved problems to find solutions for new problems, generating new concepts out of old ones. Each such cognitive ability is selected to suggests a principle necessary for the harder feat of engineering insight. The features such abilities presuppose in a cognitive system are addressed. A core set of mechanisms able to support such features is proposed. A unified system framework in line with cognitive research is suggested, in which the knowledge-encoding supports the variety of such processes efficiently.

1 Introduction

We are still far from building machines that match human-like visuospatial intelligence, creative problem solving, or the more elusive trait of insight. Creativity and creative problem-solving have fascinated humans ever since individuals able to wield such skills with great prowess have existed, generating many legends and anecdotes. Thus Archimedes is said to have had the insight of how to measure the volume of a crown while immersing himself in a bathtub (Vitruvius Pollio, 1914). Watson has recounted to have dreamt of spiral staircases before settling on the double helix solution for the problem of the structure of DNA. In a speech given at the German Chemical Society, Kekulé mentioned to have day-dreamt an Ouroboros-like snake biting its tail or a tibetan knot before discovering the structure of benzene (Fig. 1).

These introspective and sometimes second-hand accounts cannot be taken as facts, but as descriptions of various phenomenological experiences of insight in problem-solving (or assumptions about these experiences if the account is second-hand).To discriminate the myth from the fact studies in empirical settings on insight problem-solving and creativity have been employed (Maier, 1931; Duncker, 1945)

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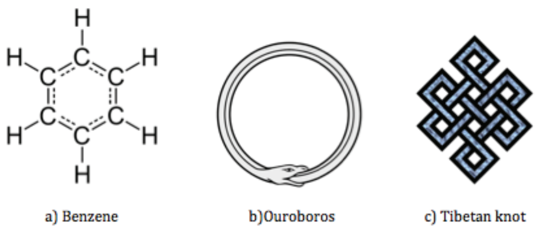

Fig. 1 A depiction of Kekulé's day-dream: a) The benzene molecule; b) Ouroboros symbol of a serpent eating its own tail; c) Tibetan knot.

and creativity tests developed (Kim (2006) offers a review of one of the most used such tests - TTCT - the Torrance Test of Creative Thinking).

Yet some of these accounts coalesce in their narrative, pointing at similar phenomenology. This invites the question whether such similar phenomenology is the result and indicator of a certain set of cognitive processes or the phenomenological narrative converges because a narrative schema[1] about insight has become ingrained in our culture. If the answer is the former, these accounts might hold some reverse-engineering potential for cognitive and AI scientists, which could work their way back from phenomenological effects [2], using as a lead the cognitive processes that have generated them, to further decypher the hidden mechanisms of insight.

Phenomenological complications aside, insight and creative problem-solving generally figure amongst the pinnacle of human cognitive abilities (other animals are capable of creative tool use (Köhler, 1976) and some analogy-making (Gillan et al, 1981), however we are unaware of any experimental set-up able to test for insight in animals). Individuals able to produce great leaps of thought seem to have always existed among us (Watson, 2005, 2011), yet creative problem-solving is something many normal human beings do on a day-to-day basis - when putting a new mechanism together out of known parts, improvising a tool when lacking one, coming up with new ideas, concepts and strategies, adapting older problem-solving strategies to new situations. Compared to the achievements of other primates or artificial intelligence agents, even the smallest human creative intelligence accomplishments are remarkable.

We define *productive cognition* (cf. Wertheimer (1945)) as the general ability to create new knowledge, concepts, tools and objects, mechanisms, theories and

[1] Several different proposals which aim to summarize all macro-narratives exist, a compelling one being offered by Booker (2004), however for a computational treatment of micro narrative schemas see Chambers and Jurafsky (2010). In the context of insight, the established narrative schema could be about inspiration that comes to the discoverer after a lot of work in a spontaneous flash, in which various parts of the problem are "perceived" together with similar inspiration-conducive objects.

[2] This can hold true only if the imagery which accompanies insight is real and in direct relation to the causal processes of insight - i.e. visual imagery is perceived because visual components of concepts are activated and worked upon with visual and other processes in order to propose a solution

systems of thought. The emphasis here is on producing a new object or a solution that has not existed or was not known or experienced before. Research into creativity, creative problem-solving and insight, all aspects of productive cognition, has valuable potential impact for both AI and cognitive science. The engineering applications are related to smarter, more robust AI systems, which can solve tasks in new environments with higher flexibility and an ability to adapt their previous knowledge to the new problems they encounter. Ideally these agents should be able to produce new information (concepts, theories, new relevant relations, hypotheses on how to represent problems), the usability of which can then be tested by classical computational paradigms. The benefits for cognitive science are in what the computational modeling of and experimentation with such abilities can tell us about how they function in their natural state in human cognition.

For artificial systems, creative problem-solving poses a high complexity challenge, bringing about the question how new types of knowledge and hypotheses can be created that are actually useful, other than by logical inference. For cognitive science, the issue is rather what kind of representations and processes enable the functioning of such abilities. These two questions connect and this chapter deals with them in tandem.

