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Doctoral Thesis

A Cognitive Systems Framework for Creative Problem Solving

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Declaration of Authorship

I, Ana-Maria OLTEŢEANU, declare that this thesis titled, 'A Cognitive Systems Framework for Creative Problem Solving' and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
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"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."

Sternberg and Davidson

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Abstract

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A Cognitive Systems Framework for Creative Problem Solving

by Ana-Maria OLTEŢEANU

Creativity, problem solving and insight have been studied through different methods by cognitive science, artificial intelligence and the new field of computational creativity. This thesis proposes to close this interdisciplinary gap by addressing the topic of creative problem solving by cognitive systems. A cognitive theoretical framework (CreaCogs) for types of knowledge organization which can support creative processes is proposed and formalized, as to account for a wide set of creative processes in a unified manner. Processes which use cognitive principles of similarity, association, structured representation, re-representation and restructuring are supported by the type of knowledge organization proposed in CreaCogs. Creative search and substitution mechanisms, together with creative construction mechanisms are described in CreaCogs, in the context of various creativity tasks.

Different methods have generally been used in the literature for the evaluation of human versus the evaluation of computational creativity. In the context of this framework, the various prototype systems implemented are evaluated either in comparison to normative data from humans performing creativity tests, or analyzed with the same tools as human answers would be analyzed across these tasks. Various prototype systems are implemented to showcase the use of the CreaCogs framework.

One such system is comRAT, which computationally solves a human creativity test - the Remote Associates Test. This comRAT-C system uses language data from the Corpus of Contemporary American English which is organized and searched with associative convergence principles posited in the CreaCogs framework. comRAT-C is evaluated using normative data from human participants solving the compound Remote Associates Test. The performance of comRAT-C can be successfully compared to human solver counterparts: the system gives both plausible and correct answers, and its ability to find an answer correlates with human difficulty when solving the task. As no creative test which can be given in different modalities exists up to date, the formalization of the Remote Associates Test made here is used to develop a visual variant for the test. Human participants are subsequently given this task to solve; they also provide visual associates for the cognitive knowledge acquisition of comRAT-V, a system which solves the visual variant of the Remote Associates Test successfully. Early data analysis shows that the

correlation between the system's ability to solve these queries and human performance holds in the visual variant as well, showing promise for future cross-modal explorations of the Remote Associates test from both the computational and empirical perspective.

Another prototype cognitive system for object replacement and object composition (OROC) showcases another side of CreaCogs principles. Cognitive knowledge retrieval and encoding are discussed in an object domain, and multi-feature similarity is explored. Various results of object replacement and object composition queries are described, together with the types of queries which can be answered by OROC using a small set of CreaCogs principles. OROC's object replacement abilities are then used to answer a human creativity test - the Alternative Uses Test. OROC's performance is evaluated with the same tools as human participants, including an evaluation of the Novelty, Likability and Usability of its alternative uses made by human participants. Think aloud data and human answers to the Alternative Uses test show that OROC matches many of the cognitive processes used by humans in such a task.

A set of classical and new practical object insight problems are described and given to human participants in a think aloud protocol. The processes used by human participants in such problems are encoded and shown to correspond to processes posited in the CreaCogs framework. This work prepares the future modeling and computational solving of such problems, and strategies for creating more of them as to further explore practical insight in object affordance domains.

Together, these experiments and data analyses show that the creative processes and framework proposed here can account for a description of creative problem solving across a variety of tasks. Furthermore, the prototype systems implemented here show promise in generating creative tests of their own, which could be further used in the empirical exploration of creative processes.

This work generally argues for adapting the definition of problem solving to allow for the processes required for creative problem solving. Classical problem solving is shown to be a subset of problem solving initiated after processes of interpretation and representation of the problem have already been deployed.

The approach taken here, of seeking comparability of artificial cognitive systems and their products to human solving of creativity tests is shown to be productive. This approach opens computational creative systems to improvement via cognitive influence, and turns such systems into useful adaptable tools for studying the human creative process from a computational perspective. Both the goals of artificial intelligence and cognitive psychology are thus served by this type of approach, in the interdisciplinary spirit of cognitive science.

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When working on a thesis, one is supposed to accumulate knowledge, skills and abilities. If lucky, one also accumulates a debt of gratitude to the many people that have served shape, challenge and encourage one's ideas to turn into science. It is my belief that this debt of gratitude cannot be expressed in words, and can only be payed forward, by honouring what one has learned in these years through what one becomes. However, a warm thank you goes to the following:

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Contents

List of Figures

List of Tables

Abbreviations

AI	**A**rtificial **I**ntelligence
CogSci	**Cog**nitive **Sci**ence
ACC	**A**nterior **C**ingulate **C**ortex
fMRI	**f**unctional **M**agnetic **R**esonance **I**maging
CreaCogs	**C**reative **Re**-representation using **A**ffordances in **C**ognitive **S**ystems
RAT	The **R**emote **A**ssociate **T**est
comRAT-C	**com**putational **R**emote **A**ssociate **T**est Solver of **C**ompound queries
vRAT	The **v**isual **R**emote **A**ssociate **T**est
comRAT-V	**com**putational **R**emote **A**ssociate **T**est Solver of **V**isual queries
C	**C**oncept
RS	**R**epresentation **S**tructure
PT	**P**roblem **T**emplate
OT	**O**bject-based **T**emplate
OROC	**O**bject **R**eplacement and **O**bject **C**omposition

*In memory of Aglaia Leonte, my extraordinary Nana,
and for Ştefan Smărăndoiu, my maths teacher. Your set of values
combined with your belief in me made seeing myself through your
eyes both the highest motivation and the biggest self-indulgence.
My work is dedicated to you, as I am part of your work.*

Chapter 1

Introduction

1.1 Motivation

When solving problems creatively, humans do more than search well defined problem spaces where they know for sure there is a solution to be found, with a specific goal in mind. Humans create possible solutions, possible tools, new problems and new ways of looking at old problems, new ways of looking at and using old tools, be it practical (objects) or abstract (concepts, heuristics). This is the productive side of human cognition.

The subject of creative problem solving and productive cognition is a topic of great interest to both Artificial Intelligence and Cognitive Science, and can also contribute to the theoretical foundations of Computer Science and Philosophy of Information. For Artificial Intelligence, the topic can set the foundations to enable the next generation of creative assistive systems - systems which can make associations and propose solutions or lines of enquiry which are easy to comprehend by humans and integrate in a normal workflow. For Cognitive Science, systems and hypotheses in this direction might contribute to the proposal of further cognitive models of creativity. AI and CogSci working together have historically yielded many great achievements and ways of looking at the core questions of what a mind is and what does it take to make one.

For Computer Science, the topic can set to explain how new (valid) information can be created out of old information. Finally, for Philosophy of Information [46], the topic might help us define limits of generative systems, and new ways of measuring informativity.

Creativity [9] has been studied lately in more computational terms, with computational creativity [25] systems being created. However, most such systems aim to implement artistic endeavours - like poetry writing [23] and painting [21], with only a few tackling creative problem solving [67]. Furthermore, most of these systems do not set to account for the cognitive mechanisms producing these creative results, and are merely inspired by the results of the creative mind rather than trying to elucidate its processes. Thus the differences between various creative processes are not accounted for, the special status of some such processes - like insight [8] - are not investigated in the computational creativity community (with some exceptions [67]), but mostly in the cognitive psychology literature. Psychological hypotheses on the stages of such processes are not taken into consideration, thus no further elaboration and investigation of these stages comes as a result of designing such systems. Nor are such systems able to be tested with the same tests which we give to humans [36, 101, 108].

To fill this gap between cognitive psychology, AI methods and the new field of computational creativity, this thesis will aim to design hypotheses and systems a) in line with the existing cognitive science literature; b) at levels of description which are adequate for cognitive science (discussing possible representation and processes) and c) on which further cognitive models can be developed and empirical hypotheses of how such creative processes work can be explored and tested. Furthermore, some of these systems and the hypotheses on which they are constructed are evaluated using tests given to humans and products of human creativity as a comparison. Some others, as a result of this work, are put in a form which allows such evaluation in future work.

A main hypothesis of the following work is that knowledge organization is a key factor when approaching creative problem solving. We posit thus that knowledge organization approaches which can naturally and with ease support creative processes in computational systems need to be designed and refined. Throughout this work, knowledge organization is approached and implemented in ways which enable creative search, re-representation of previous knowledge, combinatorial creativity, associativity with similar terms and convergence upon solutions.

This is an issue of knowledge organization, not knowledge representation. The forms of representation chosen in the framework and implemented in the various systems here can be changed while maintaining similar results. However the organization of said representations is a core principle, enabling the creative process to happen without high computational costs, in the same way in which various data structures are better at dealing with and representing various processes.

1.2 Contributions

This thesis has been written in an interdisciplinary spirit, proposing a unified framework [115] for various creative problem-solving tasks, formalizing processes which can be implemented in a variety of creative problem-solving domains, and helping the further development of cognitive models and more sophisticated systems. The thesis makes the following contributions:

1) A theoretical framework of the creative problem-solving process is proposed. This addresses various creative problem-solving capabilities in a unified manner, is cognitively-inspired and aims to enable AI cognitive systems with a wide scale of creative problem-solving capabilities.

2) A formalization of the knowledge organization and processes for this theoretical framework is made. A set of core creative mechanisms for search and composition is proposed. Examples of how these processes can enable and describe creative problem solving in various domains are given and discussed.

3) Prototype systems have been implemented using these principles, to show the breadth of the theoretical framework and its principles of knowledge organization in different domains. Some of these systems solve tasks which are comparable to classical human creativity assessment tasks, thus bridging the gap between computational creativity and cognitive modeling. The systems are:

1. A compound Remote Associate Test computational solver (comRAT-C), which offers correct and plausible results to the human Remote Associate creativity test. This has been compared to human normative data. The system can also generate RAT queries, and be used to model hypotheses via predicting correct answers given by humans.[1]
2. A computational solver for a visual version of the Remote Associate Test (comRAT-V). This prototype was built to show the same principles can be used to solve RAT queries in the visual domain.
3. A creative object replacement system which operates on a practical everyday object domain (the OR part of the OROC system). The results of this system are comparable to the human Alternative Uses test. This enables the future modeling of various hypotheses on how humans solve the Alternative Uses test.
4. A creative object composition prototype (the OC part of the OROC system) which operates on a practical everyday object domain, proposing what new objects can be constructed out of the various objects in a particular environment.

The core principles of the framework are applied in these systems, with refinements relevant to the task domain being approached. The performance of the systems is compared to human data, or appraised with similar tools as human performance would be appraised in creativity tests.

4) Empirical data on human creative problem solving. This has taken different forms:

1. comparability data between the comRAT-C system and normative human data;
2. the creation of an initial prototype of a visual variant of the human Remote Associates test, and related data;
3. comparability data between the object replacement system and human answers to the Alternative Uses test; data on property use in new answers to the Alternative Uses test;
4. the creation of new practical object insight problems and a methodological outline of creating such problems. Data on human problem solving of a set of insight problems, and a set of think aloud codes to model the solving process.

[1]The system will be released in the public domain, to enable cognitive psychologists to model and study various hypotheses on how humans solve this test.

1.3 Thesis structure

This thesis is structured as follows: Chapter 2 provides a state of the art and theoretical background of the various research threads which lead to this thesis: creativity and creative problem solving from the perspective of creative cognition, artificial intelligence, computational creativity, etc. The link between knowledge organization and the process which it enables is explored in the light of creative processes. Main psychological tests used for creativity assessment and evaluative tools from the computational creativity community are also reviewed here. Chapter 3 details the theoretical framework proposed, together with the ways in which it deals with various creativity tasks. Chapter 4 details the formalization of the core creative processes in this framework, giving examples of how such mechanisms can account for the accomplishment of various creative tasks. Chapter 5 shows the applications of some of these principles in the buildling of a Remote Associate Test (a test for human creativity) problem-solver, and an extension of this test and solver to the visual domain. Chapter 6 applies the principles of the framework to a household objects domain, yielding results relevant to creative object replacement and object construction/composition. Chapter 7 examines the principles of the framework using them to compose a set of codes and analyse a think aloud protocol for practical object insight problem solving. A final big picture discussion, conclusions and further work are presented in Chapter 8.

Chapter 2

Theoretical background and State of the Art

Problem solving and creativity are often addressed together [144] as higher level cognitive abilities. Both have been held in high esteem and long considered to be human-only abilities, and then proven to exist to a smaller yet still impressive extent in animals. Other animals are capable of some creative tool use [84] and analogy-making [59], and frameworks for the study of animal creativity have been proposed [5, 79]. However, creativity and creative problem solving are at their pinnacle in human cognition.

Extraordinary leaps of thought have been an integral part of human history [65, 124, 161, 162], brought forth by individuals or groups. Nonetheless, creativity is encountered in the everyday life of most people. Despite the universality and the diversity of levels creativity takes, various difficulties relating to knowledge representation, common sense knowledge and the amount of cognitive functions involved in higher level cognitive abilities stand in the way of directly modeling such processes.

Both creativity and problem solving have been addressed in psychology, AI and cognitive science, and can be conceived of as interdisciplinary fields of research. Different kinds of matters pertaining to these subjects have been studied, depending on the field doing the inquiry. Thus, a question formulated by *cognitive psychology* would be : *"How does a certain creative process function in humans? How can we model it?"*. An *Artificial Intelligence* type of question: *"How can we define problem solving so that it is computable by machines and that computation can be optimized?"*. Questions relating to *cognitive science*: *"What kinds of representations and processes are necessary and sufficient to have creativity in a cognitive system?"*. An important question asked by the newly emerging field of *computational creativity* is *"What are the required criteria to call a system creative, and how can one evaluate such creativity?"*. This question seems to come loaded with the fact that new research shows that as soon as humans *know* by which process the system is generating its creative products, they become much more reluctant to call it creative. The field of computational creativity is leading the applied work in this field, and has recently seen a boom of newly implemented creative systems, however it is somewhat lacking on the problem solving part, and on the cognitive implications and comparability of these systems.

In the following, a large amount of literature from these various domains will be approached systematically by grouping these subjects in the following way:

- **Creativity, Problem Solving and Insight** (2.1) - This section describes relevant theories of creativity, problem solving in its well structured and ill-structured forms and insight - an empirically studied creative problem-solving process. The section concludes drawing a possible relation between visuospatial intelligence and creativity.
- **Knowledge organization for creative problem solving** (2.2) - The question of what kinds of representation and processes are of use to implementing and modeling is of importance to all the fields dealing with creative problem solving. Various representations and processes relevant to creative problem solving will be reviewed. The interplay between representation and process will be presented as a motivator for knowledge organization with specific relevance to enabling processes of creative problem solving
- **Computational Creativity systems** (2.3) - This section will review formal and applied work on creative systems, presenting a selection of models and computational creativity achievements. This review can only offer a selective taster of the field, and many other interesting systems have been realized in the last years.
- **Evaluation of human and computational creativity** (2.4) - In this section, the latter work in evaluation of computational creativity is reviewed side by side with psychology work on assessment of creativity in human participants. This juxtaposition is meant to enable a fruitful comparison.

A Discussion which (i) sets up an outline of a new view on creative problem solving and (ii) sets up some working principles for the factors an interdisciplinary creative problem solving framework needs to take into account will take place in Section 2.5.

2.1 Creativity, Problem Solving and Insight

This section begins with the description of a few classical and modern theories of creativity (Section 2.1.1). Problem solving in its well structured and ill structured forms and their relation to creativity are explained in Section 2.1.2. Insight is presented in Section 2.1.3 as an empirically studied process, representative of how ill-structured problems can be solved. Further, neurological background work on understanding the process of insight is briefly presented (Section 2.1.4). The section concludes bringing forth current literature which might be representative for a relation between visuospatial intelligence and creativity (Section 2.1.5).

2.1.1 Creativity

Boden [9] differentiates between the concepts of **historical creativity** (h-creativity) and **psychological creativity** (p-creativity). In her taxonomy, historical creativity is the creativity which is original on the scale of human history, while psychological creativity yields contributions which are creative from the perspective of the individual. 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 about exploration of variations, and changes to/restructuring of the conceptual space. The term conceptual space is, according to some [126, 165], vaguely defined. This makes it hard to compare to similar terms in the literature, for example the conceptual spaces used by Gärdenfors [52].

Another term relevant for the study of creativity is that of **divergent thought**. Guildford [61] came up with the term *divergent production* in the Structure of Intellect. He discusses both convergent and divergent productions, as complementary parts of the cognitive productive capacity. Guilford builds a common model for convergent and divergent productions, arguing that problem solving and creative production are the same. Table 2.1 shows the differences posited by Guilford between divergent and convergent productions.

Table 2.1: Difference between divergent and convergent productions, according to Guildford [61]

Divergent productions	Convergent productions
Loose and broad problem, or incomplete grasp of it at the agent level	Answer can be rigorously structured and forthcoming
Few restrictions	Many restrictions
Broad search	Narrow search
Vague and lax criteria for success (stress variety and quantity)	Sharper, rigorous, demanding criteria

The **generative-exploratory** model (Geneplore) by Finke, Ward and Smith [44] differentiates between two phases of creative thought: generation and exploration. In the generative phase, preinventive structures (which are mental representations) are constructed by the individual. In the exploratory phase, these structures are used to generate new ideas.

Gabora has proposed creativity to be a **honing** process [2, 50]. The honing theory postulates that creativity is a process by which an individual hones, at multiple stages, their world view. Thus creativity is seen here as a process of self-organization of a worldview, which aims to solve inconsistencies between ideas, attitudes and knowledge.

The Explicit-Implicit interaction model (EII) [67] proposes a unified framework for understanding creativity in problem solving. The Explicit Implicit theory has been implemented in the CLARION cognitive architecture and relies on the following principles:

(a) the coexistence of and the difference between explicit and implicit knowledge;
(b) the simultaneous involvement of implicit and explicit processes in most tasks;
(c) the redundant representation of explicit and implicit knowledge;
(d) the integration of the results of explicit and implicit processing and
(e) the iterative (and possibly bidirectional) processing.

Other models of creativity have also been proposed [134, 145]. Other concepts of creativity, like concept blending, analogy and metaphor, will be discussed as processes in Section 2.2.2.

2.1.2 Problem solving

Part of the difference between creativity and creative problem solving comes from what the results of each are, and how those results are evaluated. Thus, when speaking of creativity without the context of problem solving, one tends to generally consider the processes of creating works of art or products which are original (the field of computational creativity is not devoid of this bias). Such works can then be evaluated in terms of their aesthetic qualities, their novelty compared to other works in the similar genre or with other works of the author, or their novelty in terms of process[1]. Creative problem solving on the other hand has to satisfy problem constraints, and the usefulness of the solution can as much be a factor in evaluation as novelty. The field of creativity gets closer to the fields of problem solving and reasoning when it deals with innovation, scientific discovery and scientific reasoning [81, 91, 112].

In order to understand creative problem solving, one must thus revisit classical problem solving definitions in Artificial Intelligence (AI), and aim to refine them according to creative problem-solving accounts in cognitive systems.

In AI, and later in computer science, problem solving in its classical form is defined [116] in terms of:

- An initial state
- Operators or successor functions which define reachable states $f(x)$ from any state x
- A state space, constituted of all the reachable states, based on applying the operators to initial states in whatever sequence
- Paths – sequences through the state space
- Path cost – a function used to evaluate the best heuristics
- Goal state or goal tests (to determine if the goal state has been reached)
- Heuristics which can be defined based on their success and cost (optimality)

However, a difference can be made between well structured and ill-structured problems [114]. Well-structured problems can easily be described in terms of the classical problem solving definition, while ill-structured problems have ambiguous initial states, operators

[1] Ways of assessing computational creativity systems will be described in Section 2.4.2.

or goal states. Meanwhile, ill-structured problems are more often encountered in real environments [138].

The Gestalt psychologist Wertheimer [163] differentiates between **productive** and **reproductive** thinking. He considers reproductive thinking to be a function of repetition, conditionings, habit and familiar ways of thought. Meanwhile, productive thinking is considered to produce new ideas and be insight-based. Applying this definition to problem solving, productive problem solving can be defined as a process which brings about new heuristics and new ways of looking at the problem, while reproductive problem solving would mean applying the same known heuristics to the same types of problems.

In order to understand why certain ill structured problems are hard to solve and require productive problem solving, the case of insight problem solving can be taken as as an example.

2.1.3 Insight

The legend has it that Archimedes jumped out of his bathtub because an insight on how to measure the volume of a crown while observing himself immersed in the water [155]. Watson told stories about his dream of spiral staircases helping him solve the problem of the structure of DNA by settling on the double helix solution. Kekulé recounted to have day-dreamt an Ouroboros-like snake biting its own tail or a tibetan knot before discovering the structure of benzene (Fig. 2.1) in a speech given at the German Chemical Society.

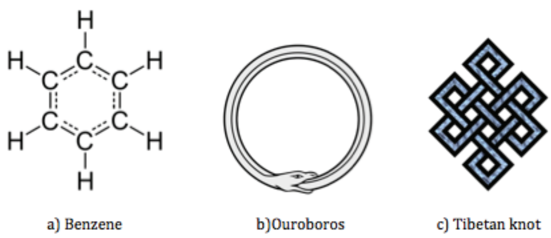


FIGURE 2.1: A depiction of Kekulé's day-dream: a) The benzene molecule; b) Ouroboros symbol of a serpent eating its own tail; c) Tibetan knot.

To differentiate between the introspective account or anecdotical story and the empirical study of insight [18], empirical tasks for the study of insight will be presented in section 2.4.1.5. In any case, implicit processing is assumed to have an important role in the insight process, in both modern [67] and earlier accounts.

Helmholtz [68] and Wallas [157] put together the four step model to creativity and insight, which involves the stages of preparation, incubation, illumination (or insight) and verification (or evaluation), in some taxonomies followed by elaboration. The core four steps are described as follows:

1. **Preparation** The participant gets acquainted with the problem. Various attempts are made at solving it, but they are unsuccessful.

2. **Incubation** The participant stops trying to (consciously) solve the problem, directing her attention to something else. This stage varies in length.
3. **Illumination or Insight** The participant has a sudden idea of how to solve the problem, with all elements appearing at the same time as if *"fully formed"* in consciousness.
4. **Verification or Evaluation** At this stage, the participant tries to apply the insight in the real world or on the problem, to check if it provides the desired solution

Whether this model is entirely accurate is still debated in the literature, with some assuming that insight problem solving is a gradual process, rather than involving an actual flash of insight, and some considering that it can be both [45, 137]. However, inability of solvers to accurately predict their closeness to the solution [109] (unlike for normal problem solving) is generally taken as support for this model.

Batchelder and Alexander [8] summarize the set of characteristics for insight:

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.

Not many models of insight have been implemented in the literature - exception being an implementation using the CLARION cognitive architecture of the the Explicit-Implicit interaction model - EII [67], which focuses on explicit and implicit processes and their relation.

However, research in insight problem solving shows the role of the problem representation as a productive or not productive structure to be essential. Arriving at a productive representation can thus be seen as an exercise in productive thinking [163]. Restructuring [98, 118, 119] and re-representation or representational change [77, 82] are assumed to play an important role in arriving at such a productive representation. Performance in solving insight problems has been shown to sometimes improve when given enough practice [74].

It is worth noting that the role of re-representation in creative problem solving might be to transgress the boundary between ill-structured and well-structured problems. This point will be discussed further in the context of knowledge representation and organization (Section 2.2) and in the Discussion Section (2.5). Meanwhile, an overview of studies in the neural correlates of insight will be presented.

2.1.4 Neural Correlates of Insight

In terms of neural correlates of insight, the right hippocampus and a wide area of cerebral cortex (frontal, temporal, parietal and occipital) have been shown to be involved in insight events [95]. In an event-related functional magnetic resonance imaging (fMRI) experiment, participants were given 45 most interesting Japanese riddles (rated out of a set of 300) to solve [95]. The 16 riddles which each participant found the most interesting but could not solve where collected in a scanning session, and their answer was shown to the non-solving participants, eliciting "Aha!" effects. The authors posited that it was the formation of novel associations between already existing conceptual "nodes" that activated the hippocampus. The hippocampus has been previously shown to have a role in the formation of associations [158], pattern completion and conjunctive representations [129].

Another event-related fMRI study [97] presented participants with incomprehensible sentences, followed by solution cues which triggered alternative interpretations of the concepts in the sentences, thus triggering an "Aha!" reaction. Activation in the anterior cingulate cortex (ACC) and left lateral prefrontal cortical areas has been observed, areas supposed to mediate cognitive conflict. Thus a mental impasse was assumed to be broken with the presentation of the solution cues, redirecting the interpretation of the participants in a productive manner.

In a high-density event-related potential (ERP) study [100], 120 Chinese riddles of two degrees of difficulty were presented to the participants. After each riddle, the participants were given a cue which was consistent with the assumed initial direction of thought of the participant, or which required changing the initial mental set (thus manifesting "Aha!" effects). Results concluded the ACC was involved in the breaking of the mental set, with a peak latency of 380 msec (N380). The ACC was also observed to be more involved in the condition in which the puzzles where hard to predict, than when puzzles were constructed on similar structural principles [96].

In active solving of chinese logogriphs [125], dipole analysis localized a P200–600 in the left superior temporal gyrus and parietotemporo-occipital cortex areas (thought to be involved in initial association formation), a N1500–2000 on in the ACC (thought to reflect the breaking of the mental set) and N2000-2500 generator in the posterior cingulate cortex (PCC), which authors posit to be related to the emotional "Aha!" effect.

Finally, a relation between resting-state brain activity and problem strategy applied (with or without insight) has been explored [85].

These studies support the importance of making new associations, pattern completion and re-representation (with cues of cognitive conflict between multiple interpretations) in creative and insightful problem solving.

2.1.5 Visuospatial intelligence

Arguments have been made for visualization being essential for reasoning [76]. Others consider spatial reasoning to be a form of interface for abstract reasoning [49]:

> *"We may interpret non-spatial concepts by mentally transforming them into spatial concepts (i.e., understanding them in terms of spatial concepts), carrying out mental operations in this visualizable and graspable domain and transforming the result into the original domain. In this way, spatial inference engines may have a much more general function than the term suggests: rather than generalizing by forming a common abstraction for various domains we generalize by forming suitable analogies to a well-understood concrete domain."*

Mandler [102] extrapolates from empirical developmental data to form a theory according to which spatial concepts are the functional base for developing abstract concepts. Some of the spatial concepts which she proposes as primitive are: PATH, START PATH, END PATH, PATH TO, LINK, CONTAINER, (IN)TO, (OUT) OF, THING, $\pm$MOTION, etc.[103]

Further work shows the possibility that abstract spatial concepts like cardinal directions are further grounded in body-referenced axes [151]. Priming with such concepts influences further trajectories in concrete tasks. This is an example of top-down influence from priming with abstract spatial concepts, back onto an affordance of bodily motion, and implies a strong connectivity between the two.

If abstract concepts are indeed grounded in spatial concepts, then such spatial concepts will be relevant for the creation of new concepts and general creative problem solving.

Also, a shape bias [72, 88, 104] has been observed in children. Children who do not know the name of an object tend to extend to the unknown object the name of a previously known object of a similar shape. This has shown that (in the object domain) shape is important in the categorization of objects (more so than color, size or material).

Image schema theory supports the view that perceived spatial relations are at the foundation of abstract conceptual reasoning. Image schemas are supposed to also play a structuring role in metaphors [87].

Finally, an interesting point about the link between perception, visuospatial intelligence and re-representation can be made via the example of ambiguous figures. Ambiguous figures, like Fig. 2.2, are figures in which two different objects can be seen, albeit not at the same time.

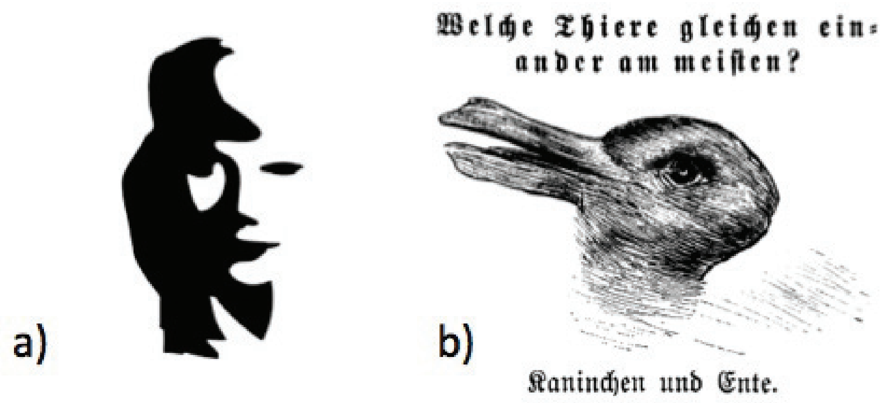


FIGURE 2.2: Ambiguous figures: a) girl/saxophonist; b) duck/rabbit

This perception-based process brings to mind a certain similarity with the issue of re-representation. Thus if in ambiguous figures, visuospatial features can be grouped in two different objects, in creative problem solving, objects of the problem might be grouped or paid attention to in different ways, invoking different known heuristics, as to bring about a productive problem representation.

We might be yet to hear the final word on the influence of visuospatial processes on creative problem solving. As things stand, we should consider this set of findings as being representative of the fact that we should not think of knowledge only as verbal or propositional when considering types of knowledge representation and processes which could implement creative processes.

2.2 Knowledge organization for creative problem solving

An important question related to how creative problem solving happens in natural cognitive systems and how it could be implemented in artificial cognitive systems pertains to knowledge representation and processes. When implementing or trying to understand creative problem solving, one has to deal with the question of what kind of knowledge representation and processes support it.

The relationship between knowledge representation and processes, from a computational point of view, is tight. Thus certain types of knowledge representation can support with more ease the deployment of certain processes, similarly as certain data structures are more productive in the implementations of certain algorithms.

Well structured problems and ill-structured problems have been defined as easier or harder to solve (requiring creativity) in natural and artificial cognitive systems. Considering the difference between them might be based on a difference of problem structure, the following section will focus on structure topics: (i) structured representations proposed in AI; (ii) types of processes proposed in creativity and (iii) restructuring as a process of creative problem solving which points towards the need for implementing creative systems in which knowledge organization is supportive of it.

2.2.1 Representations and structure

One of the themes which emerges when looking at some of the constructs proposed to be used for representing knowledge in cognitive science and AI is the theme of structured representation. In the following, constructs of knowledge representation which have in common an interest for structure will be described.

Frames are knowledge representation schemes initially proposed by Minsky [110] which were meant to capture and express essential properties of concepts and often encountered situations, like going out for dinner or being in the living room. Frames offer a short and poignant systems of expressing knowledge in an object-oriented manner [43] and are useful for the semantic web [93]. The concept of frames later led to the development of frame-based systems, which generally share the following properties [43]: a) frames are organized in tangled hierarchies; b) they are composed out of slots (attributes) for which fillers (scalar values, references to other frames or procedures) need to be specified or computed) and c) properties are inherited hierarchically from superframes to subframes in accord to some inheritance strategy.

If **schemata** are psychological constructs [13, 130] which aim to account for atomic parts of human generic knowledge, Minsky used frames to describe representation schemes for both psychological description and artificial intelligence. The somewhat similar construct of **scripts** [133] refers to schemata which represent stereotyped sequences of action - i.e. the sequence of actions required for the scenario of a person ordering something in a restaurant. The word schema is also sometimes used to refer to sequences of events, like in the case of narrative schemas [15].

The term of **image schemas** has widely been used with various meanings, and has been approached in the context of metaphors in the work of Lakoff and Johnson [86, 87]. The use of image schemas further supports compositionality, and some conceptualization of spatial schemas [53]. Some evidence points at the existence of image schemas in the human brain [127].

Analogical representations [139] are representations in which some of the properties and relations between parts represent corresponding properties and relations in the world (or in some hypothesised/imagined world). Sloman contrasts analogical representations to Fregean representations. Sloman mentions maps, images and scaled models as analogical representations, with predicate calculus, programming languages and natural languages (but not exclusively) Fregean. In our opinion, some analogical representations preserve structure implicitly, requiring further interpretation in order to extract specific information already existent in a particular representation.

The concept of **mental models** was first proposed by Kenneth Craik [27]. Mental models were meant to be molecular models of reality built by the human cognitive system in order to reason, anticipate events and provide explanations. Models have been further supposed to be constructed in the working memory [75, 105]. One of the defining characteristics of mental models, which makes them very similar to Sloman's concept of analogical representation [139], is that the structure of the mental models is in a relation of correspondence with the structure of the world that is being represented.

The argument for **structured representation** goes further, when connected with the topic of creativity and creative problem solving, and this will be discussed in Section 2.2.3. However, a look at creative processes is first warranted.

2.2.2 Creative Processes

Various processes have been proposed to account for mechanisms of creativity.

Bisociation is a concept developed by Arthur Koestler [83], which discusses it in "The Act of Creation". Bisociation can be seen as an ancestor concept of concept blending, and is defined as the moment when two or more matrices of thought (considered to be the totality of possible moves) intersect.

Discussing the need for the discoverer to be prepared (which he calls "ripeness'), Koestler makes a point similar to that of the Preparation phase. He also refers to the need for something similar to an incubation phase by talking about the unconscious mind as the generator of discoveries: "The creative process of discovery depends on the unconscious resources and presupposes a regression to modes of ideation which are indifferent to the rules of verbal logic". In this phrase, he also alludes to different modes of ideation, in which verbal language does not play as much a part. Koestler also differentiates between creativity as being the "production of a new recipe", compared to "the skilled routine of providing variations for it".

The study of human concept formation had yielded a variety of theories: prototype theory [128], exemplar theory [106], theory theory [111]. A connected issue of importance to creativity is that of the process of concept creation. Amongst others [2], the process of **conceptual blending** has been proposed as a form of creating new concepts [41]. Concept blending is defined by Fauconnier as a basic mental operation of constructing a partial match between two inputs, projecting selectively from those inputs into a "blended space" which has as a result the emergence of a new structure and of new meaning.

Associativity is a relevant process for creativity. According to Csikszentmihalyi [29] "Cognitive theorists believe that ideas, when deprived of conscious direction, follow simple laws of association. They combine more or less randomly, although seemingly irrelevant associations between ideas may occur as a result of a prior connection". This supports an associationist view of creativity. Various principles from hebbian learning [66] to semantic networks [143] can be used for implementing forms of associativity.

Analogy [54, 71], an important mechanism in creativity and scientific discovery [35], is the process of understanding a concept, process or situation via another. Thus a concept, process or situation that is familiar (called the source analog) might be used to understand another less familiar concept, process or situation (the target). It is currently assumed that various stages are part of the analogy-making process. A mapping or aligning of the representational structures [39, 54, 55] allows projections of inferences. An evaluation of analogy and the inferences produced by it follows. After this, one or both initial representation might change, being adapted or re-represented. Analogy making is a process which has been amply studied in the literature, with various computational approaches [38, 39, 47, 63, 70].

It is worth noting that Gabora's honing theory is also supportive of associative, structure-relevant processes, as she thinks the process of analogy is "constrained by content-addressable structure of associative memory to naturally retrieve items that are [...] structurally similar" [50, 51].

Metaphor is the process of using one concept, process or situation to designate another. For example, the phrase *"The wheels of justice turn slowly"* is based on a metaphor. Metaphors make implicit comparison between two concepts, processes and situations (in the example here, between the concepts "justice" and "machine"). Metaphors differ from similes by not using language (e.g. words such as "like", "as", etc.) to make such a comparison overt. Lakoff and Johnson [86] discuss the role of structural metaphors as allowing people to use the structure of a concept in order to structure another. They further posit the existence of structure in the metaphorical system as a whole, as "neural connectivity of the brain makes it natural for complex metaphorical mappings to be built out of preexisting mappings"[87]. Various formal approaches to modeling metaphors exist [62, 73].

2.2.3 Restructuring or re-representation and the link between knowledge representation and process

Support for a structured creativity approach comes from empirical psychology as well [12, 159, 160]. Thus Ward [159, 160] shows that category structure has an important role to play in creative generation. In one of his works, the participants in a test [159] are given the task of creating imaginary animals that could live on a different planet in the galaxy. The participants created drawings and descriptions of such animals, of members of their species and of members of other species. The responses generated for this task were structured by properties of known earthly animals. Furthermore, when asking the participants for animals with a particular attribute (e.g. feathers), categorical knowledge was shown to be called upon and influence the imagined animal, which also held other attributes correlated with that particular feature (e.g. beaks and wings). Ward has shown that similar knowledge base categorical constraints apply to creative writers, for examples science fiction authors, and proposed the concept of *structured imagination*.

A further set of experiments was performed using categories of *animals, tools and fruit* [160]. First, lists of exemplars were gathered for these categories from some participants, as to determine accessibility of different category exemplars. Then, other participants were asked to draw and describe novel categories of those exemplar, which might live on an imaginary planet. Items rated as highly accessible in the lists provided by the first participants had a higher influence in imaginary production of new exemplars.

These experiments show the importance and influence of the structure existing in the knowledge base of the cognitive agent when approaching a creative task. This is noteworthy, considering that *restructuring* or re-representation are considered to play an important role in insight and creative problem solving [31, 36, 78].

Thus a link between the process of knowledge representation (as structured) and the creative process (as a process of restructuring) can be drawn. **A type of knowledge organization which allows restructuring and re-representation seems essential for the implementation of creative processes.** The implication of this on the well-structured — ill-structured divide are discussed in Section 2.5.

2.3 Computational Creativity systems

Computational creativity has seen a bloom in recent years. Thus computational creativity systems have been implemented in domains as varied as mathematics [20, 22, 94], music [121, 140], art [19, 21], poetry [23], architecture and design [135], discovery of physical laws [89, 90, 92], magic trick making [167], video games [26], etc.

In the following section, we will give a short description of a few such systems: Aaron [19], the Painting Fool [21], poetry systems [23], BACON [89, 90, 92] and a magic trick making framework [167].

The AM system [94] by Lenat acts in the domains of elementary set and number theory, and paved the way in concept formation and conjecture making. AM had a database of 115 elementary concepts, like sets and bags, each defined on a frame representation with 25 facets, and 242 heuristics. AM reinvented set and number theory concepts and some known conjectures, by choosing which heuristics were to be applied to a specific task (like inventing a new concept) and applying those heuristics. As such heuristics had multiple tasks and subtasks, part of the computational work of AM was to choose which tasks to apply first. This decision making process was guided by adding values to concepts, their facets and actions which could be taken on the concepts, which were then used to calculate a task value. A second part of the decision making process was to assess interestingness using other heuristics, based on interesting properties, related conjectures to a concept, whether examples of a concept have been found or not, etc.

The HR system [20], named after the mathematicians Hardy and Ramanujan, is meant to produce theories in pure mathematics domains, taking as input simple concepts and axioms. HR produces new mathematical concepts and forms new theories by using a predefined set of production rules. Such production rules act as structure and constraints propagators within the new formed concepts. Third party automated reasoning software is used by HR in order to attempt to prove the new conjectures. The search for new concepts and mathematical conjectures is driven by various measures of interestingness

[22]. Such measures of interestingness involve properties of complexity and surprise of both concepts and conjectures.

Aaron

Aaron [19] is a drawing and painting computational creativity system on which Cohen started working in the mid seventies from the cognitive question "What is the minimum condition under which a set of marks functions as an image". Aaron started as a simple program which could distinguish between figure and ground, closed and open forms, and perform simple structure manipulations, with a feedback mode, which allowed it to consider its overall goal in relation to its current accomplished parts of the drawing. After observing the behaviour of children in scribbling, in which *"a scribble migrates outwards and becomes an enclosing form for the rest of the scribble"*, Cohen added to Aaron a simple strategy to trace a path around core figures, which greatly enhanced the complexity of the forms it generated, and their similarity to forms drawn from visual experience.

Aaron continued to be developed over time, with the addition of physical ambience around its figures, knowledge of anatomical parts (as complex connected parts) and postural rules, while still operating with knowledge of two and a half dimensional figures. Then, in order for it to turn from a drawing expert system (the drawings of which Cohen painted himself) to a painter system, a three dimensional knowledge base was added. Many of its knowledge sets of points are derived from medical illustrations of the skeleton. In order to achieve different points of view, Aaron places its figures, after constructing them and transforming them to the appropriate pose, in a three-dimensional world, and then places its point of perspective (its *eye*) in the same world. Aaron specifies its plans at the highest level of abstraction, with the lower levels generating instances of such plans. Its drawings and paintings have been exhibited publicly from as early as 1979.