A unified framework (Newell, 1994) aimed at exploring and implementing cognitively-inspired creative problem-solving and insight is proposed. Here the scientific interest is focused on determining what kind of knowledge representation-processing pairs can generally support a variety of creative problem-solving processes with more ease than previous computational paradigms. To determine such types of knowledge representation and processes, an essential set of cognitive abilities and the features they presuppose in a cognitive system is analysed. These abilities each illuminate a different cognitive mechanism needing implementation in order to reach higher abilities in productive systems. The way all these mechanisms can be integrated to participate in the higher-level abilities of creative problem-solving and insight is then shown. Furthermore, the framework is constructed on an initial visuospatial inference ability, which if replicated should account at the problem-solving level for similar phenomenological effects as Watson's and Kekulé's accounts.

The rest of this chapter is organised as follows. Section 2 gives a flavor of the matters which have preoccupied researchers in the various aspects of productive cognition: creativity, creative problem-solving and insight, thus presenting the issues involved in the construction of a creative problem-solving framework. Section 3 defines such a framework in four steps, elaborating on the cognitive features which need implementation and proposing knowledge organization and knowledge processing mechanisms, in a path from visuospatial intelligence to insight. Section 4 concludes the chapter with a discussion about the cognitive abilities the system presupposes as essential, a birds-eye view about how the mechanisms that are proposed at each level interact, and future work required to implement, test and refine this theoretical framework.

2 Aspects of productive cognition: creativity, creative problem-solving and insight

2.1 Creativity and creative problem-solving

Boden (2003) distinguishes between historical creativity (h-creativity), which produces results original on the scale of human history, and psychological creativity (p-creativity), which yields contributions that are creative from individual perspective. She further differentiates between combinatorial and exploratory-transformational creativity. Combinatorial creativity is a form of producing new, unusual combinations or associations out of known ideas. Exploratory-transformational creativity is an exploration of variations, and changes to/restructuring of the conceptual space. As the term *conceptual space* is not very clearly defined (Ritchie, 2001; Wiggins, 2001), its compatibility with uses by others (Gärdenfors, 2004) is hard to determine.

Another lens through which creative processes are approached is that of the difference between convergent and divergent thought (Guilford, 1967). Convergent thought is assumed to employ previously known reasoning strategies, familiar heuristics and data, as to arrive to an accurate, logical solution. By contrast, divergent thought is a search for many different potential solutions, with various degrees of correctness, where the emphasis is on production of a diversity of possible solutions, not on accuracy. Thus divergent thought is assumed to be creative and associative in nature, exploring multiple possible solutions and courses of action, and evaluating them in a quick and rough manner. Such solutions don't need to be logical or traditionally used heuristics - they can be associationist in nature, using previous knowledge from different fields to enable what is popularly described by the term of "leaps of thought". However, this categorization is rather abstract, with each category being able to contain many processes, and creative problem-solving is the type of endeavor which assumes both abilities - a divergent stage to find possible different solutions, and a convergent one to follow through the consequences of such solutions.

Implicit processes are generally considered to play an important role in creative problem-solving, with some models focusing on explicit-implicit process interaction (Hélie and Sun, 2010). The incubation stage in insight is considered to be a process which takes place under conscious awareness. However, the relationship between the concepts of divergent thought, implicit processing and the incubation stage has not been clearly disseminated in the literature (though one can assume some degree of overlap).

Important roles in creativity are played by analogy (Holyoak and Thagard, 1996) and metaphor (Lakoff and Johnson, 1980, 1999). Both analogy and metaphor are generally considered to be processes of transferring knowledge from a known field (source) to a less known field (target), with various purposes, like: enriching the unknown field, having some starting assumptions and knowledge to test, explaining that field to a learner in a fashion which is connected with knowledge that the learner already possesses as to allow for a quick comprehension start in the new field, aesthetical effects (with comprehension consequences).

An important aspect that any theory of creativity needs to account for is concept generation or composition. Concept formation literature in its various forms (prototype theory - Rosch (1975), exemplar theory - Medin and Shoben (1988), theory theory - Murphy and Medin (1985)) has not traditionally dealt with aspects of concept composition. More recently theories have been proposed on this matter (Aerts and Gabora, 2005; Fauconnier and Turner, 1998). The latter, a conceptual blending account, proposes that various elements and relations from different scenarios or concepts are blended in an unconscious process, as to produce new concepts. This account finds its ancestry in Arthur Koestlers concept of bisociation of matrices (Koestler, 1964).

Concept discovery (Dunbar, 1993) and restructuring (possibly linked to Boden's transformational creativity processes of restructuring the conceptual space) are an important feature in other creative cognition activities - scientific discovery (Nersessian, 2008; Langley, 2000; Klahr and Dunbar, 1988) and technological innovation (Thagard, 2012).

The essential difference between creativity and creative problem-solving seems to be one of evaluation type. Creativity is not enough to problem-solve, as an emphasis is put on the utility of the solution, or of the new knowledge and exploration forms (conceptual tools, ideas) created in the problem-solving process. Ultimately, the aesthetic and originality value of a creative solution fades in front of its utility or lack thereof.

This adds hardship in the construction of such a system, but helps in the evaluation process. The constraints bring about the benefit that utility is measured with more ease than aesthetic value and even originality. However, a system's ability to propose new solutions, hypotheses or approaches towards a problem, which might not ultimately work in practice but are valid proposals with chances of success from a human perspective, is a good enough criterion for satisficing creative problem-solving demands.