The **Painting fool** [21] has been initially designed as an art project, as to work in real time, adding strokes to a canvas one by one. Colton would like the Painting Fool to be taken as an artist in its own right, rather than as a creativity simulation machine, and has invested interest in what helps people perceive a work or process as more valuable and creative than others. The works of the Painting Fool have received wide media coverage, have been entered in exhibitions and competitions, and videos of the Painting Fool at work can be found online[2]. Besides its ability to simulate various styles in charcoal, acrylic, chalks and pencil, the Painting Fool has various artistic styles in its knowledge base annotated based on emotion keywords. This enabled the system to create a painting in a style corresponding to a given emotion. Such an emotion can also be read as an input by a machine vision program from the face of a person. A further mix with HR and an expansion based on an evolutionary approach enabled the Painting Fool to produce scenes which have been optimized for fitness functions created by HR, the choices on what to optimize thus being made computationally as well.

Poetry systems [23] demonstrate an interesting use of structure (as templates), word associations and similes. Thus content is generally mined from a corpus or from a

[2] www.thepaintingfool.com

pre-established lexicon. Corpuses thus mined can be very large, like the 85 million words parsed from the British National Corpus for the Electronic Text Composition (ETC) poetry engine [14]. At a smaller scale than poetry systems, but still dealing with linguistic creativity, systems exist producing *compound similes* [154] and producing and validating *neologisms* [153]. The corpus used by the former is also used for poetry generation in [23] - demonstrating re-use of resources in computational creativity.

BACON

BACON.3 [90] is a production system aimed at data-driven discovery of physical laws. Named after the philosopher of science Sir Francis Bacon (1561-1626), the system applies principles in the spirit of his beliefs. Bacon thought that when one has gathered enough data, its regularities will *leap out* at the observer [90]. In a similar manner, BACON.3 aims to see regularities in its data, and develop its observations based on these regularities. According to his author, BACON.3 has rediscovered Kepler's law of planetary motion, the ideal gas law, Ohm and Coulomb's laws, the pendulum and constant acceleration laws of Galileo. It is important to observe that there is quantitative data which can be given to the system as input data for these regularities to be observed, until a law it is deduced.

Unlike its predecessor BACON.1 [89] and allegedly more succesful because of it, BACON.3 doesn't make a sharp distinction between data and hypotheses. BACON.3 allows hypotheses which aim at explaining data to be used as data themselves, thus allowing for different levels of description. Thus regularities observed in description at one level (which are equivalent to hypotheses) become descriptive clusters at a higher level. BACON.3 containst 86 OPS2 [48] productions, with descriptive clusters being variable-value pairs.

BACON.5 on the other hand [92] also implements a simple form of reasoning by analogy, in order to make the discovery of laws containing symmetric forms easier. With BACON.5 the following laws were rediscovered: conservation of momentum, Snail's law of refraction, Joule's formulation of conservation of energy and Black's specific heat law.

Magic trick making

Williams and McOwen [167] use experimentally derived perceptual and cognitive data together with mathematical principles in order to create and optimize magic tricks. Thus they provide computational tools for magic trick making, or assistance with magic trick making. Two case studies are approached in order to exemplify their methodology - a magical jigsaw and a mind reading card effect. Genetic algorithms are used to evolve solutions which satisfy psychophysical constraints known from empirical literature, thus optimizing the trick in order to make it more compelling for human perception. The tricks so created are then evaluated in empirical settings and via public performances.

2.4 Evaluation of human and computational creativity

One cannot talk about creativity without discussing the way creativity can be evaluated. In the following, two views on evaluation of creativity will be explored. One deals with evaluation of creativity in humans via empirical means, mainly through the use of creativity tests (Section 2.4.1). The other describes recent work on constructing forms of evaluation for computational creativity systems (Section 2.4.2).

2.4.1 Creativity testing in humans

Creativity is an inherently hard thing to measure in humans, as we have no complete definitions of it. However, empirical tests for measuring creativity do exist. In the following section, some of the most important such tests are presented, and what they measure is discussed. These tests are:

1. The Alternative Uses Test (2.4.1.1)
2. The Torrance Tests of Creative Thinking (TTCT) (2.4.1.2)
3. Riddles (2.4.1.3)
4. The Remote Associates Test (2.4.1.4)
5. Empirical Insight Tests (2.4.1.5)

2.4.1.1 The Alternative Uses Test

The Alternative Uses Test has been developed by J.P. Guilford [61], and it involves the following procedure: participants are given an everyday object, and a certain amount of time (generally a few minutes) to think of as many possible uses for that object as they can come up with. Then the procedure is repeated with another object.

This test is assumed to measure divergent thinking (the ability to diverge from subjectively familiar uses and think of other uses), and is normally graded across four different dimensions:

- Fluency - the number of uses the participant can come up with;
- Flexibility - the number of conceptual domains the answers relate to (for example tools, accessories, musical instruments are different domains);
- Originality - a measure of how uncommon the uses are, as compared to the uses other participants came up with, or Novelty - measured through the assessment of human judges;
- Elaboration - a measure of how detailed these answers are (though one can see how there is a trade-off between Fluency - coming up with many different uses - and Elaboration - coming up with them fully formed).

This is a task no classical AI classical system has previously solved.

How does this test inform us on what we need to do when constructing a creative AI system? The test starts from the assumption that being able to use an object in more than just its traditional setting is a creative matter. The term *affordance*, coined by Gibson [57] to represent *action possibilities* latent in the environment, has also been defined as *a relationship between the properties of an object and the capabilities of the agent that determine just how the object could possibly be used* [117]. The creative skill that is emphasized in the Alternative Uses Test is related to affordance knowledge and ability to infer new, original affordance knowledge out of previous knowledge about the objects, their features, and the world.

2.4.1.2 The Torrance Tests of Creative Thinking (TTCT)

This test is part of the Torrance Tests of Creative Thinking (TTCT) [146–150] and has been developed by Ellis Paul Torrance (for a critical review see [80]). The TTCT has two main components: TTCT-Verbal and TTCT-Figural.

Both TTCT-Verbal and TTCT-Figural have two parallel forms (A and B). The stimuli for TTCT-Verbal are pictures to which people answer in writing in five different types of tasks: ask-and-guess, product improvement, unusual uses, unusual questions and just suppose. TTCT-Figural consists of three different types of tasks: picture construction, picture completion and repeated figures (lines and circles). In the first task, participants are given a shape (looking like a pear or jellybean) as a stimulus and asked to construct a picture which includes the shape. In the second task, a set of 10 incomplete figures is given to the participants, which must make of it an object or a picture. In the third task, the participants are given pages of lines or circles which they must us as part of their picture.

One of the most interesting parts of this test is the incomplete figure test. This is not a test of image completion in the Gestaltist sense, as the picture presented is never only a few lines away from pattern completion, but rather requires quite a lot of elaboration to be "completed".

It is also not clear what the correlation between having a higher drawing skill and scoring well at this test is, or whether part of the deployed creative intelligence does not also rely on a mix of motor intelligence and drawing skill - like drawing something around the line, then checking again what object could be constructed out of the current drawing, in a much more interactive process than simply "seeing" with immediacy what bigger picture the part could belong to. Obviously, the solution set is rather unconstrained in this test, unlike in some creative or insight problems, where one has to navigate constraints to find a very unlikely but only possible solution, given the resources or objects at hand.

The TTCT is scored on five subscales:

- Fluency, representing the number of ideas produced;
- Originality, a statistical measure of infrequent or unique ideas;
- Elaboration, showing ability to develop or detail ideas;

- Abstractness of titles, scale relying on the premise that creativity and abstractness fo hand in hand and
- Resistance to premature closure, relying on the premise that creativity is linked to personality traits of open-mindedness and cognitive traits of an ability to consider large and various amounts and types of information before closing in on the solution.

2.4.1.3 Riddles

Though no comprehensive set of riddles test exists, performance on riddles has been used to study or enhance creative problem-solving skills [125, 164]. Answering riddles correctly and even being informed of the answer to a riddle the solution of which eluded the solver can trigger flash of insight effects.

Different types of riddles exist, depending on the process and resources required to solve them. One categorisation system splits them into two types - enigmas and conundra. Enigmas are the riddles which are phrased in metaphorical or allegorical language, thus requiring a form of what we could call metaphorical reverse-engineering from the part of the solver. The conundra type of riddles involve word play - thus words that can have double meaning.

Other types of riddle categorisation exist, however following the categorisation system mentioned below, the riddles which we find the most interesting and characteristic of the riddle genre are the ones from the enigma category.

Some riddle examples are the following:

Ex. 1 - Poor people have it. Rich people need it. If you eat it you die. What is it? (Answer: nothing)

Ex. 2 - A box without hinges, key or lid, yet golden treasure inside is hid. What is it? (From Tolkien - The Hobbit; Answer: egg)

2.4.1.4 The Remote Associates Test

The Remote Associates Test [108] is a creativity test aimed to measure ability to use associates to come up with an answer. The Remote Associates Test is administered as follows: the participant receives three words, like MANNERS, ROUND AND TENNIS, and is required to come up with a forth word that connects with each of them. In this example, a correct answer is TABLE, with the three connections being TABLE MANNERS, ROUND TABLE and TABLE TENNIS. The Remote Associates Test has been widely used in the literature [3, 10, 33].

The test itself starts from the premise that association is used in creativity, and the ability to make associates between remote concepts across wide domains shows a higher degree of creative ability. This test uses response times and percentage of queries solved to measure performance of the solvers.

2.4.1.5 Empirical Insight tests

Various empirical insight tests exists. However, depending on the type of knowledge they elicit, they can be split into various categories. Thus, a differentiation can be made between mathematical insight problems, verbal insight problems, spatial insight problems and practical object insight problems. In the following, we will give an example of each in the first three categories:

1. Mathematical insight problem
Which would be worth more, a pound of 10 dollar pure gold coins or half a pound of 20 dollar pure gold coins; or would they be worth the same? Explain your answer.

2. Spatial insight problem
Given fig. 2.3, without lifting your pencil from the paper, show how you could join all 4 dots with 2 straight lines.

FIGURE 2.3: The four dots problem

3. Verbal insight problem
The legendary runner Flash Fleetfoot was so fast that his friends said he could turn off the light switch and jump into bed before the room got dark. On one occasion Flash proved he could do it. How?

The solutions for these are the following:

- 1. A pound of gold is worth more than half a pound.
- 2. Exit the imaginary space created by the for dots, like in fig. 2.3
- 3. He went to bed during the day.

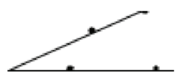


FIGURE 2.4: The four dots problem solved

Some such empirical insight problems can be called object problems or practical insight problems, due to their use of objects and object affordance in their formulation and solving. Some such problems are the candle problem [36] and the two strings problem [101]. These will be presented and discussed in Section 7.

When solving such problems with objects, human participants sometimes encounter functional fixedness [1, 4], that is a cognitive bias which limits the solver to only seeing one particular traditional way of using an object. This generally prevents participants from using objects for atypical functions, and thus solving such insight problems. Functional fixedness has been shown to affect solvers from technologically sparse cultures as well [56]. Some authors compare fixedness in approaching the problem with getting stuck in a mental rut [141].

2.4.2 Creativity evaluation in computational creativity systems

Various attempts at and theories about assessing creativity in computational systems exist. In the following, an overview of four such systems of evaluation is presented: (i) Wiggins's model of the universe of possibilities and transformational creativity (Section 2.4.2.1); (ii) Ritchie's typicality criteria and the inspiring set (Section 2.4.2.2); (iii) process, novelty and quality based evaluation in the work of Pease, Winterstein and Colton (Section 2.4.2.3) and (iv) the FACE and IDEA descriptive models (Section 2.4.2.4).

2.4.2.1 Wiggins's model of the universe of possibilities and transformational creativity

Wiggins [166] proposes a model for the description, analysis and comparison of creative systems, starting to formalize Boden's descriptive hierarchy of creative processes. In this process, he defines the notions of *creative system*, *creative behaviour*, *novelty* and *value*. These terms are defined in his work as follows:

- **Creative system** – A collection of processes, natural or automatic, which are capable of achieving or simulating behaviour which in humans would be deemed creative.
- **Creative behaviour** – One or more of the behaviours exhibited by a *creative system*.
- **Novelty** – The property of an artefact (abstract or concrete) that is the output of a *creative system* which arises from prior non-existence of like or identical artefacts in the context in which the artefact is produced.
- **Value** - The property of an artefact (abstract or concrete) that is the output of a *creative system* which renders it desirable in the context in which it is produced.

This definition of the creative system aims to circumvent the fact that humans are considered capable of creativity, while machines performing similar feats might encounter critics. This is due to the fact that it is easier to understand creative processes when these have been computationally implemented, and some of the computational creativity critics might view such processes as less creative if they are easier to understand than in humans.

Wiggins's definition of Novelty can be seen as one of process. Thus the creative system which produces an artefact is supposed to produce it in a context in which no identical or "like" artefacts are produced. The "like" part is hard to assess in this context - is it supposed to mean identity or similarity? If it means similarity, of what kind and what degree? Similar but varied artefacts might in some cases be an exhibit creativity in themselves - like theme and variations forms in music.

Wiggins's notion of Value adds a socio-economical component to creative products. This definition of Value can be compared to a definition of Usefulness in the context of creative problem solving.

After defining this terminology, Wiggins proceeds to define a universe of possibilities as U which contains all possible non-identical concepts. This universe of concepts is multidimensional, and contains both concrete and abstract concepts. Wiggins aims his proposal of $\mathscr{U}$ to be compatible to a state-space interpretation. Thus Boden's conceptual spaces are defined as $\mathscr{C}$, non-strict subsets of $\mathscr{U}$. No $\mathscr{C}$ can be equal to $\mathscr{U}$ as this would make transformational creativity unnecessary. Wiggins then defines $\mathscr{R}$ as the set of rules which constrains the space, and $\mathscr{T}$ as the set of rules which allows for the traversal of this space (i.e. a search strategy). Thus $\mathscr{R}$ represents the type of artefact to be created, while $\mathscr{T}$ is the way in which an artifact is produced by an agent.

Wiggins further defines $\mathscr{E}$ as a set of rules which allows evaluation. While not defining the work of $\mathscr{E}$, Wiggins then characterizes exploratory and transformational systems under this notation. Furthermore, he introduces the idea of unreachable concepts. Thus given $\mathscr{C}$, a concept $c \in \mathscr{C}$ might be unreachable - depending on the traversal strategy $\mathscr{T}$ which is being used. In Wiggins's account, traversal strategies are thus dependent on the *properties of a given creator*. A discussion on changing the traversal strategy itself ($\mathscr{T}$ to $\mathscr{T}'$) prompts the author to consider Boden's boundary between exploratory and transformational creativity as ill-defined. The author then proposes as interesting for future work the changes that happen in the rules of evaluation ($\mathscr{E}$), which might lead to adopting different constraints for artefacts ($\mathscr{R}$), and then offers a new definition of transformational creativity as acting at the meta-level of representation.

Wiggins then uses this theoretical framework to propose how implementations and their properties could be described (and in a sense evaluated).

2.4.2.2 Ritchie's typicality criteria and the inspiring set

Ritchie proposed a way of assessing creativity which takes into account the *inspiring set* [126]. An *inspiring set* is for Ritchie the union of explicit and implicit knowledge. Ritchie proposes fourteen criteria of assessing creativity, mainly in terms of typicality, quality and novelty. These are further implemented in the evaluation of a poem generator (Wasp), a conceptual blender (Divago) and a sentence paraphraser (Dupond) by Pereira et al. [123].

Ritchie's criteria are the following:

1. Average typicality
2. The ratio of typical results to all results
3. Average quality

4. The ratio of good results to all results
5. The ratio of good typical results to all results
6. The ratio of good atypical results to all results
7. The ratio of good atypical results to atypical results
8. The ratio of good atypical results to good typical results
9. The ratio of results in the inspiring set to the inspiring set
10. The ratio of all results to the results in the inspiring set
11. Average typicality of new results
12. Average quality of new results
13. The ratio of typical new results to new results
14. The ratio of good results to results

2.4.2.3 Process, novelty and quality based evaluation - Pease, Winterstein and Colton

Pease, Winterstein and Colton [122] propose an evaluation of creativity which takes into account the input, output and process by which the output is achieved by the creative system. Using Ritchie's definition of an inspiring set, Pease et al. propose methods for creativity evaluation. These methods are related to novelty, quality and process. Different types of novelty are considered, and measures proposed to deal with them:

- Novelty relative to a body of knowledge (e.g. a concept space) - a *transformation measure* is proposed
- Novelty relative to complexity - a *complexity measure* is proposed
- Novelty relative to an archetype - an *archetypal measure* is proposed
- Novelty as surprise - a *surprise measure* is proposed
- Perceived novelty - a *perceived novelty measure* is proposed

The following types of quality factors and measures are proposed:

- Quality relative to emotional response - an *emotional response* measure is proposed, depending on intensity and type of such a response
- Quality relative to aim - a *pragmatic measure* is proposed

In terms of process, a measure of *randomness* is proposed. Evaluation in general is considered to be bipartite by Pease, Winterstein and Colton [122]. They posit that part of the evaluation should deal with the created artefact, while part should deal with the process of creating the artefact. Thus, they propose an *evaluation of item* measure and an *evaluation of process* measure.

2.4.2.4 The FACE and IDEA descriptive models

The FACE and IDEA descriptive models where introduced by Colton, Charnley and Pease [24] as a computational creativity analogue for computational learning theory in machine learning. The FACE model describes creative acts as tuples of generative acts, while the IDEA model describes the impact of creative acts. These models are aimed at describing software, with no claims that they might have value in describing human behaviour.

Under FACE, creative acts are described as a non-empty set tuple of generative acts, which contain exactly zero or one instance of eight types of such acts. Considering that (i) a concept is an executable program which can take input and produce output; (ii) an expression of a concept is an instance of an input-output pair which results from executing a concept's program; (iii) an aesthetic measure is a function of a concept-expression pair which outputs a real value between 0 and infinity and (iv) framing information is natural language text which adds value to a generative act, the eight types of generative acts are:

1. E^g - an expression of a concept;
2. E^p - a method for generating expressions of a concept;
3. C^g - a concept;
4. C^p - a method for generating concepts;
5. A^g - an aesthetic measure;
6. A^p - a method for generating aesthetic measures;
7. F^g - an item of framing information and
8. F^p - a method for generating framing information.

The g and p superscripts define ground and process level acts, thus $\langle F^g, A^g, C^g, E^g \rangle$ denotes a creative act described by a 4-tuple of generative acts.

Colton, Charnley and Pease propose to use the FACE model in a variety of ways. A quantitative way to use it might be to compare the volume of creative acts between creative systems. A cumulative way might evaluate creative acts which produce an aesthetic and framing as more creative than the ones which only produce concepts and expressions. A comparative way would include orderings in which taking some generative act is seen as more creative than another, etc.

The IDEA model replaces the notion of value of solutions with that of impact of creations made by a computational creativity system. The IDEA model stands for an (I)terative (D)evelopment-(E)xecution-(A)ppreciation cycle, which includes the steps of engineering the system and its exposure to an ideal audience. Six stages of development are suggested, depending on the difference between the knowledge information given to the system and the artefacts it generates, and using two thresholds - a lower threshold which denotes too much similarity between given examples and generated artefacts, and an upper bound threshold which denotes too high dissimilarity which makes assessment impossible because of too little context. These stages are: (i) Developmental stage; (ii) Fine-tuned stage; (iii) Re-invention stage; (iv) Discovery stage; (v) Disruption stage and (vi) Disorientation stage.

Using a human assessment based on well-being (indicating liking or disliking) and cognitive effort, the IDEA model describes measures of disgust, divisiveness, indifference, popularity and provocation for the human assessment stage, followed by measures of the impact of the creative acts based on provocation. These measures aimed to assess types of impact like: acquired taste, instant appeal, opinion splitting, opinion forming, shock, subversion and triviality. Thus the model defines impact as any other measure achieved than triviality.

These FACE and IDEA models were used by the authors to exemplify a comparison of mathematical invention and visual art computational creativity systems (like AM [94], HR [20], AARON [19], the Painting Fool [21], NEvAR [99]) and later used to build a poetry-based generation system which can be evaluated using all the FACE metrics [23].

2.5 Discussion

In light of the previously presented literature, various points seem of major importance when aiming to study, model or implement creative problem solving:

(a) Elaborating the definition of problem solving as to include creative problem solving processes;
(b) Developing unified cognitive frameworks, in which various different types of creative problem solving tasks can be analysed;
(c) The ability to implement types of knowledge representation which enable creative processes similar to those of humans, like association and restructuring;
(d) From a methodological perspective, the ability to evaluate artificial creative problem solving systems using comparable tools to those used to evaluate creativity in human cognition.