A specific though challenging kind of creative problem-solving which might shed some light on the cognitive mechanisms at work is insightful problem-solving.

2.2 The general problem of insight

In the context of Boden's taxonomy (Boden, 2003), two types of insight can be determined - a p-creative one (finding the representation which can lead to solving a problem that has been previously solved by others) and a h-creative one (finding a new solution or problem-representation altogether, a case found in the realm of scientific discovery and technological innovation). In order to address the issue of knowledge organization and processes a machine would need to possess to be able the have insight the way humans do, we will focus here on red thread features generally associated with insight (of both kinds). We will however address this distinction again in section 3.4.

Encyclopaedia Britannica defines insight (2014) as:

> ”immediate and clear learning or understanding that takes place without overt trial-and-error testing. Insight occurs in human learning when people recognize relationships (or make novel associations between objects or actions) that can help them solve new problems”

In Sternberg and Davidson (1996) insight is:

> ”suddenly seeing the problem in a new way, connecting the problem to another relevant problem/solution pair, releasing past experiences that are blocking the solution, or seeing the problem in a larger, coherent context”

One example of an insight problem which has been studied in empirical settings is the candle problem (Duncker, 1945). The participant is given a box of thumbtacks, a book of matches and a candle. The task is to fix the lit candle on a wall so that the candle wax won‘t drip onto the table below. The participants give various solutions, including attaching the candle with a thumbtack to the wall, or glueing it with part of the wax. The traditional correct solution to this problem is to use the box of thumbtacks as a platform for the candle, and attach it to the wall using one of the thumbtacks. The accuracy and speed of the participants in solving this problem increases when the box of thumbtacks is presented empty, with the thumbtacks out. A possible reason for this is that participants find it harder to see the box as a platform while its affordance as a container is already used (through the box being full).

In Maier’s classical two string problem (Maier, 1931), the participants are put in a room which has two strings hanging from the ceiling. Their task is to tie the two strings together. It is impossible to reach one string while holding the other. However, various objects are scattered across the room. The traditional solution to this problem is to use a heavy object (normally the pliers), attach it to one of the strings, then set that string in a pendular motion. Finding this solution can be triggered by the experimenter touching the string, thus making salient its motion affordance and directing the subjects to think of the string as a pendulum.

The literature on insight generally uses a four-stage process proposed by Wallas (1926). The four stages are: familiarization with the problem, incubation (not thinking about the problem consciously), illumination (the moment of insight) and verification (checking if the solution actually works in practice). Whether the illumination phase presupposes sudden or incremental problem-solving processes is still debated, and various researchers insist on the importance of various stages. A good general set of characteristics for insight problems is proposed by Batchelder and Alexander (2012):

1. They (insight problems) are posed in such a way as to admit several possible problem representations, each with an associated solution search space.
2. Likely initial representations are inadequate in that they fail to allow the possibility of discovering a problem solution.

3. In order to overcome such a failure, it is necessary to find an alternative productive representation of the problem.
4. Finding a productive problem representation may be facilitated by a period of non-solving activity called incubation, and also it may be potentiated by well-chosen hints.
5. Once obtained, a productive problem representation leads quite directly and quickly to a solution.
6. The solution involves the use of knowledge that is well known to the solver.
7. Once the solution is obtained, it is accompanied by a so-called “aha!” experience.
8. When a solution is revealed to a non-solver, it is grasped quickly, often with a feeling of surprise at its simplicity, akin to an aha! experience.

The main challenge in replicating insight in artificial systems is that insight problems are not search problems in the traditional (Newell and Simon, 1972) sense. The problems are ill-structured (Newell, 1969) for a classical search-space type of solving, and defining an appropriate representation is part of the solution (cf. Simon (1974)). For humans, this is the point where functional fixedness gets in the way - with solvers getting stuck in representation types which are familiar and sometimes seem implied by the problem, but are actually inappropriate. Thus a machine replicating such phenomena will have to be able to do some form of metareasoning and re-representation.

3 A framework for creative problem-solving based on visuospatial intelligence

Various work relates visuospatial intelligence to the creation of abstract concepts, and to the process of abstract thought in general (Mandler, 2010; Freksa, 1991, 2013). Thus Mandler proposes that complex abstract concepts are built developmentally on top of already acquired spatial concepts. This would explain the pervasiveness of spatial templates (Lakoff and Johnson, 1980, 1999) in human metaphor, spatial priming influences (Tower-Richardi et al, 2012) and shape bias (Landau et al, 1988; Imai et al, 1994). In his analysis of 100 scientific discoveries (Haven, 2006) and 100 technological innovations (Philbin, 2005), Thagard (2012) draws the conclusion that 41 out of the 100 scientific discoveries involve visual representation (spatial representations is unaccounted for in this analysis though some references are made to kinesthetic ones), with the figure rising to 87 out of the 100 in the technological innovations category. A cognitive architecture which proposes the use of spatio-analogical representations (Sloman, 1971) in the modeling of human spatial knowledge processing, without linking them to creative problem-solving is Schultheis and Barkowsky (2011).