As seen in Sections 2.1.1 and 2.1.2, creativity and problem solving are often addressed separately in the cognitive and artificial intelligence literature. The classical (AI) definition of problem solving needs to be updated in order to be able to include the cognitive processes of creativity, and explain the phenomena of insightful problem solving described in Sections 2.1.3 and 2.1.4. As most problems in the world are ill-structured, a wider definition of problem solving should include the ill-structured to well-structured step before proceeding to accounts of the classical problem-solving steps.

Because of the interplay between knowledge organization and process explained in Section 2.2, both knowledge representation and process have to be tackled together in an account of creative problem solving. As the field of computationally creative systems has started gaining considerable traction (Section 2.3), an unified cognitive theoretical framework should allow the possibility of building systems in which various different types of creative problem-solving tasks, like the ones in Section 2.4.1, can be studied. Moreover, such a unified view should include the ability to study creative problem solving in a variety of modalities, as to include manifestations of visuospatial intelligence and creativity, because of the reasons described in Section 2.1.5.

A cognitive systems implementation of such knowledge organization and creative process has to also take into consideration the various types of process which seem relevant to creative cognition - including association, use of structure and similarity, and re-representation, as shown in Section 2.2.

Different types of evaluation are currently deployed for computational creativity systems and human participants in creativity tests, as shown in Sections 2.4.1 and 2.4.2 respectively. An approach aiming to be of use to both AI and cognitive empirical studies would need to implement a type of evaluation closer to human creativity evaluation for the cognitive systems it yields, but to which computational creativity types of evaluation might still be relevant.

Chapter 3

A Theoretical Framework for Cognitive Creative Problem Solving

Because of the importance knowledge representation, structure and restructuring and re-representation seem to have on creative problem solving, it is worth taking another look at the classical definition of problem solving and aiming to improve it as to include creative processes. Section 3.1 will focus on refining the definition of classical problem solving, as to allow for ill-structured problems and thus for creative problem solving.

A framework in which creative problem solving can be studied in an interdisciplinary manner will have to take the following factors into account:

- be a unified framework [115], aiming to account for a diverse group of creative problem-solving tasks;
- aim to account for creative problem solving in a multi-modal manner - thus having explanatory processes for stimuli that are visuospatial as well as linguistic;
- be based on a limited small set of processes, for which some cognitive translatability can be assumed; such processes should involve association, similarity, ability to structure and restructure the problem space;
- give comparable results to human answers in empirical creativity tests as to allow further development of hypotheses about creative process and
- provide results which can be assessed in terms of computational creativity frameworks.

A set of possible desiderata for such a framework is put together in Section 3.2. This leads to an analogy between a mechanism made of simple machines and the components of a knowledge base during the creative problem-solving processes.A framework of knowledge organization which allows restructuring and re-representation processes of both search and construction is described theoretically in Section 3.3. The implementation of the processes from 3.2 is then explained theoretically in the context of the framework in

Section 3.4 (while more formal concerns regarding these processes will be refined in the Section 4). A short discussion over the use of space and structure in this framework concludes this chapter in 3.5.

3.1 Refining the definition of creative problem solving

The classical definition of problem solving presupposes an orderly initial state. Perhaps this is a reflection of a well-structured problem, or perhaps this misses the initial step of "structuring" the problem - which happens in the mind of the programmer or problem-solver. Thus, this initial state already contains all the objects, be it abstract or concrete, necessary to solve the problem.

A revised version of problem solving which includes creative processes, used in creative problem solving and the tackling of ill-structured problems could include:

- An initial set of features;
- An initial set of representations in the knowledge base of the solver;
- Interpretation steps act upon the set of features, translating them into representations of what the objects are, what the salient elements are, what the problem is. Such steps are a form of structuring the problem which aims to bridge the gap between an ill-structured problem and a well-structured problem, most likely using structured knowledge (and ways of structuring) present in the knowledge base of the solver;
- This yields an initial state, with afferent operators and paths (which depend on the operators known or strongly associated by the problem-solver to those representations);
- The next steps are applied as in classical problem solving. If the process is not successful: a) restart at the interpretation step (re-represent features, objects, what the problem is) or b) change currently held representations or c) bring new features in.

3.2 Refining desirata for a unified theoretical framework for creative problem solving

This section will tackle a set of diverse problems and processes that a unified creative problem-solving framework could aim to solve. The processes described in this section include: visuospatial inference (3.2.1), creative use of affordance (3.2.2), concept generation and structure transfer (3.2.3), insight and re-representation (3.2.4). Visuospatial inference, while not a creative mechanism by itself, can support creativity; thus it will be described in its compositional and creative forms here, and used as an example to explain restructuring at the higher creative problem-solving levels.

3.2.1 Visuospatial inference

Visuospatial inference has been previously analysed by Sloman [139] as a rational (but not necessarily logical) process of inference often performed by human beings. One of Sloman's examples depicts a mechanism of pulleys and levers. A human looking at the example in Fig. 3.1 (a) and knowing where the motion is initiated in the system can infer the way the system will move and what type of motion the end tip of the right lever will perform. As shown in Fig. 3.1 (b), in this case the right side of the right lever will move downwards. Humans are thus equipped with a variety of inference-making sensory-based processes. These processes are not propositional or "logical" in nature, but come from the sensorial experience humans have with their environment, from previously observed and encoded features of various natural or human made "objects", and their motion.

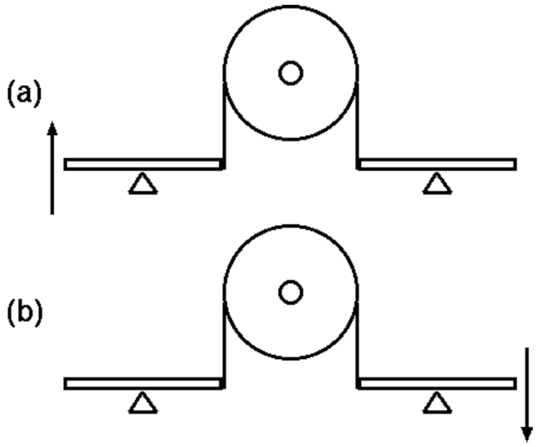


Figure 3.1: The original pulley and levers example by Sloman

What would an artificial cognitive system take to solve Sloman's example? A system able to tackle such a domain will need to know types of motion for a variety of objects (in this case levers and pulleys), then be able to assemble or transfer such motion compositionally to the level of the mechanism. At the creative level, such a machine should be able to fill in various parts of the mechanism when they are missing, or create its own mechanisms when a certain type of motion is required (this is essential for insight problems situated in the physical domain, such as the Two Strings problem - Fig. 7.3, which require knowledge about motion and maybe its mental simulation). Moreover, this type of inference is of use for creativity cases where visuospatial inspiration is integrated into a different domain, or the problem is synthesized in an abstract form into a visuospatial problem. Also, this type of problem will be used as an analogy in our proposed framework for solving insight problems, in a manner which will be explained in section 3.2.4.

3.2.2 Creative use of affordance

Problems of creative use of affordance[1] can be easily explained in the physical domain as object problems in which an agent requires a specific tool or set of objects to solve

[1] For more on the concept of affordances see Gibson [57].

a specific problem, but one of these objects is not given in its environment - e.g. an agent needs a cup to pour water in, but there is no cup available. In this case, humans can find other objects with similar properties which can solve the problem, because they have a similar affordance. In the missing cup example, a bowl, pot, or even boot can be used by a human, depending on how desperate the circumstances are.

At an abstract level, creative use of affordance reflects the ability of using different concepts when some are not available or have somehow failed short (e.g. in mathematics: use of different proofs, constructs or concepts; in literature: use of different words, parts of plot development, narrative style; in research: use of different experimental tools and tests).

Creative use of affordance in the physical domain (objects) can also be seen as the same ability which is tested empirically by the Alternative Uses Test (previously described in 2.4.1.1). In consequence, introducing creative use of affordance in a creative problem-solving framework is useful because: (i) artificial systems implementing creative use of affordance can be evaluated comparatively to humans, and (ii) hypotheses about how creative use of affordance works in humans can be implemented in models and falsified via computational experimentation.

3.2.3 Concept generation and structure transfer

Various theories have been proposed for concept formation: prototype theory [128], exemplar theory [106], theory theory [111]. The issue of concept formation is connected to, but not entirely overlapping the process of creative concept generation. Concept discovery [34], concept combination [2] and concept blending [41] are themes of importance in both cognitive science and computational creativity. The ability to generate new concepts out of new observations or old knowledge is thus another creative ability which a unified framework should aim to implement. This is not identical with concept blending [41], which can be considered a special case of concept generation.

Various ways of generating concepts can be envisaged, however we will focus on only a couple of interesting processes which, if implemented by a framework, would prove headway in the direction of concept generation. The processes which we will focus on are: a) the use of visual templates and b) concept generation via overlap and synthesis.

a) Consider the case of an instance of the object *chain* (depicted in Fig. 3.2), in which a cognitive agent observing or representing this instance is able to understand its elementary components (the loops) and the relationship between them (a specific type of connectedness). Let's say two other objects are known, which have similar features with the elementary components of the *chain*, a *scissor* (part of its handle is loop like) and a piece of *string* (because its property of being easily twisted, a string can become a loop). Then a creative cognitive system should be able to transfer the specific template of connectedness and realize it with the two new objects.

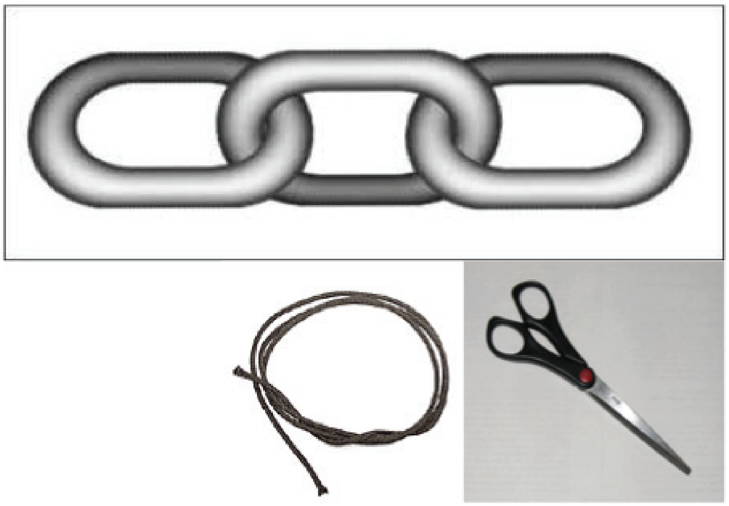


FIGURE 3.2: An instance of a chain representation used as a structuring template

b) Consider a case in which a *bigger than* relationship is observed over the same object domain twice - Fig. 3.3 a) and b). A new concept, that of *growth* could be derived if the representations of those instances are overlapped and reinterpreted as in 3.3 c) . The template of this process (the relationships and essential features) can be separated from the non-essential (the object themselves), and transferred to a new set of objects 3.4, where it can be used to recognize the same relationship or order those objects (productive use). Then, a synthesis of the *growth* concept can be re-represented graphically like in 3.4 c).

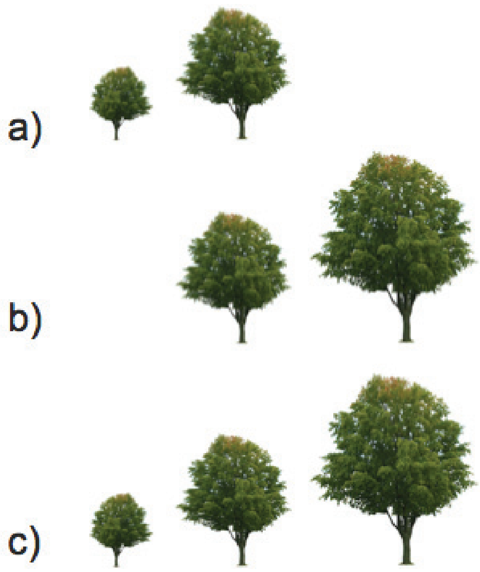


FIGURE 3.3: Inference of a new relationship *growth* in c) via overlap of *bigger-than* instances a) and b)

As mentioned previously, these are but a part of the concept generation mechanisms a creative cognitive system should be able to perform, and more of them will be discussed

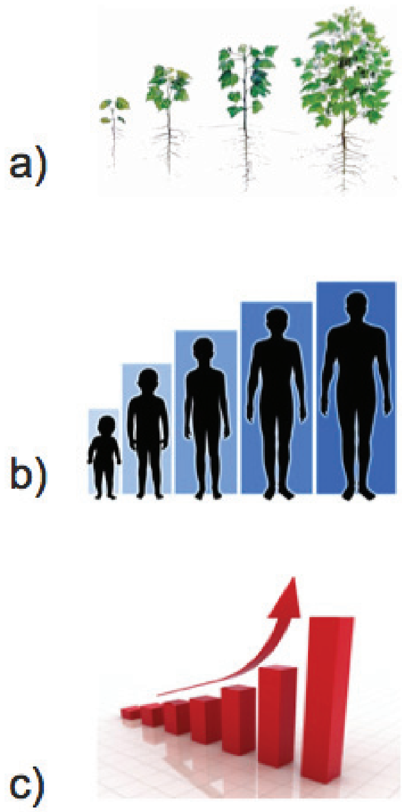


FIGURE 3.4: a) to b) Adaptation of the growth template to a new domain; c) synthesis via compression to defining features

in 3.4.3.

As for the process of structure transfer, some of it is already observable in the cases explored above. However, a unified framework for creative problem solving should provide types of knowledge organization and processes which support ampler cases of structure transfer. This is necessary to account for the already studied processes of analogy [54], and also to enable the ability of transferring known problem templates to new problem spaces and the use of elements of such problem templates to create new templates. These abilities are necessary in order for creative problem solving to occur.

3.2.4 Insight and re-representation

Insight is based around the restructuring and re-representation of a specific problem. Such restructuring makes the problem center on different features, and helps solvers look at it with a different mental toolset. This makes structured representations and the ability to restructure them essential to the pursuit of modeling creative problem solving and insight in artificial cognitive systems.

In the following, a way of looking at insight and re-representation is proposed, based on an analogy with the simple machines example shown in Section 3.2.1. This "clockwork" principle represents a core aspect of the theoretical framework we propose.

In the simple machines example, a system which can compositionally solve the motion inference over a set of connected simple machines was imagined; this system could fill in a particular missing piece through knowledge of the components and their motion (where also multiple solutions can be applied). The simple machine elements in this example can be replaced with concepts. The motion ability of the simple machines can be replaced with concept affordances. Then various combinations of such machines can be thought of as problem templates used to achieve a particular end action.

Sometimes parts of such a system of simple machines are present, and parts need to be filled in. This can be seen as knowing some elements of a problem, and needing to bring forth different concepts and their functionality to obtain the desired affordance, or end result. Not all the known or given elements are useful, nor their actual right combination is initially known[2].

However, some elements need to be used in some problems, corresponding to the fixed points in a simple machine mechanism. Multiple different strands of known concepts can be organized around the fixed points. The fixed points can be looked at as being a possible part of multiple mechanisms. The ability to restructure knowledge and one‘s problem space is equivalent to the ability to navigate between these compositional possibilities. Insight is the moment in which all the elements fall into place, allowing the motion to be passed across the entire mechanism freely.

Simple machines can bind together when the motion of a machine can be carried on by the other (a locking point). Similarly, concepts can bind together when some of their features are similar. Simple machines can be replaced by other machines or groups of machines which afford a similar type of motion. Similarly, concepts can be searched for and replaced by other concepts with which they share features

This allows us to think of insight and creative problem solving in a piece-wise fashion. As we will see further, various fixed points in the machine can organize their motion inference (or affordance inference) strands in parallel, with the insight being obtained via a convergence moment of the different strands of motion (or affordance inference). Various types of re-representation are possible (making/constructing parts of the mechanism out of different representational cogs or simple machines).

The cog to clockwork inspiration has warranted this framework the name CreaCogs. The name stands for Creative Re-Representation using Affordances in Cognitive Systems[3]. However it can also stand for Creative Cogs, Creative Cognition, Creative Cognitive Systems, etc. Notice how this principle actually is a small depiction of the principle of re-representation - a set of features can be represented and interpreted in multiple ways, each triggering their own associated meaning.

[2] Functional fixedness in this analogy is the act of assembling such concepts in a way which is most comfortable and comes automatically to the mechanism assembler or clockmaker.

[3] Abbreviation CReACogS could have been used but its spelling has been deemed too cumbersome.

3.3 The Framework: CreaCogs

The theoretical framework proposed here is based on a way of encoding knowledge which permits processes of fast and informed search and construction for the purposes of creative problem solving. These processes take place conceptually at three levels, which are visually depicted in Fig: 3.5. The purpose of these three levels and their interplay is explained in a theoretical manner, starting from the bottom level, in the following sections: L1 - Feature spaces; L2 - Concepts; L3 - Problem templates.

L1 ***Feature spaces***
The first level is the subsymbolic level of feature maps or feature spaces. Whenever an object is observed, its various known sensory properties, together with its observed actions (or actions the agent can perform towards it) are encoded in the various feature spaces of the framework. Thus, visuospatial properties like shape or color will be encoded in different feature maps, motion in another feature map, etc. Each observed or retrieved object (or concept in its more general form) will be an activation over these distributed feature maps. This expresses a way of tackling the grounding problem in line with cognitive grounding theories [6, 7].

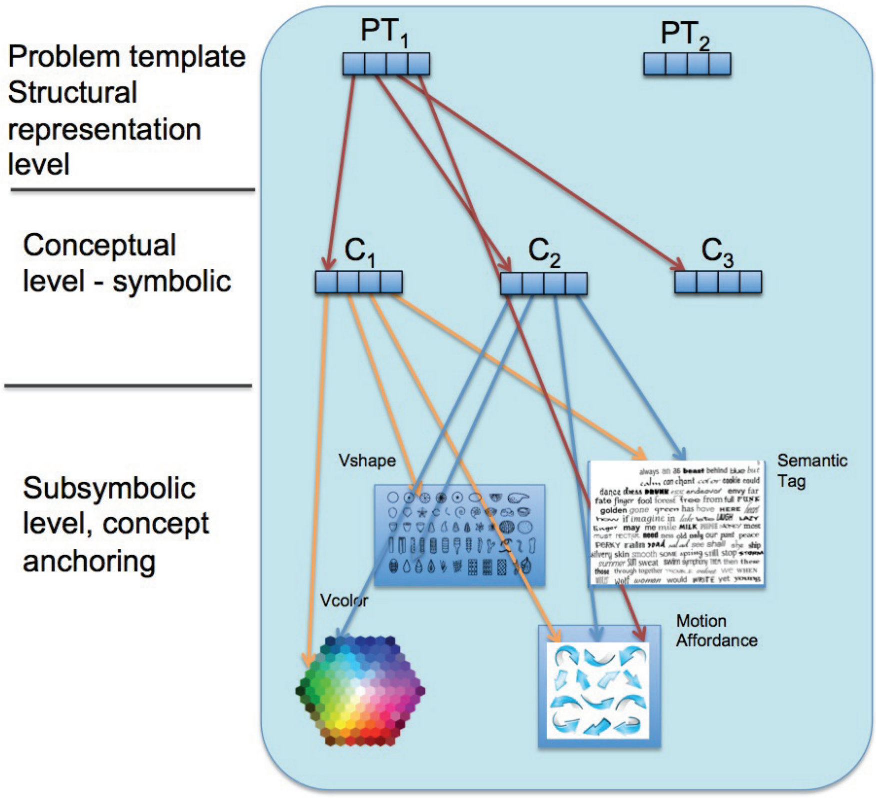


FIGURE 3.5: A visual depiction of the theoretical framework

Such grounding doesn't only affect the way concepts are stored/retrieved, but turns to have important uses for the creativity domain. This is due to the encoding of various feature maps in an organized fashion, according to a distance metric relevant to the space in question (e.g. color similarity, shape similarity).

L2 ***Concepts***
The various known concepts are thus grounded in a distributed fashion in organized feature spaces, and represent the second level of this theoretical framework. This allows concepts with similar properties to have common or close points encoded across various feature maps, thus making concepts similar on diverse properties accessible to search. The name of the concepts is encoded in a different semantic tag map, thus functionally constituting another feature. This is reasonable as ability to name objects can be lost (anomic phasia - word selection anomia) independently of the ability to comprehend objects and concepts. With the semantic tag being only a feature, not the entire concept, encoding meaning more than encoding concept names and concept meaning can be recalled independent of name recall.

Thus a concept's meaning is the collection of features, facts, actions and relations over which that concept has been encoded. A concept can be fully identified or recalled not only by name, but also by other sensory properties (the way it looks, moves, etc.), if these are uniquely pointing to that concept, or with a subset of such features, when the name is unknown. Concepts do not need a name to exist in the mind that beholds them (though obviously that can impede their communication), and it is posited that some problem templates also behave like concepts over time (when they are used multiple times, compressed or named).