The framework proposed here takes into account the importance of visuospatial representations and processes, starting from the general hypothesis that analogical representations and visuospatial (and structure-oriented) processes can be a good representation-process pair for the recognition, manipulation and modification of structures and relation-sets which is necessary in creative problem-solving. Such mechanisms might also offer a bridge over the explanatory gap towards introspective imagery phenomenology which sometimes accompanies moments of insight or creative problem-solving. The rest of this section sets to explore whether abstract creative problem-solving mechanisms can indeed build on simple visuospatial inference mechanisms.

3.1 Step 1 - Visuospatial inference

In his paper, Sloman (1971) talks about "formalisation of the rules which make non-linguistic, non-logical reasoning possible". He also gives an example (Fig. 2) of visuospatial inference. Fig. 2 a) shows a mechanism made of two levers and a pulley, the upward arrow being an indication of the initial direction of motion. The reader should have no problem in visually inferring how the motion propagates through the system, as to arrive at the result represented in Fig. 2 b).

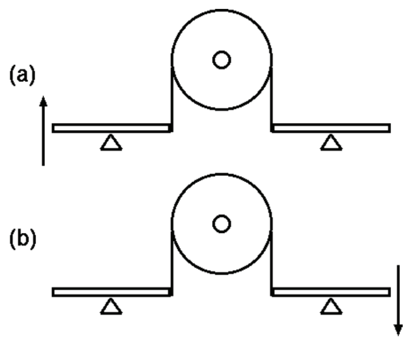

Fig. 2 Sloman's diagram of two levers and a pulley: (a) motion onset and (b) inference result.

For a human with cultural familiarity with pulleys and levers, such an inference is visually very simple. However, we take its simplicity for granted, as it comes from our complex visual system‘s ability to anticipate the motion of objects which it has already learned. Visuospatial inference seems simple because it is a native feature of the human visual system.

To be able to replicate such an ability in artificial intelligence terms, one would have to implement some of the properties of the cognitive visual system that humans generally take for granted. This problem could be translated in AI terms, by giving an artificial system a subset of the six simple machines of antiquity (levers, wheel and axle, pulleys, inclined planes, wedges and screws), together with visuospatial and motor knowledge about each of them. The system could be asked to perform a qualitative assessment of what a machine assembled out of some random set of these components will do - the way the motion will propagate via the so assembled mechanism. This is but a step away from Sloman's example as it involves visuospatial inference with multiple parts and can be thought of as a perceptual task.

This task can be solved by a system via a form of perceptual simulation. One can encode motion affordances together with the pattern recognizer for each specific object in such a way that seeing a certain simple machine shape triggers the anticipation or simulation of motion in the artificial system. Whether the simulation of the entire motion is necessary, or just the beginning and end result of such motion can be accessed (once encoded) is something to be settled by cognitive empirical investigation. The system then needs to be endowed with qualitative rules on how motion propagation works between objects which are in contact, and the various ways in which motion changes, or (allowed to learn from) motor simulations of such transitions.

However, as mentioned before, this can be thought of as perceptual inference. In order to talk about problem-solving, two other tasks can be given to the system, in the same problem context:

– to put together a machine starting from a set of known components as to propagate motion in a desired way (multiple solution possible)
– given a set of fixed components, to add missing components so that the mechanism performs a certain type of motion at the end. The number of missing components can be specified or unspecified, however they will be produced out of the system's memory of known machines.

Such problem-solving can rely on the same perceptual simulation (complete or partial) and rules of motion transfer (thus can be entirely visuospatial). In fact it could be a learning trial-and-error process of compositionally adding objects together and checking their motion affordances. The compositionality features allow for objects to be thought of both in terms of simple machines and new composed machines with varying motion affordances.

The implementation of such a system will solve motion anticipation problems with simple machines, and compositionality problems with simple or composed machines based on their capacity for motion. Besides having interesting features for visuospatial reasoning (maybe an equivalent for a " block-world" classical problem setting), this problem sets the scene for the next steps towards creative problem-solving and insight in a variety of interesting ways. It deals with simple compositionality and decompositionality of objects: an object can be made of various atomic simple machine parts and different compositionality structure can mean different motion affordance, therefore the structure of assembly is essential. The problem can allow for multiple solutions from the part of the solver, and it requires use and manipulation of previous knowledge structures. It is solved based on affordance and compositionality. These features are primitives which we will relate to in the next steps.

3.2 Step 2 - Creative use of affordance

Humans are used to perceiving the world not just in terms of motion anticipation, but also in terms of the affordances (Gibson, 1977) that various objects can offer a user, depending on the task at hand. Knowledge of affordances can be considered as a part of commonsense knowledge which displays cultural aspects (as various cultures can be more accustomed to certain objects or tools than others). The cultural variation element does not play a role here, as knowledge of affordances can be treated as a knowledge database which can take whatever form, and thus belong to whatever culture.

Of interest here is the human ability to make creative use of object affordances. When trying to find something to pour liquid in, to carry liquid with and drink from, in conditions in which no cup is available, humans can use a pot, a bucket, or - depending on how desperate the circumstances are - a boot. When wanting to put nails in the wall in the absence of a hammer, humans can use shoes, stones of appropriate size, or other objects. Thus humans can creatively solve problems of the following form: Find an object with a certain affordance, when the object(s) you normally use is not available. Humans can find such objects even if the objects are not normally associated with such an affordance, by speculating on the various properties objects have, and their knowledge about the properties which are normally associated with the affordance.