L3 ***Problem Templates***
The third level of the framework is constituted by problem templates. These are known ways of solving problems which contain diverse objects. They are structured representations which are encoded over multiple concepts, their relations, and the affordance the problem template provides. A concept can be connected in various templates, where different parts of its features are emphasized, or become functional. As shown in Fig. 3.6, a hammer encoded in a problem template with a walnut will have its affordance to break things emphasized, while when in conjunction with a nail, it will display a fastening affordance at the level of the problem template.

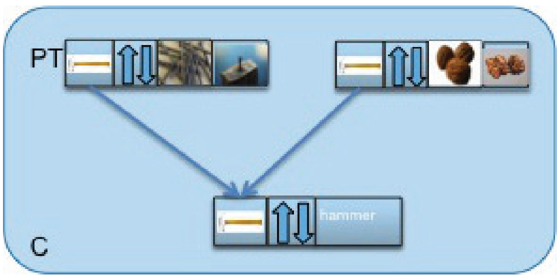


FIGURE 3.6: Concept in multiple problem template contexts in CreaCogs

The knowledge organization employed in CreaCogs has multiple advantages for the kind of processes required in creative problem solving, including:

a) *grounding downwards*; concepts are grounded in feature maps, while problem templates are grounded in concepts. This allows easy search and substitution of missing parts. If a needed object is missing, a similar object can be found by looking downwards in the knowledge base or comparing needed features with the objects present in the environment. This allows the agent to use a shoe when a hammer is not present (the shoe has a similar weight, a solid sole which affords hitting with similarly to the head of a hammer, and a part which can be grasped).

b) *anchoring upwards* in context; concepts gain different meaning (and hold different relational roles) through the various templates they participate in.

c) *re-use of structure* (or structure transfer) because of structure and content being kept separately, but in relationship. The structure of a template can be used to recruit new concepts. The structure of a concept can be used to recruit new features.

d) use of *sensory experiences as structuring elements*. Thus the features of a visuospatial symbol representation (e.g. the Ouroboros snake) can be amplified into a problem template and replaced with other conceptual elements (e.g. the elements of the benzene molecule).

Besides the structuring and restructuring functionality, CreaCogs allows for creation of new relations, concepts and templates via different forms of overlap. Some of these are residual, and can be viewed as generalizations over multiple correlations. As an example, some features can be associated across multiple concepts (as some concepts can be associated across multiple problem templates). If a feature to feature overlap happens across multiple concepts, it can be strengthened and leave residual effects on the knowledge base, which trigger interesting ways of perceiving meaning. For example, the colour RED is sometimes perceived as being somehow *related to* speed and violence or fire and energy - which allows further speculation of feature use and meaning creation in the arts.

The next section explains theoretically how the previously mentioned desirable processes can be encoded and solved in such a theoretical framework. A formalization is provided in Chapter 4.

3.4 Theoretical explanation of processes

In Section 3.2 some processes were set forward as desiderata from a unified creative framework. The way these can be theoretically deployed in CreaCogs is explained in this section as follows: visuospatial inference (3.4.1); creative use of affordance (3.4.2); concept generation and structure transfer (3.4.3); insight and re-representation (3.4.4).

3.4.1 Visuospatial inference in CreaCogs

a) ***Single case*** Visuospatial inference of one object involves activating the knowledge of that object, and simulating the specific previously encoded motor affordance. Thus, with a lever, two motor inferences can be encoded - when the lever is pushed down or on the left side, or pulled up on the left side, the effect of the resulting motion being to place the right side of the lever up or down respectively.

If the visual features of a lever have been observed in the environment, and have previously been encoded in the agent's knowledge base together with the concept of a lever, and knowledge about the start of motion is given, the system can then deploy one of the two motion simulation routines attached to that object or concept to simulate and anticipate the result of that motion.

b) ***Compositional case*** In the case in which a mechanism is being observed, the system can deploy the same type of knowledge compositionally. Thus the motion inference made on the first object will then be propagated into the motion beginning pattern of the second object. This can be applied to compositional cases of multiple objects. The agent can then simulate and follow the motion as it propagates through the system[4] until the last inference has been made about the exit motion (motion at the end of the last part of the mechanism). In Fig. 3.7, the disambiguation of a problem containing two cogs via repeated reference to and substitution with knowledge from the cog concept is presented visually. Here, an initial problem (PT level- up left) inquires about the end motion in a mechanism made of two cogs, given the an initial upward motion. The first of the two cogs is matched to the conceptual representation of a cog and the motion affordance known to be produced by the initial upward motion from the left of the cog (C level - down left). This is used to elaborate the representation of the mechanism (PT level - up right, first three slots). The inference made about the motion of the first cog is then used to find the afferent motion affordance of the second cog at the conceptual level (C level - down right). Once this has been located, the problem representation is elaborated again and the end motion is inferred (PT level - up right slots 4-6).

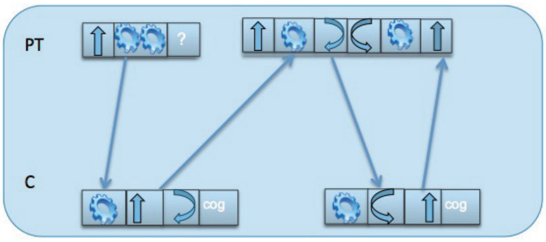


FIGURE 3.7: Compositional visuospatial inference in CreaCogs

c) ***Creative case*** In the case in which a mechanism needs to be reconstructed, with various stable points (fixed machines) and a certain type of motion flow expected, the piecewise knowledge about the elements and previous experience with mechanisms (which can be encoded as problem templates) can be used to construct the mechanism. This can be done in multiple ways, via inference, template or property guided search, trial and error, filling in previously known templates, using replacement parts or equivalent sub-mechanisms until these sub-parts fit to allow for the expected end motion, etc.

[4]This is a non-parallel, no-interference case. That is to say, in this case motion is assumed to flow on one strand, not on multiple parallel strands (possibly by having the initial object connected to multiple different objects).

This can be depicted both symbolically and subsymbolically, however as we do not have precise symbolic terms about motion, a subsymbolic implementation will probably be more expressive and direct (also a more accurate depiction of natural cognitive systems).

The example discussed here talks about visuospatial motion inference in a restricted domain, where only knowledge about simple machines or mechanisms can be used. This has been done here to simplify matters and showcase the inferential process theoretically. However, in the next cases, it is to be generalized that a suitable affordance will be searched across all types of known similar (or similarly affording[5]) motion patterns.

3.4.2 Creative use of affordance in CreaCogs

Creative use of affordance can be deployed in various ways in CreaCogs. These are described here in the context of concepts, and then applied to problem template use in 3.4.4.

Because in CreaCogs each object is represented as a distributed encoding in organized feature maps, various types of search can be performed to find replacement objects in case an object is not available. Some of these are the following:

a) The affordance of each object can be used to link back to other objects that have been encoded over the same affordance.

b) If no other object is encoded with the same affordance, objects with a similar affordance can be found (nearby similarity search on affordance).

If no object with same or similar explicit affordance is found, the search can be focused on other properties of the object which enable that affordance (properties connected with the affordance in the concept itself are just a start, some properties might be highly connected with the affordance over multiple other examples). Thus, a functional property or set of functional properties (which enable the affordance) can be found. Once this has been found, one can then navigate the space of known objects (or objects at hand, present in the environment):

c) which are anchored in conjunction of the functional property;

d) which are anchored close to that functional property.

3.4.3 Concept generation and Structure transfer in CreaCogs

Multiple ways of doing concept generation and structure transfer are available in the CreaCogs framework. These involve an interplay which can be both amodal or multimodal, between the various parts of the system - concept to concept, feature to concept, template to concept (and vice versa). Here we will describe just a few to showcase this diversity, and proceed to lay down more formal concepts for these mechanisms in Ch.4.

[5]That have a similar end result.

Diversification A concept can become a template by refining its parts - i.e. a *stone* which is used for smashing things or driving wedges through things has an inherent *handle* within its body. When this handle is differentiated as a specific part, built and optimized for the grasping affordance, we get a *hammer*.

This allows not only expansion of a feature to a concept, a concept to a more complex concept or to a template, but also permits overlapping transfers (of features or structure) upwards from a feature into a concept, and from a concept into a complex concept or template.

Concept to concept overlap Sometimes concepts overlap on certain features. Such overlaps allow or can trigger composition and feature exchange. The concept *sea* has a feature which involves liquid, and so does the concept *juice*. A creative concept obtained via their overlap would be a *sea of juice* - which is probably something children have thought about with pleasure before. Overlapping *sea* with another concept with fluid properties, *blood*, we obtain *sea of blood*, but also *sea water in its blood* - depending on which concept we use as a container template. More complex templates could be *sea in the blood*, *sea waving through its veins*, etc.

Some of these overlaps might seem like poetic license, while others are well established in our spoken culture, like *pitch black*, a concept which could have been generated because of the feature *black* being so characteristic for *pitch*.

Such a type of concept generation via overlap can be observed over a variety of features, including type of motion, and sometimes involving deep conceptual structures - e.g. the concept *meme*, which is meant to describe something that spreads in the world by moving like a virus but is actually an idea. The movement of ideas in this case must have seemed similar to that of a virus to R. Dawkins [32] who coined the concept.

Some overlaps can come from previously unnamed correlations of features, previously unnamed concepts. As a concept is a correlation of features, it makes sense that further correlations will allow the generation of further concepts. Some of these overlaps are seemingly semantically unrelated previous to the overlap, however the CreaCogs framework allows for overlap via features to trigger these possible constructions, as well as overlap via concepts.

Using structure from a different concept Some concepts come with their own set of relations and structure. One can use this set of relations to create a new concept as well. Take the following examples:

Ex.1 - chain The loops of the *chain* where sparkling. A *chain* of shops opened across town (deployment of the same structure over space). Something triggered this *chain* of events (deployment of the same structure over time).

Ex.2 - stores The warehouse *stored* various objects. The day *stored* various surprises for him.

Ex.3 - shines The sun *shines* over the people today. The luck *shined* over him wherever he went (omnipresence implies structure has been taken from the *sun* concept).

Ex.4 - flight The eagle *flew* over the valley. The wooden log *flew* from her hand in the direction of the animal. His hands *flew* over the keyboard. He had a *flight* of fancy over the events of the last few days.

In this case, the objects put in the template are made to play a different role, depending on the structure of the previous concept or template which they fill in.

It is reasonable to think that such transfer has initially been done via overlapping features - i.e. like in Fig. 3.2, were the chaining template can obviously be applied to objects with similar properties - e.g. a loop of string and the eye of a scissor, which due to their elliptical structure and the bend-ability of the string can allow for the similar physical relation of chaining. After many transfers of such a template or relationship, the template itself becomes strong enough (and perhaps abstract enough) to allow association to and fill in by different and sometimes more abstract objects and domains, which do not need to manifest such resemblances, but rather inherit features from the template when put in it.

Synthesis Concepts can sometimes be re-compressed via their representative features, as problem templates can be re-compressed by being named as concepts. This was exemplified in Fig. 3.4 c).

This allows not only the shrinkage of a template to its essential features (like reducing the Tower of Hanoi problem to a movement heuristic which is required to solve it), or to a concept (e.g. velocity), or of a concept to its essential features, but also permits overlapping transfers (of features or structure) downwards from a template into a concept, and from a concept into a feature space. This allows complex concepts, like the one of the benzene molecule to be compared to visuospatial features, like the Ouroboros symbol.

Synthesis thus allows further anchoring (grounding) and further productive connections with other elements of the knowledge base.

3.4.4 Re-representation through search and construction in CreaCogs

Re-representation can happen in two main ways in CreaCogs - creative substitution of problem template (or subparts of it), and generation of a new problem template (or subparts of it). These, in their higher forms of deployment, are proposed to roughly correspond to re-representation in insight and discovery (when a new useful template is found) and creative innovation (creativity dominated by construction processes). Such high-level cognitive feats can be seen as applying the processes described above - of search of affordance, structure transfer and generation - at a larger and sometimes more abstract scale. We will exemplify this by describing these processes at the problem template level.

a) ***Creative search*** The same creative use of affordance can be made for problem templates as for concepts, when searching for a particular object or template/heuristic that can reach a particular result. If in the previous case a concept or an object with similar affordances was found, in the problem template case, templates with the required affordance or a similar affordance can be found, using the affordance itself to guide the search. If no such templates are found, the functional concept, or even functional property of a particular template can be discriminated. When these are found, the search for a useful template can proceed guided by the functional concept (a concept or object that usually manifests a particular affordance) for its connected templates. Also, constructive techniques can be applied to make a new template out of useful elements, if one has not been found.

Thus a new problem template which affords the solution can be found via re-representation. Finding a problem template brings about a new way of seeing things, of organizing the objects in the given problem, and bringing forth different information from the knowledge base of the cognitive system.

The insight effect with the appeareance of an entire new representation in the consciousness of the solver (a pop-up effect) might also rely on specific convergence mechanisms being at play. This will be further addressed in Chapters 5 and 7.

b) ***Construction*** New templates can be constructed in ways similar to concept generation. Various concepts or templates which overlap can be made into new templates, which will now yield affordances pertaining to both initial concepts or templates, or qualitatively new affordances altogether. Some such templates could emerge via processes of overlap and repeated correlation, while others might take more overt effort to constructively develop. Construction might come at the cost of losing parts of the interacting concepts or templates, and parts of the affordances. The initial participating templates could be also kept separately, or discarded and replaced with their transformation.

Parts of a template can be substituted with other templates, thus the template being enlarged and enriched. This latter process of construction as elaboration can be seen as the opposite of synthesis of a larger representation structure to some essential features.

Finally, various relations between concepts get stronger over time and can organize themselves, when brought together, into a new template. This process doesn't apply only to concepts existing only in the mind of the agent, but can be distributed across the mind and the environment of the agent. Thus concepts in the environment can keep on overlapping with concepts in the mind, or a template in the mind can receive interference from an object or layout in the environment.

3.5 How space and structure inform representation-process coupling

CreaCogs allows easy access to relevant concepts or problem templates with similar features. The divergent search can be done starting in whatever feature point, at the concept level or at the problem template level, and still yielding similar results. If the relationships are represented as a feature space (and problem templates still represent sets of concepts, relationships and affordances), then the search can be done using relationships as a focal point too. However, that would possibly give the system more power than normal human cognitive systems (which in general find it harder to start searches with relationships, as these are encoded at a more abstract level). Thus a cognitive system would allow relationship search and transfer, but not with as much ease as it allows exchange of elements.

The way space, connectedness and representation structure are used in this framework allows re-representation. Space and connectedness allow easy access to multiple other relevant elements, via explicit similarity links on the various feature spaces, and implicit similarity links when reaching for context (problem templates) in which concepts have participated and taken up a certain role (this role can provide implicit similarity due to similarity of context). The structured representation allows for re-representing the object as formed by different parts (implicit re-representation). Explicit re-representation can be realized by trying to construct the possible templates which will fulfill the requirements for a certain problem solution.

CreaCogs is thus a spatially informed and organized theoretical framework, the mechanisms of which will be formalized in the next chapter.

Chapter 4

Formalization of knowledge organization and processes

As shown in Section 2.2.1, structured representation is an important component in AI and in theories of Cognitive Science. A hypothesis of CreaCogs (Chapter 3) is that the lack of useful structure in ill-structured problems [114] must be compensated by a cognitive effort of restructuring. Thus such cognitive processes of restructuring are the precursors or in some cases the very processes of creativity in the context of problem solving.

In this chapter, formal tools are deployed with the purpose of characterizing creative cognitive processes in CreaCogs. Some such processes are aimed at helping or enabling re-representation.

The chapter proceeds as follows: first, the main components of the CreaCogs framework are described: Feature Spaces (Section 4.1), Concepts (Section 4.2), Problem Templates and structured representations generally (Section 4.3). General creative mechanisms of CreaCogs are presented in Section 4.4. These include: hypothesizing by concept similarity (4.4.1) and creative use of problem templates (4.4.2). Then, special attention is given to creative search, substitution and re-representation mechanisms 4.5, and these are contrasted to creative composition and reconstruction mechanisms 4.6. While search processes are assumed to be more predominant in creative problem solving, and constructive processes in artistic creativity, both are present in various amounts in both endeavours. Section 4.7 takes as subject multimodal and concept to template transformations. This is followed by a discussion and short conclusion in Section 4.8.

4.1 Feature Spaces

Feature spaces are spatially organized sets of features encoded symbolically or subsymbolically[1]. They constitute the bottom level of the CreaCogs framework (see Fig. 3.5).

[1]A subsymbolic type of encoding would be more realistic from a sensory perspective

The set of feature spaces (FS) in a knowledge base (KB) can be defined as follows:

$$FS = \{FS^1, FS^2, ..., FS^m\}, FS \in KB$$

Each feature space contains a set of features $FS^1 = \{f_1^1, f_2^1, f_3^1, ..., f_n^1\}$, so that the distance between features f_1^1, f_2^1 is expressed as $\delta_{1,2}^1$. Features are organized in feature spaces by a distance metric, thus:

$$\textbf{if } \delta_{1,2}^1 = |f_1^1 - f_2^1|, \delta_{1,3}^1 = |f_1^1 - f_3^1|, ..., \delta_{1,n}^1 = |f_1^1 - f_n^1|,$$

$$\textbf{then } \delta_{1,2}^1 \leq \delta_{1,3}^1 \leq \delta_{1,4}^1 ... \leq \delta_{1,n}^1$$

In general form:

$$\delta_{x,(x+1)}^1 \leq \delta_{x,(x+2)}^1 \leq \delta_{x,(x+3)}^1 ... \leq \delta_{x,(x+n)}^1$$

Each feature space contains a similarity operator $sim(f_a^1, f_b^1)$. As distance between features expresses similarity of features within that feature space, the similarity operator takes δ into account so that:

$$sim(f_a^1, f_b^1) \geq sim(f_a^1, f_c^1) \iff \delta_{a,b}^1 \leq \delta_{a,c}^1$$

$$max\ (sim(f_x^k, f_y^k)) \iff min(\delta_{x,y}^k)$$

If a new concept C_z is learned, its features are compared to known features, determining the set of features which need adding to the KB before anchoring the concept in them (X), and the set of already known features in KB (Y).
Thus for all $f_x^k \in C_z, FS^m \in KB$:

$$X = \{f_x^k | f_x^k \notin FS^m\}$$

$$Y = \{f_x^k | f_x^k \in FS^m\}.$$

As seen in the insertion algorithm in Table 4.1, features from set X (unknown) are added to the KB by being encoded in their corresponding FS at the correct $\delta_{x,n}^k$, and then connected to the new concept C_z. Features from set Y (known) are just connected to the C_z.

The feature space grounding makes possible measures of concept similarity at the sub-symbolic level. This also provides the ability to creatively use a concept or object as a replacement of another when the distance δ between the required object's functional feature and that of the creative substitute is small.

TABLE 4.1: Insertion algorithm.

Algorithm Insertion algorithm

for all $f_x^k : C_z.getFeatures()$
  distance = FS^k.size(), insertionPoint=0
  for all $f_n^k : FS_{KB}^k.getFeatures()$
    if $f_x^k = f_n^k$
      do $C_z.link(FS^k, f_x^k)$
      insertionPoint = 0
      return
    else $\delta_{x,n}^k = calcDistance(f_x^k, f_n^k)$
      if distance $\geq \delta_{x,n}^k$
        insertionPoint $= n.location + \delta_{x,n}^k$
        distance $= \delta_{x,n}^k$
  end for
  if insertionPoint $\neq 0$
    do insert(f_x, insertionPoint)
    do $C_z.link(FS^k.f_x^k)$
end for

4.2 Concepts

If KB is the knowledge base of an agent α, let $C \in KB$ be a set of known concepts, so that:

$$c_1, c_2, c_3, ..., c_m \in C$$

These concepts are anchored in the knowledge α has acquired via its various sensors (see Fig. 3.5), motor routines, semantic tags and relations. These are encoded in feature spaces (FS), where different such feature maps can be distinguished, and different points can be determined within them.