This type of problem represents a way of making creative inference and use of the affordance properties of objects. In the following we will propose the rough principles of a mechanism for suggesting useful objects in such problems to an artificial agent.

Even simple visuospatial properties such as object shape can lead to inference about affordance. The phenomenon of shape bias (Landau et al, 1988; Imai et al, 1994; Samuelson and Smith, 1999), in which children extend names from known to unknown objects based on shape, shows that the human brain considers shape features very important in the context of objects and tools - possibly because of a connection between shape and affordance in these domains. In what follows, we will propose a mechanism which makes good use of shape in proposing hypotheses, though this can and should be refined to contain more detailed properties which are in a direct relationship with objects' affordances.

To solve such a problem in the spirit of grounded knowledge (Barsalou and Wiemer-Hastings, 2005; Barsalou, 2003; Gärdenfors, 2004), we propose to represent the various objects and tools that the agent knows as distributed concepts. The concepts are distributed over a set of spaces - an affordance space, a visual feature space, and a semantic tag space. Each of these spaces will be organized by similarity, though the similarity metric would be different, depending on what the space contains. Thus visuospatial feature spaces will be organised in terms of feature similarity (of shape, color), verbal tags in terms of semantic or context similarity, affordance spaces in terms of motor trajectories or proprioceptive routines, etc. These spaces could be encoded as self-organised maps (Kohonen, 1982). The recognition of an object, or activation of a concept in such a system, would mean the associated activation of points or regions in these spaces (Fig. 3). Thus, each concept would be an activation of features over different dimensions, part of which will be more sensory oriented (e.g. the visual features spaces), more functionally and bodily oriented (affordance and motor spaces), and more knowledge oriented (the semantic spaces). Such a cognitive concept could be triggered in a variety of ways: (i) via the semantic tag (its name), the activation of which would spread energy in the other direct links (how the object looks like, what functions does it normally perform), (ii) via vision input, or (iii) a query related to the affordance which is required.

We prefer such a type of knowledge encoding because the meaning of a concept in such a system becomes grounded in the feature maps, affordance spaces and semantic spaces which we are using (the symbolic paradigm which assumes the meaning is in the verbal form of the concept is refused). However, the proposed mechanism is a hybrid mechanism, as a concept can be interpreted as a symbol (where a symbol is a collection of features, grounded in subsymbolic processes).

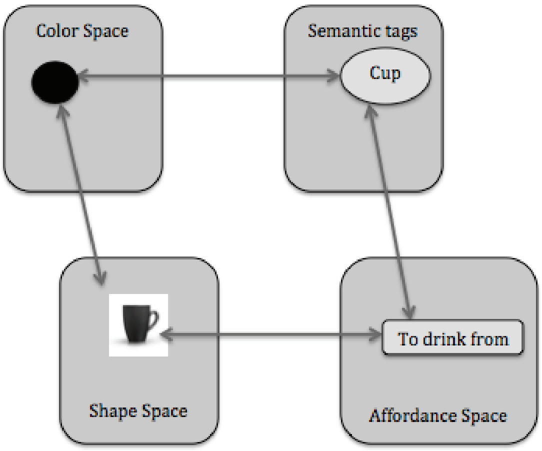

Fig. 3 Activation of the concept "cup" over two visuospatial feature spaces, a semantic tag space and an affordance space.

Such knowledge organization is useful in two ways. One is that the concept can be activated in different ways, with the entire knowledge network retained about it becoming active. Navigation between such different types of knowledge about one object is possible in natural cognitive systems. Such activation also implies a second benefit, that comes from the encoding in similarity-based maps - navigation between different encoded concepts based on different types of similarity. Thus, when a cup is the direct activation for a certain type of affordance, other neighborhood object shapes are activated as well, with the new object being able to act as a creative substitute, though it might not constitute a traditional solution, nor the type of object the user normally applies in such circumstances.

When a request is made to the system to find an object that is required for a certain affordance (Fig. 4), the system will first activate the corresponding concepts linked to that affordance (the request is in fact the activation), with the most familiar objects receiving the highest activation. Then the solution object(s) can be searched for in the environment visually. When such a search fails, the threshold of the search drops, and the object will search for something of a similar shape to the familiar solution-object (by quantitative (Forsyth and Ponce, 2003) or qualitative (Falomir et al, 2013) means) or/and to objects which are encoded closely to that object in its shape knowledge map. Thus, creative solutions which are not what one set out to search for exactly but can fulfill the function nonetheless can be obtained with limited knowledge, in a visual manner.

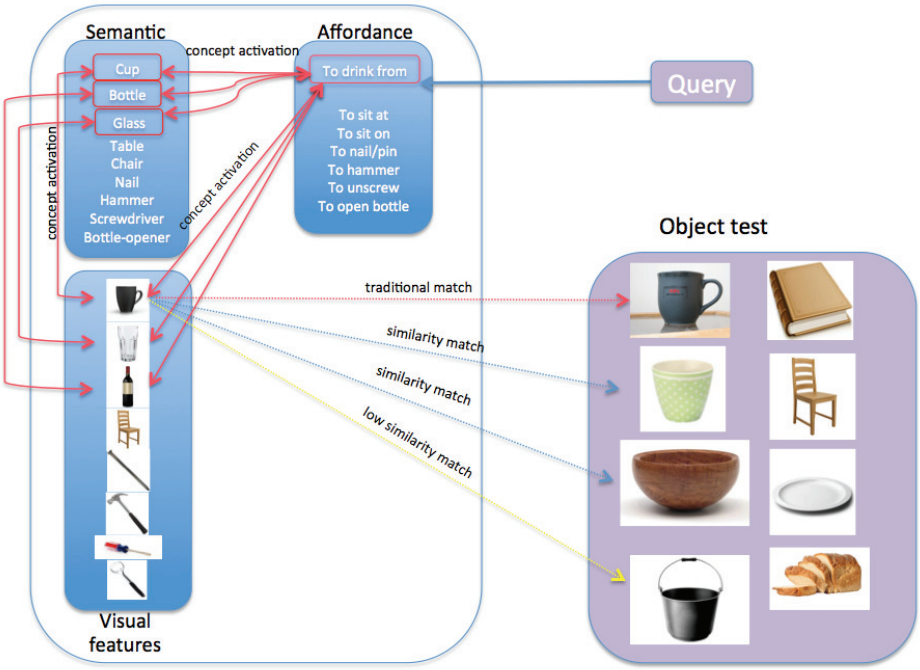

Fig. 4 Affordance-based system in action.

3.3 Step 3 - Concept generation and structure transfer

The third step in this quest for visuospatial creative problem-solving and insight is treated here in two parts. Part a) deals with the generation of new concepts, and part b) with problem structure transfer.

3.3.1 Step 3A - Generation of new concepts

Humans can make analogies, use metaphors (Lakoff and Johnson, 1980, 1999), blend concepts (Fauconnier and Turner, 1998) and sometimes put together features of previously known concepts to create entirely new concepts (like *meme*, *impressionism* or *recursive*), or invent entirely new objects from previously accessible parts or elements.

In making analogies, an important role seems to be played by concept structure and ability to compare and structurally align source and target domain (Gentner, 1983, 2010). Spatial schemas are proposed by Lakoff and Johnson (1999) as a process of metaphor creation.

In the proposed framework, the relevant cognitive properties required for concept generation are:

- Associativity of similar concepts on various feature spaces (previously explained in step 2),
- Ability to map a structure in a different feature space, and
- Ability to build concepts compositionally.

In what follows, a few visuospatial processes which make concept generation possible in an artificial system are proposed.

The first process consists of using a previously observed visuospatial relation as a template. Consider an artificial intelligence system that has encoded the relation “chaining” as a visuospatial object - starting from the analogical representation of a chain. The relations encoded in the analogical representation of the object can be used as a template for other units than chain links. First the relations could be extrapolated to similarly shaped objects - like a hoop of string and a scissor’s eye (Fig. 5). In the proposed framework, due to visual similarity in the knowledge encoding, such an inference would be natural. The system would thus propose to extend the previous relation, using its template, to other visually similar objects. Such inferences will hold only part of the time, but this is an example of productive reasoning (reasoning which creates a new arrangement of objects in this case), and of transforming the visuospatial analogical representation of a concept into a template for new object arrangements.

Though initially applied to objects with similar visual features, this particular template-relation can be applied at various levels of abstraction, up to concepts like ”chaining of events”.

Of course not all abstract concepts are derived from visuospatial analogical representation. The point here is to show how some can be derived, as an analogical representation is a very economic way to store relations, and can be used as a structural template for creating new concepts.

A second process that can be used for concept generation is compositionality over such templates. Thus, take the two-tuple relation “bigger-than” as observed in or learned from an example of two trees (Fig. 6). An artificial system could match it by size or shape similarity, or use the principle of chaining to a second bigger than relation of two other trees. Via compositionality, this would lead to a three (or more)

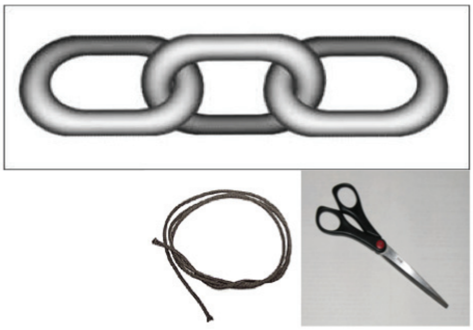

Fig. 5 Use of analogical representation of a “chain” as a template for the “chaining” relation.

tuple relation, which would lead to a representation of the concept of “growth”. This visuospatial representation of the concept could be used as a template again, via the first process, and adapted to a variety of different domains.

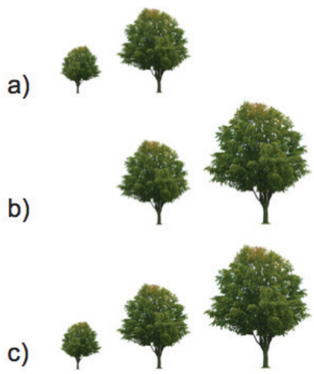

Fig. 6 Compositionality of relation - from “bigger-than” to “growth”.