Thus, without defining all possible FS exhaustively, let V be a set of known visuospatial features[2], A a set of known affordances (motor actions that have been learned to be performed, or observed in the environment), and S a set of semantic tags (names which the agent attributes to objects or associates with other types of abstract patterns), such that $V, A, S \in FS$, and the elements of each specific feature space:

$$\{v_1, v_2, v_3, ..., v_o\} \in V$$

$$\{a_1, a_2, a_3, ..., a_n\} \in A$$

$$\{s_1, s_2, s_3, ..., s_p\} \in S$$

Thus, each concept is understood as grounded in a subset of the respective known feature maps:

$$C = (V', A', S'), V' \subset V, A' \subset A, S' \subset S$$

[2]We treat visuospatial sensory features together here for the sake of simplicity, but they can be differentiated in various types of visuospatial feature maps.

and the set of known concepts C can be defined as a subset of the powerset of known features:

$$C = P(V) \times \subset P(A) \times P(S),$$

Thus in this formalization concepts can be encoded like the following:

$$c_1 = \{green, round, to\ eat, apple\}$$

$$c_{15} = \{red, round, to\ kick, ball\}$$

In this example, only *apple* and *ball* are semantic tags, the rest of the features are translated in their approximate semantic description. This is evident as the *round* in c_1 is not the same as the one in c_{15}. In a self-organized shape feature space they would be in each other's neighborhood. In translation to a symbolic description, much precision and expressivity is lost.

Not all concepts need to be activated or have a representative point on all feature maps for a concept to be encoded, thus $\emptyset \in V$, $\emptyset \in A$, $\emptyset \in S$, and concepts can be encoded on a subset of feature spaces, even if no corresponding feature has been encoded on the remaining few, e.g.:

$$\exists c_x \in C, \quad c_x = (V', A', S') = \{v_i, v_j, \emptyset, s_i\}$$

For the purpose of implementation, such concepts can be encoded as e.g. $c_x = \{v_3, v_5, a_0, s_3\}$, where a_0 is the *null* element. In a generalized form, for any specific $FS^x \in FS$, x_0 will represent the *null* element of that feature space.

When a new element is observed as belonging to a concept known by α, this element is added to the concept in the knowledge base, e.g.:

$$\text{Known: } c_3 = \{yellow, round, to\ eat, grapefruit\}$$

$$\text{Observed: } c_x = \{pink, round, grapefruit\}$$

$$\text{Then in } KB\text{: } c_3 = \{(yellow \vee pink), round, to\ eat, grapefruit\}$$

These concept elements can be disjunctive in nature, the activation of one in a concept inhibiting the activation of another (e.g. a grapefruit being either yellow or pink).

Complex concepts (the grounding of which requires other concepts) and abstract concepts (concepts for which no good physical representation exists) are better modeled by representation structures which are discussed in the next section (4.3).

Comprehension of a presented concept, object or scene is thus the activation of the known elements from the scene in the KB. If elements in the scene match elements in the KB, previous knowledge of that object can be brought forth, be it that the knowledge has been obtained in declarative, observational or interactive manner. After the objects have been identified, new knowledge present in the environment can be added to the KB. Thus knowledge is obtained, brought to bear on the problem at hand and updated in an interactive manner.

4.3 Problem templates

Complex concepts and problem templates are kept in the knowledge base as activations over previously known concepts. They can include relations, actions, and results of that set of actions. Such results can include new relations between the concepts or objects, a transformation of the initial features and objects. Previously solved problems, encoded with their solution in the KB of the agent, allow further use of their structure.

Given a set of relations R between concepts, these can be expressed as follows[3]:

$$r_n(c_x, c_y), r_n \in R$$

$$\text{E.g. onTopOf}(table, glass), \text{onTopOf} \in R$$

Given a set of heuristics - or moves H, these can be expressed as follows:

$$h_1(c_3, c_2) \in H$$

$$\text{E.g. pour}(water, glass), \text{pour} \in H$$

All problem templates PT are structured representations over: concepts (C), relations between concepts (R), heuristics or set of moves (H - which can be understood as the higher-order counterpart of motion affordances in concept encoding) and solution state representations (SOL):

$$PT \in P(C) \times P(R) \times P(H) \times P(SOL)$$

$$PT_x = (C', R', H', SOL'),$$

$$C' \in C, R' \in R, H' \in H, SOL' \in SOL$$

$$\text{Example: } PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_3, c_2), sol_3\}$$

$$PT_1 = \{table, glass, water, \text{onTopOf}(table, glass), \text{pour}(water, glass), sol_3\}$$

$$sol_3 = \{table, glass, water, \text{onTopOf}(table, glass), \text{in}(glass, water)\}$$

When a certain type of solution is required for a particular problem, the set of solution state representations SOL can be searched for previously known templates in which such

[3]Such relations can be expressed logically, but they do not have to be. They could also be expressed through a picture that has embedded or represents the spatial relations themselves, or a mechanism that learns from such pictures and makes internal structure preserving representations.

a solution state has been achieved. Then an attempt to apply the templates connected to such a solution to the current problem elements can be made.

Templates can also be triggered when certain objects or concepts which have normally been involved in a template are present in the given problem. This allows for the natural modeling of functional fixedness, by attaching an activation strength to the link between a template and its participating concepts.

Problem templates can be treated as concepts $PT_x = C_x$ after a template has been strongly encoded, compressed and provided a semantic tag which allows for naming and communication. Abstract concepts, which are not understood through direct action or physical representation, but through the relations of other concepts, or through a reference to them, are considered a form of intermediary representation between concepts and problem templates. However, as their encoding is dependent upon previous experience and encoding of a set of other concepts, many more assumptions are made when communicating about them than about concepts which have been encoded with direct sensory experience, as their encoding might not be similar in two agents. This reflects communication difficulties which humans encounter when dealing with abstract concepts, like “justice” or “freedom”, which can mean different things for different people. Deviation from a “common” meaning, if such a meaning exists, can be viewed as the sum of the deviations of all other concepts used for encoding. On an individual level, each agent can provide their particular encoding case (with different objects and events) for abstract concepts, which manifests itself in individual differences of meaning.

Acquiring or communicating a similar PT to a different agent might have more chances of success when the contributing elements, relations and actions are explained from their anchoring concept level (bottom-up). However, even if these elements are communicated, the agent which does the listening might group them in different situational PT, which are closer to the agent’s already encoded PT set.

Agents manifest preferential heuristics and interpretations because of expertise and familiarity with such heuristics and templates, which in the CreaCogs framework is represented as stronger KB associations. At the representation level, heuristics can be built compositionally, as a set of actions over given objects, that are put in certain relations:

$$h_1 = h_2(h_3(c_1, c_2), h_3(c_2, c_3))$$

For example, cooking a favorite recipe like h_{15} = *Pasta bolognese* is a collection of cooking actions like *mix, stir, chop, season, simmer* over a set of concept ingredients: $C = \{c_1\ minced\ meat, c_2\ onion, c_3\ tomatoes, c_4\ mushrooms, c_5\ pepper, c_6\ basil,$ $c_7\ oregano, c_8\ pasta\}$.

The set of actions required is:

$$\{h_1\ stir, h_2\ chop, h_3\ season, h_4\ simmer, h_5\ fry\},$$

where each of these is a primitive cooking template. Such primitive templates are structured problem templates themselves, for which no heuristic can be further decomposed in other actions: h_1 $stir = \{foods\{c_1, c_2, ..., c_n\}, pans\{c_{31}, c_{32}\}, stirrers\{wooden\ spoon\}, in(food, pan), in(wooden\ spoon, food), stirring\ motion, stirred\}$

For the template $h_{15} = Pasta\ bolognese$, the *bolognese sauce* can act as a composition of previously known actions over given ingredients:

$h_{14} = (stir(stir(fry(minced\ meat), chop(onion, tomatoes)), simmer(5min), season(pepper, basil, oregano), chop(mushrooms)), simmer(10min)), bolognese\ sauce$

$h_{14} = (h_1(h_1(h_5(c_1), h_2(c_2, c_3)), h_4(5\ min), h_3(c_5, c_6, c_7), h_2(c_4)), h_4(10\ min)), sol_5$

4.4 General creative mechanisms

This section presents general creative reasoning mechanisms which can be deployed under the knowledge organization of CreaCogs. Section 4.4.1 presents how hypothesizing can happen using concept similarity. Section 4.4.2 describes the creative use of problem templates and structured representations.

4.4.1 Hypothesizing by concept similarity

Due to the distributed encoding of concepts over features, concept similarity can be computed between concepts by comparing their elements. This can be done: a) at the similarity between features level and b) at the sharing features level[4]. E.g., due to their common feature elements on the affordance (A) and visual (V) feature spaces, $c_1 = \{a_1, a_2, v_1, v_2, s_1\}$ and $c_2 = \{a_2, a_3, v_1, v_3, s_2\}$ can be considered similar.

Both these types of similarity ratings can be used for hypothesizing. In the following we will show a few examples of the element-based similarity hypothesizing.

Consider an agent that knows:

$$c_1 = \{a_1, a_2, v_1, v_2, s_1\}$$

$$c_2 = \{a_2, a_3, v_1, v_3, s_2\}$$

Then c_1 and c_2 overlap in a_2 and v_1.

$$c_1 \cap c_2 = \{a_2, v_1\}$$

If both c_1 and c_2 are associative synaptic bindings over their elements, the activation $f_C(c)$ traveling across both associative synaptic paths of c_1 and c_2 will strengthen the connection between their overlapping features:

$$f_C(a_2, v_1) = f_C(c_1) + f_C(c_2)$$

[4]A third type of similarity is implicit: c) being involved in the same structures.

Now consider a c_3, the affordances of which are unknown:

$$c_3 = \{v_2, v_3, s_3, a_?\}$$

The system will check its similarity with known concepts, select c_1 and c_2 as most similar, and notice some degree of feature overlap:

$$c_3 \cap c_1 = \{v_2\}$$

$$c_3 \cap c_2 = \{v_3\}$$

The system will then propose that some of the affordances which hold for c_1 and c_2 might hold for c_3. A direct correlate relation between such visuospatial features and an affordance does not exist:

$$\text{The query: } ?\,\exists a_x \in A, f_C(a_x, v_2, v_3) \geq 0 \quad \text{returns false.}$$

The system could propose as a general hypothesis that c_3 inherits the affordances of the concepts it overlaps:

$$c_3 = \{?\,a_1, ?\,a_2, ?\,a_3, v_2, v_3, s_3\}$$

However, because of the previously observed strong correlation $f_C(a_2, v_1)$ and $v_1 \notin c_3$, the hypothesis can be refined one step further, with only a_1 and a_3 being proposed as possible affordances to check for in the real world for c_3.

This means that previously noticed feature associations cumulatively matter to the system. Such associations can become strong enough to be triggered whenever one or enough of the constituting members are present, thus trying to retrace a previously known pattern (in a somewhat Gestaltic fashion).

These mechanisms can trigger further inference points and implicit information in the system, the birth of new substructures and the functional fixedness phenomenon.

4.4.2 Creative use and hypothesizing with problem templates

Previous problem templates, like the one for *Pasta bolognese*, can be used and re-used. Moreover, because of the posited type of knowledge encoding, the template can pop-up whenever an open search happens in the system for a general *cook* heuristic, with some of the conceptual elements (c_1 *mincemeat*, c_3 *tomatoes*) present in the fridge. The search can also be run over timing, and cooking pasta in general.

When creative solutions are proposed by the system or forced by the absence of certain ingredients, similar ingredients will be sought. Thus *mince* can be replace with *aubergine*, *onion* with *leek* or *chalotte*, *red pepper* with *yellow pepper*, *chorizo* with other types of *salami*.

When trying to change or enrich such a recipe it is reasonable to assume that "similarity" for an expert cook presupposes a set of observed, acquired and tested taste rules - like taste relations of food items that go well together $(courgettes, mushrooms)$, $(red\ pepper, tomatoes)$, or food items that give a specific taste $(chorizo, Parmesan, herbs, spices)$.

Other problem templates can be used creatively in a similar manner, by using the concept similarity procedures to yield and replace recipe elements by other ingredients which have the same or similar features.

Hypothesizing by problem similarity can happen too. Thus, different templates with similar elements can be used creatively. Subtemplates might be created via intersection, convergence, difference of previously observed templates. This can result in effects which look like mixing previously held templates or structurally sound parts thereof to achieve a composed effect, or parts of effects from different templates.

Templates can be similar based on their components, relationships, heuristics or solution states. Replacement and creativity is possible across all these axes. Thus the following presents some possible cases.

a) Similarity of components case: one can replace components in a template with similar components (concepts that are equivalent or similar across the feature space that matters for the respective problem)

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$c_1(FS^k) = \mathbf{c_5}(FS^k) \quad \text{OR} \quad c_1(FS^k) \text{ sim } \mathbf{c_5}(FS^k)$$

$$\text{try} \quad PT_1' = \{\mathbf{c_5}, c_2, c_3, r_1(\mathbf{c_5}, c_2), h_1(\mathbf{c_5}, c_2), h_2(c_2, c_3), sol_3\}$$

b) Similarity of relations case: one can replace relations in a template with similar relations

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$r_1 = \mathbf{r_2} \quad \text{OR} \quad r_1 \text{ sim } \mathbf{r_2}$$

$$\text{try} \quad PT_1'' = \{c_1, c_2, c_3, \mathbf{r_2}(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

This also links h_1 to r_2.

c) Similarity of heuristics case: one can replace heuristics in a template with similar heuristics

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$h_1(a, b) = \mathbf{h_5}(a, b) \quad \text{OR} \quad h_1(a, b) \text{ sim } \mathbf{h_5}(a, b)$$

$$\text{try} \quad PT_1' = \{c_1, c_2, c_3, r_1(c_1, c_2), \mathbf{h_5}(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

E.g. h_1 putting thing on the cooker and h_5 putting things in the microwave might be similar, if the desired result is to cook something.

d) Similarity of solution case : one can replace a solution with a similar solution

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$sol_3 = \mathbf{sol_5} \quad \text{OR} \quad sol_3 \text{ sim } \mathbf{sol_5}$$

$$\text{maybe } PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), \mathbf{sol_5}\}$$

a') Hypothesizing similarity of components: when two templates have similar relations, heuristics and solutions, similarity can be hypothesized between them or their components

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$PT_2 = \{c_4, c_5, c_6, r_1(c_4, c_5), h_1(c_4, c_5), h_2(c_5, c_6), sol_3\}$$

$$\text{propose } PT_1 \text{ sim } PT_2, (c_1, c_2, c_3) \text{ sim } (c_4, c_5, c_6)$$

b') Hypothesizing similarity of relations: when two templates share similar concepts, heuristics and solutions, similarity can be hypothesized between them or their relations

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$PT_2 = \{c_1, c_2, c_3, r_2(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$\text{propose } PT_1 \text{ sim } PT_2, r_1 \text{ sim } r_2$$

c') Hypothesizing similarity of heuristics: when two templates have similar concepts, relations and solutions, similarity might be hypothesized between them or their heuristics

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$PT_2 = \{c_5, c_2, c_3, r_1(c_5, c_2), h_3(c_5, c_3), h_2(c_2, c_4), sol_3\}$$

$$c_5 \text{ sim } c_1$$

$$\text{propose } P_1 \text{ sim } P_2, h_1 \text{ sim } h_3$$

d') Hypothesizing similarity of solutions: when two templates that have similar concepts, heuristics and relations, similarity might be hypothesized between them or their solutions

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$PT_2 = \{c_1, c_2, c_5, r_1(c_1, c_2), h_1(c_1, c_2), h_3(c_2, c_5), sol_5\}$$

$$c_3 \text{ sim } c_5$$

$$\text{propose } PT_1 \text{ sim } PT_2, sol_3 \text{ sim } sol_5$$

Some of the hypothesizing described here requires mechanisms of creative search and is a precursor for mechanisms of creative reconstruction. These will be presented in the next sections.

4.5 Creative search and substitution mechanisms

Re-representation requires a search for a productive, result-yielding problem representation. Generally, search for a productive problem representation can be described as taking the form of filling in a template: given initial problem objects c_1, c_2, c_4 and the need to fulfill sol_5, what mechanisms can you apply to reach a representation which affords the solution?

$$\{c_1, c_2, c_4, sol_5\} \in PT_?$$

Various constraints and relations can be part of the problem requirements, requiring accurate representation and solving.

In creative problem solving, the subset of objects required to solve the problem might not be predefined, closed, or restricted to only the salient objects or concepts offered by the problem. This subset might involve objects known by the solver, or objects which the solver could create. Take the set of given objects in the problem to be O_P, the objects in the solution space to be O_S and the objects in the solver's KB to be O_{KB}. If in classical problem solving, $O_S \in O_P$, in creative problem solving $O_S \in \{O_P \cup O_{KB} \cup O_N\}$, where O_N are new objects constructed by agent α taking as input O_P and O_{KB}. Thus intelligent search mechanisms need to take place over O_{KB} for computational explosion not to occur when searching for O_S, for O_N to be produced and for a productive solving template $PT_?$ to be found. In the following, a few such mechanisms are proposed.

The search can be characterized in a variety of modes. The following characterisation is based on the relative direction the search takes from the concept level in the knowledge base, and is meant to give a few examples of how such a search can proceed in CreaCogs. After sections 4.5.1, 4.5.2 and 4.5.3 give examples of such search, the mechanism of applying the found problem representations and objects to do the re-representation are explained in section 4.5.4. A short Discussion of such search mechanisms in the context of some human creativity tests is presented in section 4.5.5.

4.5.1 Upward search

In this mechanism, the search in the KB of the agent goes up from the level of the initial concepts to their projections in the problem template space, to check problem solving or general representational structures the concept or the structure has been involved in. A check is made to whether the affordances or solutions of the such found problem-templates are similar to the solution searched for the problem at hand. If similar affordances or solutions are yielded, the problem template is kept as a representation structure relevant for the problem at hand. The solving of the problem is then tried with this representation. This is shown in Figure 4.1 and in the search algorithm example in Table 4.2.

In Figure 4.1, the yellow arrows show the direction of search: c_1 and c_2 trigger the templates they've been involved in in PT_x. Some such templates will be triggered from

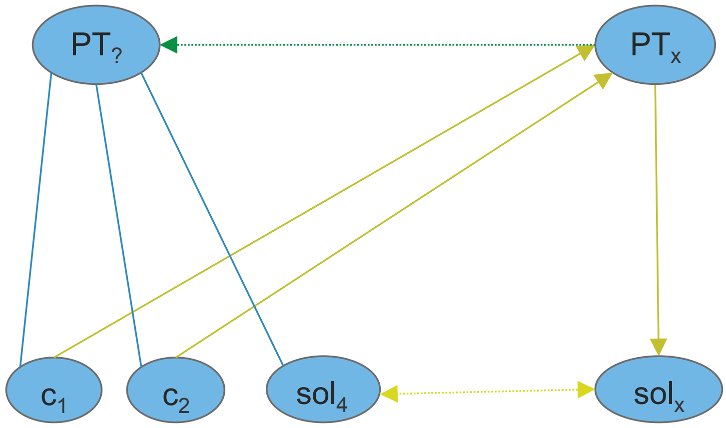


FIGURE 4.1: Upward search in the framework.

multiple concepts. If the solution of any of these templates - sol_x - is similar or equivalent with the solution searched for - sol_4 - then the PT_x in which this has been found becomes a candidate to structure the problem, and thus take the place of $PT_?$.

TABLE 4.2: Upward search algorithm.

Search Algorithm ex.1: Upward search

for all c_x : $Problem.getConcepts()$
  $PT_xList.add(c_x.getPTs())$
  $activationIncrease(c_x.PTs)$
end for
$PT_xList.sortHighActivFirst()$
for all PT_x : PT_xList
  if $PT_x.getActivation() > threshold$ **AND** $(PT_x.sim(PT_{sol})$ **OR** $PT_x.equals(PT_{sol}))$
    then return PT_x
end for

The similarity behind the call $PT_x.sim(PT_{sol})$ contains a variety of cases:

- PT_x and PT_{sol} overlap - i.e. they have common elements - where the elements can include not just concepts but also relations and affordances (all this depends on how much of the end state is known or presumed, and some initial interpretations of the end state might be wrong or reflect biases). If elements of PT_x not contained in the initial problem-space are the ones responsible for the useful affordances, then these can be important, and their reconstruction can be attempted in the given environment.
- PT_x is a subpart of PT_{sol} - i.e. it demonstrates some useful affordances, but not all the ones required. Then PT_x can be kept as a useful subpart of the future PT_{sol}, where other parts might need to be found. The required elements of the useful problem templates will then need to be used to construct PT_x (4.6).
- PT_x contains PT_{sol}.

A special case of this mechanism can be that of convergence. When various PTs are activated and checked against the problem requirements starting from the various initial problem elements, different templates corresponding to different elements might be found to have elements in common. The search thus converges upon useful elements for the productive problem template, and sometimes upon an entire solution.