Some such visuospatial datastructures could be compressed to a small subset of features which are consistent across templates, like an upward arrow and a definition of contour (Fig. 7). This could be used as an iconic compressed trigger that can activate the concept and stand in for it.

Thus analogical visuospatial representations can act as mechanisms for concept generation by being used as templates or in applying compositional principles based on similarity principles or visual routines. Such a system could keep track of relations between such templates based on its own experiences with concept generation in a visuospatial semantic map (where semantic is to be understood as meaning re-

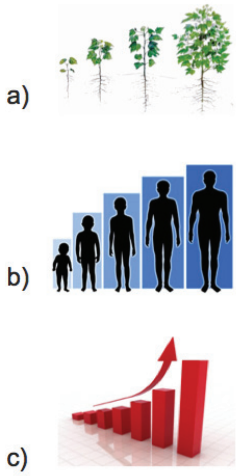

Fig. 7 Transition from (a) growth template representation, which is (b) adapted to a different concept and (c) compressed.

lations between such templates), and attempt future composition principles based on such learning (or return to a decomposed form where necessary).

Concept blending can also be implemented by treating concepts as distributed structures over feature spaces, in which the two concepts which participate in the blend each contribute in a varying degree to the structure (and positioning on the feature space) of the new concept. However, for the current purposes, the description of creation and proposal of new structures proved to be a more interesting cognitive feat.

3.3.2 Step 3B - Problem structure transfer

Problems like the tower of Hanoi are easily solved by people that have understood their heuristics, no matter the shapes of the objects used in the problem presentation. This leads to the obvious conclusion that people are able to detach heuristics from the surface features of the problem, and understand problems in terms of their structure and the heuristics that apply to various structures. General heuristics, like means-end analysis or divide and conquer, are routines which can be deployed independent of the domain. However, the surface features of a problem do play a role in problem-solving, certain problems being solved with much more ease when presented in a certain visual form than in isomorphic but different feature forms (Zhang, 1997).

Thus, for humans, a case can be made for both the importance of problem structure, and the importance of surface features in problem-solving efficiency. A system constructed in this proposed framework could deal with both, as follows. A solved problem can be encoded as a distributed structure over the objects and concepts the problem contained (at a lower level their features), the algorithmic steps that have been taken (at a lower level affordances or succesions of motor routines) and the various relationships that have been established during this solving. In the case of a new problem, similar on enough of the encoded properties above, the system could trigger via a form of pattern-completion the previous problem structure - and attempt a subset of similar steps or relation-formation.

The structure could also be elicited in a more direct fashion via remarking upon structural similarities between the problem at hand and a previously solved problem (not on features of the participating objects), or on sets of relations which are common to both. In both cases, the structure of a previously solved problem would thus be transferred to the problem at hand. In case objects of the problem solution or structure are missing, objects and concepts with similar affordances can be used (due to the ability to de-chunk the problem offered by distributed representations).

The essential points in knowledge organization for problem structure transfer are thus threefold:

- It requires the encoding various problem-structures together with their respective component elements and problem-solving procedures (set of affordances, algorithm)
- The ability to match problems to previously known problem-structures and their solutions
- The ability to decompose or recompose problems, as to use different structure-affordance pairs

The last point is further tackled in the issue of insight, when one problem representation structure is not enough.

3.4 Step 4 - Insight revisited

As previously discussed, insight is a problem of re-representation, such problems are not solvable via normal search spaces, and their solving doesn't seem to proceed in a step-wise fashion: unlike in non-insight problems, the problem-solvers cannot predict their level of progress or their closeness to the solution (Metcalfe and Wiebe, 1987).

In insight problems, it is as if finding the right problem representation is the solution itself. A good representation affords insight directly, by providing the solver with the ability to make the inferences which will lead to the solution. It is thus assumed here that in such problems a form of metareasoning or meta-search happens over the representational structures which can be fitted to the problem, in order to find the one which most obviously affords the (inferences towards the) solution.

In many insight problems, the main problem is thus finding the right problem structure, which is not the normal problem structure that will be ellicited by the objects presented. The various objects participating in the problem have been involved in the commonsense knowledge or can be involved in the commonsense inference of a human being in a variety of problem structures, they posses a variety of affordances. In this framework, insight is defined as a matter of navigating these ellicited structure-affordance pairs until the right one is found (from which further inferences can proceed to a solution). The meta-search space in this framework is richly informed. It encodes the knowledge of the system, together with its similarity metrics over various spaces, and distributed structures with generative compositional properties. The movement in such a search space happens in various dimensions via the similarity of features, context (semantics) and affordance (function) of the distributed objects and templates. This type of knowledge encoding permits informed search via movement through similar structures, or similar objects and the structures they are part of, and creation of new conceptual tools, relations and objects. The right problem structure can be found when searching for a affordance, for similar structures, relations or objects/concept sets.

A different case is that of scientific discovery problems (another variety of the Eureka step), in which it is natural to assume that the ”right” problem representation is not in fact found, but created. This framework allows for problem templates to be decomposed, blended, put together, and missing parts to be created out of similarly-affording structures, until a representation is found or created. To close the circle, in the light of the previous steps and the knowledge encoding and processes previously used, solving insight problems (in both forms) becomes somewhat similar to putting simple machines together. The search this time is not one over the known set of simple machines, for the appropriate machine or set of machines to be fitted to the problem of obtaining a certain type of motion or affordance, but for the appropriate problem representation, allowing for compositionality from problem representation fragments, in order to find a problem representation which affords a solution or set of inferences. The motor affordances of the various simple machines are replaced in this case with the affordances the various problem templates can solve.