4.5.2 Downward search

In this search mechanism, the agent goes down from the conceptual level of the given "objects" to the feature level, then tries to match their affordances to those required for the solution state. This can be used either as an eliminatory strategy - to make less salient the concepts or properties which don't work for a successful representation, or for flagging essential properties for safe-keeping. Both can be done in one if this flagging is a form of activation which strengthens the useful properties - thus useful already present elements of a successful possible structure are strengthened. This mechanism is shown in Figure 4.2 and Algorithm in Table 4.3.

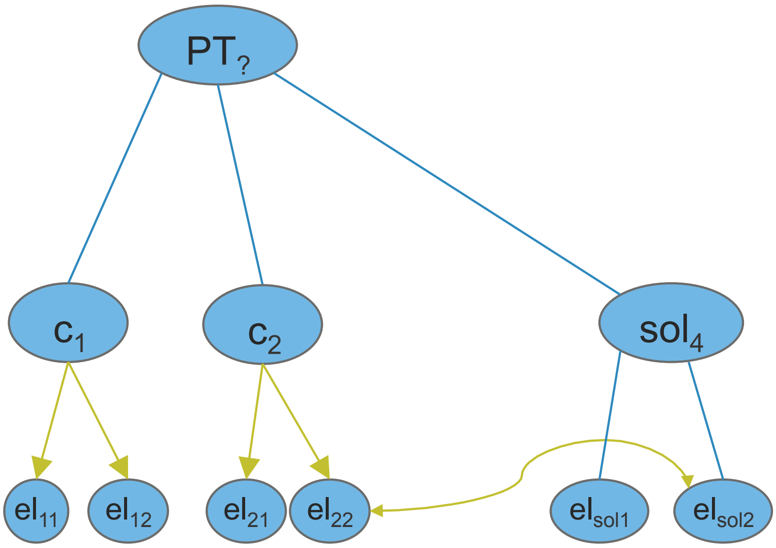


Figure 4.2: Downward search in the framework

In Figure 4.2, the yellow arrows show the direction of the search. c_1 and c_2 are searched for elements that match (elements of) the solution. These elements can then be used element-wise, all together (abstraction / generalization strategies) or in different new combinations (constructive) to search for a useful template. The concepts which they are part of might be used, or new concepts might be searched for that have been anchored in the salient properties.

4.5.3 Sideways search

In memory (KB) or environment, the agent searches for concepts or objects similar to the ones it has that can solve the problem, as shown in the search algorithm example in Table 4.4 and Figure 4.3. Similarity can happen on the various feature spaces, however some features will be functionally relevant for a particular affordance, while some will

TABLE 4.3: Downward search algorithm

Search Algorithm ex.2: Downward search

for all $c_x : Problem.getConcepts()$
  $elementList \mathrel{+}= c_x.getElements()$
end for
for all $element : elementList$
  for all $sol.el()$
    if $element.sim(sol.el)$ **OR** $element.equals(sol.el);$
      then $element.active(), element.mark()$
    else return $elementList$ -= $element$
  end for
end for

not be. If such similar concepts are found, they can become part of the solving template, or yield a solving template through one of their connections. In Figure 4.3, the yellow arrows point the direction of the search. Thus c_2 triggers a similar concept, c_x. The templates attached to c_x are searched for one which might yield the solution sol_4 or a state similar to it. If this is found, it might prompt using c_x rather than c_2 to attempt a solution. As a variant of this, the agent can also search starting from the expected solution, through all the known templates that yield it, to find a template that contains similar concepts as the ones in the problem.

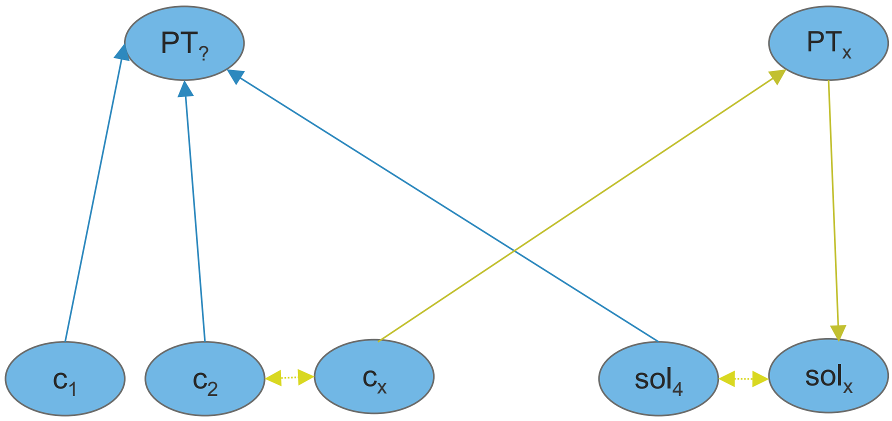


FIGURE 4.3: Sideways search in the framework

TABLE 4.4: Sideways search algorithm

Search Algorithm ex.3: Sideways search

for all $c_x : Problem.getConcepts()$
  for $c_y : c_x.getSim()$
    if $c_y.getPTs().contains(PT_{sol})$ **OR** $c_y.getPTs().containsSim(PT_{sol})$
      then $Problem.tempReplace(c_x, c_y)$
  end for
end for

4.5.4 Restructuring, creation of new objects and re-representation

Finding knowledge objects like PT_x in section 4.5.1, a set of concepts which might refine a viable PT_x in 4.5.2 and a concept c_x which overlaps the requirements of the problem in 4.5.3 helps restructure and re-represent the given problem, and sometimes recast some of the given objects as different objects (or concepts).

Given a concept made from a set of features, it can be restructured as a different concept if such a different concept can be found anchored in the same or a similar set of features. Thus given c_1 as part of the problem set, one can re-represent its features as follows:

$$c_1 = \{a_1, v_1, v_2, s_2\}$$

$$v_1 \text{ sim } v_4, c_n \in KB, c_n = \{a_n, v_4, v_2, s_n\}$$

$$\text{Restructure } c_1 \text{ as } c_n = \{a_n, v_4, v_2, s_n\}$$

Given a PT made from a set of concepts, it can be restructured as a different PT if such a template exists anchored in the same or similar subset of concepts.

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$c_2 \text{ sim } c_4$$

$$PT_n \in KB, PT_n = \{c_1, c_4, c_3, r_2(c_4, c_3), h_1(c_4, c_3), sol_5\}$$

If a new PT is anchored in a superset of a subset of the given concepts, the other concepts or objects might still be created from the existing remaining objects.

4.5.5 Discussion

After each re-representation, one can check if the new problem representation has a solution within its inference set. If a re-representation was done specifically to obtain a certain affordance, of part of the requirements of the problem (sol_x), one can attempt to solve the rest of the requirements. Upward moves can be done automatically, triggering problem templates, relations or other structured representations in which the concepts have previously worked together. This can bring about functional fixedness as some salient templates are hard to avoid, and humans are not used to manipulating larger structures (like problem templates) quite as well as other smaller structures (like concepts), which it is sensible to assume are easier to contain within working memory.

Riddles, Remote Associates Tests [108] and insight problems for empirical settings all seem to use predominantly search processes in this paradigm. Take the following riddle:

> *What can you catch but not throw?*

The *catch* and *throw* concepts used in conjunction will initially yield sport templates, of type:

$$PT_{s1} = \{ball, catch(ball), throw(ball)\}$$

A search of semantic contextual template just over *catch*, without the motion affordances, can yield the semantic context template *catch a cold*. This verifies the problem condition *cannot throw*, however is *throwing a cold* is not a usual pattern in thinking about colds. One might generally think of *giving someone else a cold*, and *giving something to someone else* and *throwing something to someone else* have the same result, if the other person *receives* or *catches* that something. However, it is unlikely this similarity will be noticed, without having cast *catch* in the context of the *cold* initially.

With remote associates, the search proceeds in parallel. Take the test containing the words: *Falling Actor Dust*. Let's say $c_1 = falling, c_2 = Actor, c_3 = Dust$. To find their remote associate, one needs to find a word c_4 so that templates $PT_1 = \{c_1, c_4\}, PT_2 = \{c_2, c_4\}, PT_3 = \{c_3, c_4\}$ exist. When one has activated $PT_1 = Falling\ Star, PT_2 = Star\ Actor, PT_3 = Star\ Dust$, or at least two of them, and the third can be verified, one has converged upon $c_4 = Star$.

The classical candle insight problem [36] is stated as follows: *You are given a candle, a book of matches and a box of thumbtacks. Fix the lit candle unto the wall so that the wax doesn't drip below.* Various saliencies draw initial attention. The template of a candle burning has effects like $\{light, wax, fire\}$. The template of fixing something unto the wall requires some material which can be *glue* or *nail*. Wax has *glue* properties, which probably explains why some people try to use wax to glue the candle to the wall. The participants need to focus on a representation of the kind $\{support, candle\}$, and find the support affordances of the *box* concept, which are not particularly salient in the $box\ of\ thumbtacks$ representation, with the affordance of the object *box* being already taken – $\{box, contains(thumbtacks), full\}$.

4.6 Creative construction mechanisms

Some of the mechanisms described above can be productive in themselves. Thus if the search is bringing two concepts together which have not been previously connected, new relations might be observed (and it is not assumed that all such relations were previously encoded). It is commonsense that some of these relations will be interesting enough to be consolidated over time in the agent's memory.

It is not hard to imagine that some transformational processes happen during this search (new templates are created, new relations are seen between concepts). However we will refer here to mechanisms which are highly generative and productive by their nature (thus not accidental associations) - whether they developed out of initial search or whether they stand as mechanisms in their own right is an empirical cognitive questions, which this analysis cannot solve.

In this framework we will differentiate between two processes of conceptual composition (cc(i) and cc(ii)), where cc(i) is a productive form of inheriting features from two concepts in an integrative fashion, while cc(ii) aims to satisfy a higher template, or can create such a new template which is structurally different (c.f. [41]).

Thus taking the extremes of cc(i) and cc(ii), if given two concepts:

$$c_1 = \{a_1, a_2, v_1, v_2, s_1\}$$

$$c_2 = \{a_3, a_4, v_3, v_4, s_2\}$$

c_3 is a concept composed via cc(i), where:

$$c_3 = \{a_1, a_4, v_1, v_4, s_{1-2}\}$$

while c_4 is a concept composed with cc(ii):

$$c_4 = \{a_1, a_2, a_3, a_4, v_1, v_2, v_3, v_4, s_3\}$$

Thus, in their extreme form, cc(i) and cc(ii) can be simplified in this framework to:

1. maintain structure (aligned in both concepts) and import-compose features
2. maintain features (from both concepts) and import-compose structure

If some similar features exist, they can provide a locking point for the composition processes (and to even bring the two templates together in the first place):

$$\text{Given: } c_1 = \{a_1, a_2, v_1, v_2, s_1\}$$

$$\text{Given: } c_5 = \{a_2, a_3, v_2, v_3, s_2\}$$

$$\text{Composed: } c_6 = \{a_1, a_2, a_3, v_1, v_2, v_3, s_3\}$$

This is different from processes of generalization, or observations of a relation through synthesis, which later requires naming:

$$c_1 = \{a_1, a_2, v_1, v_2, s_1\}$$

$$c_5 = \{a_2, a_3, v_2, v_3, s_2\}$$

$$c_7 = \{a_2, v_2, v_3, s_?\}$$

Thus cc(i) and cc(ii) are generative processes of a different nature than varying some features over the similarity neighborhood of one and the same concept (like choosing vegetarian ingredients that taste similar for an initially non-vegetarian cooking template).

Combination of problem-solving templates or representation structures (RS) larger than concepts is a step of higher complexity. Many new relations can be established between concepts, and (depending on the problem domain) many more constraints are at play when searching for an RS or sub-RS that needs to fit a particular solution, affordance or relationship criterion.

Depending on the new relations, emergent affordances can be made available. Thus a problem template $PT_{15} = h_x(h_1([C]a, [C]b, [C]c), h_2([C]d, [C]e))$, where $[C]a, [C]b, [C]c$ are conceptual placeholders for a 3-slot template, will have to account for some of the relationships between whatever sets of concepts are tried on to see if application of h_1 is possible, or if new (damaging) side-effects don't appear as part of that combination.

However, similarity of elements in problem templates and the structure of such RS can be used in a variety of ways:

(a) synthesis and generalization of new relations. If $PT_1 \cap PT_2 \neq \emptyset$, for a synthesis PT_3 keep the common elements of both templates and the relationships and heuristics which apply to both of them. For example:

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$PT_2 = \{c_1, c_2, c_5, r_2(c_1, c_5), h_3(c_1, c_2), h_4(c_2, c_5), sol_3\}$$

$$\text{then synthesize } PT_3 = \{c_1, c_2, r_1(c_1, c_2), h_1(c_1, c_2), h_3(c_1, c_2), sol_x\}, \text{maybe } sol_x \subset sol_3$$

(b) hypothesizing based on already observed strong relations - if a template contains pre-existing elements of already known templates, hypothesize that the results of those templates could be achieved as a consequence

(c) chaining - If a template PT_1 presents in its solution set part of the elements of PT_2, then perhaps the two templates can be chained in $PT_3 = PT_1 \cup PT_2$

$$PT_1 = \{c_1, c_2, r_1(c_1, c_2), h_1(c_1, c_2), sol_3\}$$

$$PT_2 = \{c_2, c_3, r_2(c_2, c_3), h_3(c_2, c_3), sol_5\}$$

then chain $PT_3 = \{c_1, c_2, c_3, r_1(c_1, c_2), r_2(c_2, c_3), h_1(c_1, c_2), h_3(c_2, c_3)\}$, and maybe $sol_x \cap (sol_3, sol_5)$

(d) extending by replacement or via recasting - if part of the elements of PT_1 can be used for another template PT_2 without destroying them, extend PT_1 to $PT_1' \supset PT_2$

(e) superset with emerging structure - keep all elements of template PT_1 and PT_2 and see if new relations appear when attempting to construct PT_3 which includes them both.

(f) element mix, keeping existing common structure - mixing elements from both templates

$$PT_1 = \{c_1, c_2, c_3, r_1(c_1, c_2), h_1(c_1, c_2), h_2(c_2, c_3), sol_3\}$$

$$PT_2 = \{c_1, c_2, c_5, r_2(c_1, c_5), h_3(c_1, c_2), h_4(c_2, c_5), sol_3\}$$

$$\text{try} \quad PT_3 = \{c_1, c_2, c_3, r_1(c_1, c_2), \mathbf{h_3(c_1, c_2)}, h_2(c_2, c_3), \mathbf{sol_x}\}$$

If (a) to (d) can be done with search, (e) and (f) are more likely to belong to composition processes. Such productive representation construction processes as the ones in (e) and (f) can be defined as combining previously known RSs in an RS which inherits properties and/or structure from both elements. In this process, other generative, associationist and comparative processes come into play, creating new concepts, hypotheses and relations in the work necessary to come up with a new RS the properties of which can support solving of the problem.

This comparison shows that productive and generative processes are closer towards the spectrum of creative discovery and innovation, while search for a known representation that can fit the problem followed by the restructuring of the problem elements under that representation is more akin to empirically studied insightful problem solving.

4.7 Multimodal and concept to template transformations

In the previous examples, V was used to stand in for visuospatial feature maps. However multiple modalities can participate in the creation of such a map, having as a consequence multiple different such feature spaces (e.g. for shape, color, orientation, etc.).

Looking at the above described mechanisms, one could assume the type of feature map engaged in such operation is not of importance, and the mechanisms can apply in a general form to any sensory feature map. However, when characterizing a system with multiple sensory modalities, a creative interplay is also possible **between** the different modalities.

Thus, a concept of growth observed visually can be compared to or translated into a concept of growth based on auditory intensity, or pitch height. A concept experienced in a certain sensory modality, like *balance* - which is generally experienced through proprioceptive and visual modalities, can be transformed in a concept of balance in one's actions, as personally evaluated in various categories. A problem template could also bring multiple concepts from different domains into account.

Besides multimodal transformations, complex sets of features can act as concepts or as problem templates themselves. This is shown best by the anecdotical examples of Kekulé using Ouroboros snake (iconic image) as a template for inspiring organisation of the benzene molecule, and Watson quoting dreams of spiral staircases (iconic image from a concept) as possible organizational (problem) template for the double helix discovery.

4.8 Discussion - the relation between imperfect recognition, constructive memory and re-representation

It is worth noting that, in this framework, the process of object recognition itself does not require perfect matching of observation to pre-existing knowledge in the KB, and this reflects cognitive realities of operating in real-world environments. It is thus unlikely that an object in the environment will present itself to its observer bearing all identifying traits which the observer has encoded in its KB about the object. Recognition then operates by offering the best possible match in the KB, and switching to interactive learning soon after. This allows new traits of known objects to be learned from the environment. However, this type of recognition also has as a consequence the bias that new objects will be initially compared to similar objects the agent has previously encountered. In this context, hypothesizing over the possible uses of new objects will be made by projecting pre-existing knowledge of already known objects, before a completely new concept will be built for that particular object. This is also how human cognition operates according to literature, and how known psychological effects like the shape bias are possible [72, 88].

Much recognition is therefore constructive - the agent assumes about an object, concept or type of event that certain properties which the agent has already encoded will be present. Such a type of operating is known as constructive memory [131, 132], and has both negative and positive side effects. Notable negative side effects of constructive memory are its ability to bias witness testimony [30]. On the positive side, constructive memory is an ability without which we could not navigate real world environments with any speed, as we would be required to retest all our assumptions about the world at all times. Constructive memory, with its less productive side effects, is thus a great mechanism of cognitive adaptation which generally enables fast though imperfect recognition, on which fast decision making and survival are based.

Functional fixedness, the human tendency to apply and generally only see a certain set of known and familiar solutions to a certain problem, to the detriment of other, simpler or more productive solutions, is a side effect of having encoded problem templates closely knit with their practically used solutions.

Functional fixedness seems based on similar processes as constructive memory. The process of re-representation is the ability to reconsider our direct assumptions, and re-encode the elements of the problem in a manner which is more productive. On a lower level, the equivalent of this is to not take our constructive memory premises for granted and examine the objects in the environment, to see if our assumptions about their properties hold (and thus our recognition of them as part of a specific category). However, at the problem template level, this can be harder to do, as problem templates are ampler structures, and one has to inhibit such knowledge in order to regroup elements in potentially more productive templates, or create such templates as an adaptation of previously known ones. In human insight, an assumption about how this process of restructuring is enabled, is that the incubation phase dissipates the functional fixedness, by diminishing the activation of normal patterns, and allowing for wider searches and new templates to be grouped together and applied, until one emerges which fits the problem, with all parts falling into place - the Illumination stage [157].

Insight and creative problem solving can thus be viewed under this framework as processes of memory management, with both associationist and gestaltic (template pattern-filling) underpinnings, and recasting - restructuring processes using memory and environmental resources.

The experiments in the next chapters cannot cover all the possible range of the mechanisms detailed here. However, they cover a reasonable amount of varied mechanisms in variate domains, implemented under the CreaCogs framework, showcasing its capabilities and comparing them to human performance.

Chapter 5

A cognitive system that solves the Remote Associates Test computationally (comRAT)

Various psychological tests have been used to measure creativity [61, 80]. As described in Section 2.4.1, some of these are empirical tests using insight problems [36, 101]. Such tests however can take a long time to administer to humans, as insight problems are quite hard and can take a long time to solve. Because of this, the various empirical tests on insight cannot contain many items, reducing the amount and inherent strength of data coming from them.

A smaller test which is thought to measure a similar ability as the insight test is the Remote Associate Test (RAT), initially proposed by Mednick and Mednick [108]. The ability to perform well at this test has been shown to correlate with the ability to successfully solve insight problems [136]. The advantage of the RAT is that many items of this test can be administered relatively quickly. Furthermore, Mednick [107] held a domain-independent associative view of creativity, thus the RAT is designed to measure creativity as a function of the participant's ability to associate remote items.

In this chapter, associative and convergent CreaCogs processes are implemented in order to test whether they can be used to computationally solve the RAT. First, the test itself is described in more detail in Section 5.1. The main CreaCogs mechanism implemented and its place in the framework are described in Section 5.2. The proposed computational solver for the RAT task (comRAT) is described in Section 5.3. The RAT, together with preferred answers and query item contribution to answers are formalized in Section 5.4. A set of normative human data [11] is used for evaluation and testing in Section 5.5. An empirical analysis of the principle of preferred convergence is performed in Section 5.6. The correlation between human difficulty in solving a RAT query and comRAT's probability of finding an answer based on frequency is analysed in Section 5.7. The generative abilities of comRAT are described in Section 5.8. An extension of the RAT task and of the comRAT system into the visual domain is described in section 5.9. A discussion about the comRAT and proposals for further work regarding it are presented in Sec 5.10, followed by conclusions in Section 5.11.