4 Discussion

Productive systems deal in a flexible fashion with the problems they encounter, as to be able to propose new possible solutions based on the knowledge at hand. The framework explored here presupposes a few cognitive properties as being essential for building efficient such productive systems. Efficiency is understood here as computational ease of processing. The proposed framework supports through its knowledge encoding exactly such types of search for a creative solution and re-representation, as to account for cognitive economy principles.

One of these properties is a multidimensional (multisensorial) encoding of concepts (Barsalou, 2003), which allows for dynamic memory access based on affordances, visual features or semantic tags. Beside such dynamic access, distributed encoding of concepts allows further grounding in learned, similarity-based organized knowledge and associativity (with traditions in hebbian learning (Hebb, 1949), semantic networks (Sowa, 1992) and associationism). Such grounding allows for easy navigation of the knowledge space. In a sense, the knowledge space thus becomes the equivalent of a search space in classical problem-solving. However, not all possible states or solutions are mapped. The knowledge encoding merely acts as a map which enables the aforementioned processes to produce more knowledge in a structured, organised manner.

A connected third cognitive property assumed here as essential is flexible, relaxed pattern-recognizing constraints; this allows for non traditional but similar objects to be recognized and accepted as solutions. Essentially this is related to the reality of our imperfect, constructive memory. Though when compared to its machine counterparts a less than optimal part of the human experience, human memory and its imperfections support learning, interpretation and re-interpretation, classification and re-classification, generalization and, by extension in this framework, creativity and creative problem-solving (rather than a perfect ability to reproduce the things we have perceived with accuracy).

The four steps presented here construct in a coarse manner the necessary abilities of a productive system from the ground up.

- Step one - visuospatial inference - associates visual features, shapes and structures (for the 3D case) with motion affordances, in order to enable motion anticipation in a mechanism composed of simple known parts. This allows simple compositionality principles of affordance, and pattern-fill principles when a small number of objects is given and a mechanism has to be constructed.
- Step two - creative use of affordance - extends the distributed concept encoding, with supplying feature maps organized on similarity principles. This supports a natural search for objects with similar features, affordances or that have been experienced in similar contexts. The flexible threshold in pattern recognition, together with the associativity links enable solutions to be proposed that are not traditional.
- Step 3a) deals with processes for generating new concepts. This creates a conceptual map in which some analogical representations can be used as (1) relation-templates, (2) compositional units that together create new relations, and (3) compression to essentialized visual features. Moreover, the map can keep track of the generative process, and keep relations between the analogical representations which have created new representations through such processes.
- Step 3b) discusses transfer of problem structure into a different problem, based on affordance knowledge (and other possible similarities) of the two structures. This gets closer to the principles of meta-representation, which is attained in step 4. Step 3b) deals with the ability to transfer a set of heuristics, or a problem structure, rather than a small set of relations, that are enclosed in an analogical representation, like in 3a).
- Step 4 puts all the aforementioned principles together. All concepts are grounded in similarity-based maps, where the similarity metric depends on the type of map itself (be it a feature map, an affordance map or a semantic context map). New concepts, conceptual objects and sets of relations are generated as in step 3a), and kept in relations to each other. Problem structures can be transferred in other ob-

ject spaces. This type of knowledge representation and the aforementioned processes allow for easy re-representation and creation of new problem templates. The framework at this level supports meta-search over known pairs of problem-structure and affordances, enabling the system to find a suitable representation for the problem at hand. If no such problem-structure exists or is known, the knowledge representation and processes allow the system to attempt and create a problem structure compositionally out of known representations.

This framework needs to be implemented and tested. Success criteria of the system are clearly presented in each step: visuospatial inference, creative use of affordance, generation of new concepts, use of problem structure transfer, and solving insight problems, or problems which require creative re-representation. There is a possible difference between the latter two. Insight problems in their reduced form might require only finding a good representation which affords the solution - though this representation might be quite far away from the natural representation a human would assume for that problem. Problems requiring creative re-representation are closer in kind to scientific discovery, technological innovation, or problems requiring significant change in the conceptual space and tools of the cognitive agent. In these cases, a new representation might need to be created out of known parts, and only once this representation is put together, the parts afford the solution together.

Many of this framework's principles are in line with current cognitive empirical research and theory. However, the cognitive assumptions and and their ensuing implications need to be tested, to see if the framework can hold as a cognitive theory of creative problem-solving, or is a cognitively inspired framework for an artificial intelligence system.

In conclusion, a theoretical framework has been proposed, with a type of knowledge representation and organization meant to support in a unified manner a variety of creative problem-solving abilities and the re-representation features necessary to simulate insightful problem-solving. Each of the various steps has been chosen to underlie an instrumental cognitive ability or mechanism further used in higher level abilities. This theoretical proposal has also been linked to visuospatial types of inference, which might help bridge the gap to the phenomenological experiences of visuospatial insight.

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