5.1 The Remote Associates Test (RAT)

The Remote Associates Test [108] is a test meant to measure creativity; it has been widely used in the literature [3, 10, 33]. The test is of the following form: given three words, the participant has to find a fourth word which can be associated with all the given three words. For example, the following 3 items are given:

COTTAGE - SWISS - CAKE

In this case, an answer considered correct is *CHEESE*, because of the following associates: *cottage cheese, swiss cheese and cheese cake* [108].

With each test consisting of only three words, and taking a minute or less to solve, the RAT makes possible the administration of 90 or more items for a normal testing session per participant, thus yielding rich data. If the correlation in performance between insight tests and RAT previously demonstrated empirically [136] holds, then the RAT could be used to gather much more data and tap much faster into mechanisms which are similar to the ones responsible for insight. This makes the RAT worthy of modeling, and the following work aims to set the precedent for an automated Remote Associates Test solver.

The Remote Associates Test solver has been translated and adapted to a variety of other languages than English [17, 64, 113]. However, not all test items on the initial Mednick test [108] are equal: Worthen and Clark [168] remarked that this test contains a mix of *functional* and *structural* associates. *Functional* associates elicit a relationship which is functional between them (e.g. between *bird* and *egg*) and may or may not translate into a language relationship (i.e. the items often being closely associated in language use). *Structural* associates are items which are generally associated together in language, generally in the same syntactic structure (i.e. *sweet* and *tooth*; *black* and *magic*), but amongst which a functional relationship doesn't necessarily hold. Worthen and Clark proposed a remote associate test based on functional associates (FRAT).

CreaCogs in its current form posits processes which could support both functional and structural associates. *Structural* associates are the same with *compound* associates (i.e. those obtained from a syntactical compound - like a phrase or a compound noun). Due to access to normative data on compound associates [11] which makes evaluation possible, in the following, an automated solver for structural or compound associates is proposed.

5.2 RAT solving in CreaCogs

The process of solving the Remote Associates Test has some phenomenological overlap with solving insight problems. Participants attest to having a solution come to mind instantly, the equivalent of the illumination phase in insight problem solving. Because of this we assume most of the search to happen "under the radar", or "under the hood", i.e. unconsciously.

The hypothesis presented here about how the RAT is solved by humans is the following. The associations from the given terms to the previously encountered compound terms are activated in the memory of the agent. Then, common items are found via convergence, which manifests itself as an overlap of activation. This convergence makes a term pop-up from the long-term memory of the cognitive system. Various constraints could be applied to this activation, or its strength, depending on the familiarity of that compound term to the user, whether the terms are related semantically, etc.

This process implementation of this hypothesis is represented in the CreaCogs framework by a refinement of the mechanism of upward search 4.2. Concepts activate all the problem templates (in this case compound terms) in which they have been involved, which in turn activate other concepts present in these compound terms (other than the given ones). The overlap of activation sent to a concept from multiple compound terms is the convergence and helps find the answer term.

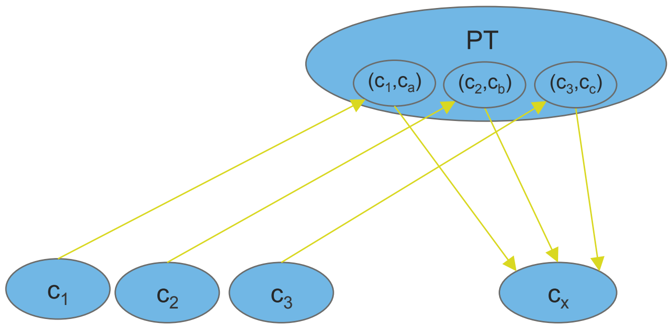


FIGURE 5.1: comRAT search mechanism as pertaining to previous formalization. C stands for concept, PT for problem templates, and the tip of the arrows shows the direction of the activation.

In the following, the implementation of this mechanism in an automated comRAT solver will be described, together with the knowledge treatment and algorithm implemented.

5.3 A Computational RAT Solver (comRAT)

The following section is organized as follows: the data used by the system and its preparation for this specific task is described in Section 5.3.1; the acquisition of the knowledge and its organization, fundamental for the CreaCogs framework, is discussed in Section 5.3.2; the process of solving the comRAT queries and the algorithm applied is presented in Section 5.3.3.

5.3.1 The RAT Knowledge Base

In order to build the RAT Knowledge Base (RAT-KB), language data of compound terms was needed. For this, 2-grams of the publicly available, genre-balanced Corpus of Contemporary American English (COCA)[1] have been used. These 2-grams are indexed on part of speech according to the UCREL CLAWS7 Tagset[2] and contain data on frequency of use.

The steps for acquiring and preparing the data were the following. First, the 1 million most frequent 2-grams of this corpus were acquired. Based on the part of speech the data is classified as, a pruning process was applied, in order to remove items not relevant for the RAT task. The items categorized with the tags displayed in Table 5.1 were kept as possibly relevant for the RAT task. As a result of this tag-based pruning process, approx. 200 000 2-gram items were obtained.

TABLE 5.1: Tagset used for extraction of items from 2-grams of the Corpus of Contemporary American English.

Tag	Description	Example
FU	unclassified word	
FW	foreign word	*chateau*
JJ	general adjective	*blue*
ND1	singular noun of direction	*north*
NN	common noun, neutral for number	*sheep, cod*
NN1	singular common noun	*book, child*
NN2	plural common noun	*books, children*
RA	adverb, after nominal head	*else, galore*
REX	adverb introducing appositional constructions	*namely*
RR	general adverb	*down*
RT	quasi-nominal adverb of time	*now, tomorrow*
VB0	be, base form	finite, imperative, subjunctive
VVG -ing	participle of lexical verb	*giving, working*
VVN	past participle of lexical verb	*given, worked*

No a priori evidence whether this set will contain the necessary or useful data to solve the RAT was obtained previous to experimentation.

5.3.2 Knowledge Acquisition and Organization by Association

comRAT-C is endowed with three types of knowledge structures (Classes): Concepts, Expressions and Links. In this implementation, Concepts are one word lexical items, Expressions are the equivalent of a representation structure containing two Concepts (words), and Links are bidirectional connectors between Concepts and the Expressions they are part of.

[1]Corpus of Contemporary American English (COCA): http://corpus.byu.edu/coca/.

[2]For a complete list of the UCREL CLAWS7 Tagset see: http://ucrel.lancs.ac.uk/claws7tags.html

comRAT-C is presented sequentially with each of the 2-grams from the set pruned from the corpus. When a 2-gram is presented to the system, an item of the Expression class is constructed for it. The system then checks if it already has the Concepts contained in this Expression in its KB. Any concept that is unknown is constructed as an object and added to the system's KB. Links are attached between each of the two Concepts and the Expression they are part of. The bidirectionality of the Links ensures that, when given an Expression (e.g. *"Self Defense"*), this is linked to both Concepts it uses (e.g. *"Self", "Defense"*), and that each of these Concepts has a Link to the Expression, to the other concept it has formed an Expressions with through the Expression, and to other Expressions it has been part of and Concepts it has been associated with. After a while, each Concept is thus connected by Links to all the other Concepts it has formed an Expression with, each Concept thus forming a hub of incoming and outgoing connections.

Some of the RAT queries might refer to compound nouns which appear not split in the corpus: e.g. *"Healthcare"* is a compound noun, however for solving the compound RAT, *"Healthcare"* must be taken as an Expression, with the Concept *"Health"* being linked to the Concept *"Care"*. Compound words are not marked by the tagset in Table 5.1. To solve this issue, after all the Expressions have been acquired, the system proceeds to compare each Concept with other known Concepts, in order to obtain knowledge about compound words. If the system recognizes a Concept as *part-of* another Concept, it will then try to match the second part of the now assumed compound (lexical unit) to the other Concepts it knows. If the match is successful, this compound word is also added as an Expression, and Links are set between its composing lexical units.

This concludes the knowledge acquisition and organization process. Now the system is ready to accept queries.

5.3.3 Solving the compound RAT (cRAT) queries

In the following we will refer to the compound RAT queries and test as cRAT and the computational RAT solver for compound queries as comRAT-C. Whenever a 3-item RAT query is received, the cRAT solver (comRAT-C) searches its KB for matching Concepts, which are then activated (3 or less). All the Expressions in which these Concepts have been known to participate are activated via the Links. Then all the Concepts which are Linked to these Expressions elicited by the original 3 query words are activated. This happens independently of whether the given cRAT query items are in the first or second position of an Expression. Thus the second item in all 2-item Expressions which contain the initial query items become active, as it is shown in Table 5.2.

The system then checks for answers by searching its most activated concepts. Thus for the query illustrated in Table 5.2, the activation coming from the items $COTTAGE$, $SWISS$ and $CAKE$ converges upon the Concept $CHEESE$. However, more than one convergence item is possible. Such queries thus elicit only the conceptual and problem template layer in CreaCogs, as shown in Figure 5.2.

Table 5.2: Example of activation of linked items for the query COTTAGE, SWISS, CAKE.

(Cottage + *) OR (*+Cottage)	(Swiss + *) OR (*+Swiss)	(Cake + *) OR (*+Cake)
cottage **cheese**	Swiss Alps	cake batter
cottage garden	Swiss army	cake decorating
cottage industries	Swiss ball	cake flour
cottage ...	Swiss chard	cake layer
... cottage	Swiss **cheese**	carrot cake
... cottage	Swiss chocolate	**cheese** cake

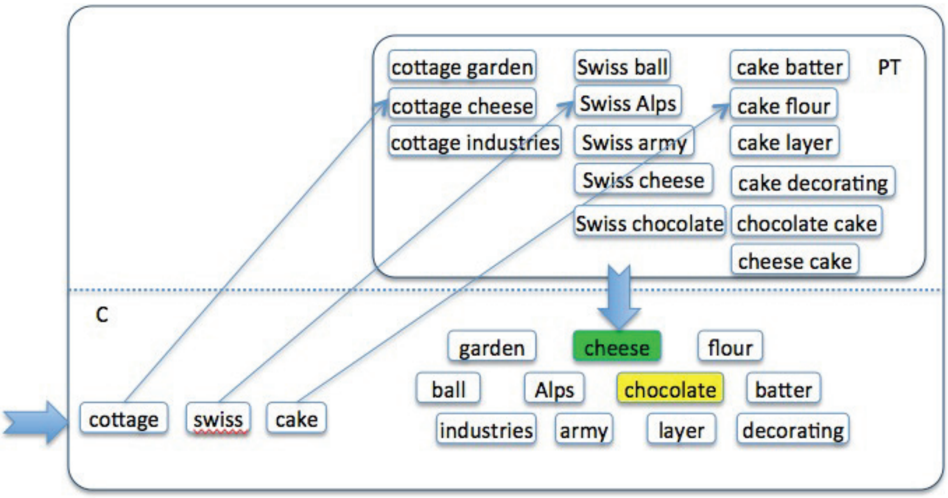


Figure 5.2: comRAT-C process in terms of CreaCogs

At the concept level, various items are thus activated because of their association with query items in various compound templates. Overlap of activation of such associates yields convergence to various common terms. A visual depiction of this mechanism at the concept level is shown in 5.1. As can be seen here, the term *chocolate* is activated by two of the initial query items, and the term *cheese* by all three. Multiple results coming from a 3-item convergence are possible with this process.

Normative data like the one offered by Bowden and Jung-Beeman [11] only offer one correct answer. For comparability, in the case in which convergence happens to yield multiple results, the system is set to initially offer the first Concept found with highest activation (which is simply set initially as activation coming from all 3 items). As multiple items might be activated from all three concepts, a different though still correct answer to that obtained by the normative data could be offered.

Furthermore, some of the compound terms which are known by the human participants which solved the queries in the normative data [11] might not be known by the automated solver. Thus other 3-item convergence answers could be offered due to differences in the KB. If no 3-item convergence is found, the system will propose the first encountered 2-item on which convergence has happened.

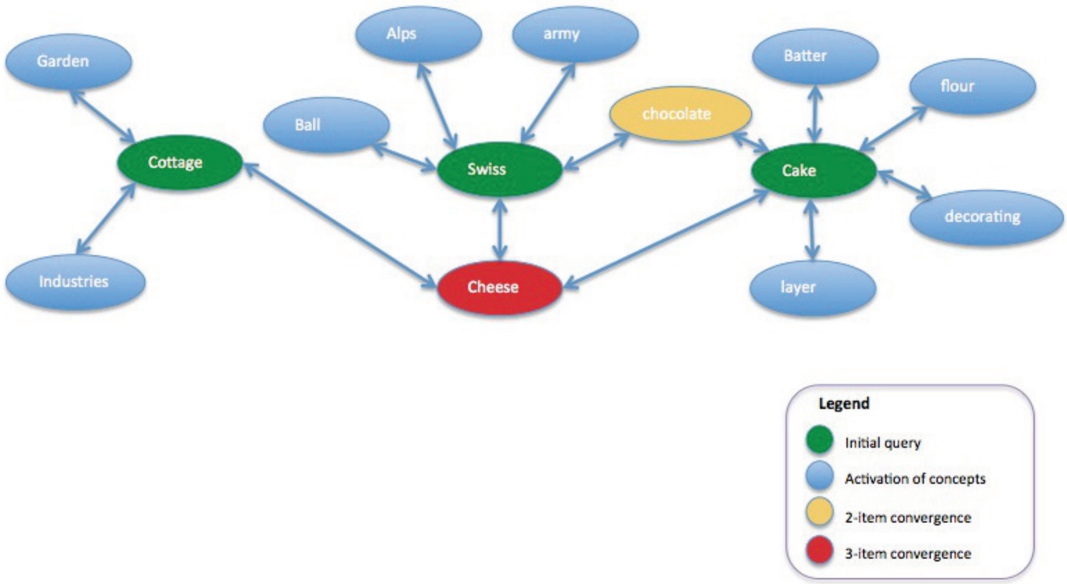


FIGURE 5.3: Visual depiction of the activation during a comRAT query

The algorithm implementing this process is shown in Table 5.3.

TABLE 5.3: comRAT-C Solver Algorithm

Algorithm Finding convergent terms in comRAT-C
int maxValue = 0
$cList = c_1.getLinkedC() + c_2.getLinkedC() + c_3.getLinkedC()$
for all $c_x : cList$
$KB.c_x.updateActivation()$
if $KB.c_x.getActivation() > maxValue$
answer = c_x
maxValue = $KB.c_x.getActivation()$
end if
end for
return answer, maxValue

This algorithm is quite fast - $O(n)$, where n stands for the sum of the (variable) number of links of each of the 3 given terms. However, this requires a pre-ordering of all the concepts and their links based on the expressions in the knowledge base. As multiple answers are sometimes possible, a hypothesis based on frequency data is formalized in the next section on why humans prefer a certain answer, and the contribution of the different query items to answers. This modifies the *updateActivation*() function using frequency data from the 2-grams in the COCA corpus.

5.4 Formalizing preferred answers and item contribution

This section formalizes the RAT, and shows the approach we propose in order to answer two questions: a) why is an answer preferred over another? and b) how do the various items contribute?

We define all known words in our knowledge base (KB) as set W and all known two-word expressions (or 2-grams) as set E, so that:

$$w_1, w_2, w_3, ..., w_m \in W, W \in KB$$

$$e_1, e_2, e_3, ..., e_n \in E, E \in KB, e_k = (w_x, w_y)$$

As our known words are acquired from 2-grams, for each $w_x, \exists\ e_k \in E$, so that either $e_x = (w_x, w_y)$ or $e_x = (w_y, w_x)$ (both can also exist). Thus for each known word w_x there exists at least one expression which w_x is known to be part of, be it that it is the first or second term in that expression. Compound words or expressions made from the same words in a different order are not equivalent, as it is made clear by the example of the compound words *boathouse* and *houseboat*, thus:

$$(w_x, w_y) \neq (w_y, w_x)$$

For now, whenever we refer to term w_x as being part of e_x, it can appear in either positions - (w_x, w_y) or (w_y, w_x)[3].

Any RAT query is of the form:

$$q_{abc} = (w_a, w_b, w_c),$$

and its result will be set S_{abc} (which includes the empty set):

$$w_x \in e_a \cap e_b \cap e_c, \quad w_x \in S_{abc}, \quad S_{abc} \in W$$

For our further analysis, we assume the probability of the three initial query terms to be equal:

$$P(w_a) = P(w_b) = P(w_c) = \frac{1}{3}$$

For each of the given terms - w_a, w_b and w_c - the set of expressions they participate in with other terms is e_a, e_b and e_a, e.g.[4]:

$$e_a = \{(w_a, w_1), (w_2, w_a), (w_3, w_a), ..., (w_a, w_m)\}$$

$$e_b = \{(w_b, w_1), (w_{12}, w_b), (w_{30}, w_b), ..., (w_b, w_n)\}$$

$$e_c = \{(w_c, w_9), (w_{12}, w_c), (w_{22}, w_c), ..., (w_c, w_k)\}$$

[3]Ordering influences will be addressed in section 5.10.

[4]The indices are not incremented by one unit because that would imply every one of the given 3 words to be connected with all the others. Instead w_b might only be connected to w_1, w_{12}, w_{30}, etc.

Each of the expressions the given terms participate in will have associated with them a frequency in our corpus. The total frequency of expressions (fr) in which the given terms participate is calculated as:

$$\sum_{i=1}^{m} fr(e_a) = \sum_{i=1}^{m} (w_a, w_i) \tag{5.1a}$$

$$\sum_{i=1}^{n} fr(e_b) = \sum_{i=1}^{n} (w_b, w_i) \tag{5.1b}$$

$$\sum_{i=1}^{k} fr(e_c) = \sum_{i=1}^{k} (w_c, w_i) \tag{5.1c}$$

For all possible answer terms $w_x \in S_{abc}$, the likelihood that they will be the preferred answer if frequency of use is the factor deciding the preferred answer, is calculated as follows.

Simple probability that each answer should appear is computed using the number of favourable cases that answer appears in combination with each of the items ($fr(w_a, w_x)$, $fr(w_b, w_x)$ and $fr(w_c, w_x)$) and the number of total cases of each of the given query terms ($\sum_{i=1}^{m} fr(e_a)$, $\sum_{i=1}^{n} fr(e_b)$, $\sum_{i=1} k fr(e_k)$).

Thus the simple probability formula: P(x) $= \frac{\text{Favourable cases}}{\text{Total cases}}$ becomes:

$$P(w_x \mid w_a) = \frac{fr(w_a, w_x)}{\sum_{i=1}^{m} fr(e_a)} \tag{5.2a}$$

$$P(w_x \mid w_b) = \frac{fr(w_b, w_x)}{\sum_{i=1}^{n} fr(e_b)} \tag{5.2b}$$

$$P(w_x \mid w_c) = \frac{fr(w_c, w_x)}{\sum_{i=1}^{k} fr(e_k)} \tag{5.2c}$$

The total probability that w_x should be the preferred response based on frequency of expressions is:

$$P(w_x) = \frac{P(w_x \mid w_a) + P(w_x \mid w_b) + P(w_x \mid w_c)}{3} \tag{5.3}$$

This is then done for all possible answers. Thus, given possible answers w_x, w_y, w_z, with $w_x, w_y, w_z \in S_{abc}$, the preferred answer based on frequency will be w_p, where:

$$w_p = max(P(w_x), P(w_y), P(w_z)) \tag{5.4}$$

Bayes's theorem is then applied a posteriori to see how much each of the given terms contributed to finding preferred answer w_p:

$$P(w_a \mid w_p) = \frac{P(w_a) \times P(w_p \mid w_a)}{P(w_p)} \tag{5.5a}$$

$$P(w_b \mid w_p) = \frac{P(w_b) \times P(w_p \mid w_b)}{P(w_p)} \tag{5.5b}$$

$$P(w_c \mid w_p) = \frac{P(w_c) \times P(w_p \mid w_c)}{P(w_p)} \tag{5.5c}$$

For each solution (preferred or not) in S_{abc}, a triple $c_{abc,x}$ can be calculated for the contributions of each initial term w_a, w_b, w_c to solution w_x. Thus for the preferred solution w_p:

$$c_{abc,p} = (P(w_a \mid w_p), P(w_b \mid w_p), P(w_c \mid w_p)) \tag{5.6}$$

and the maximum contributing item is $max(P(w_a \mid w_p), P(w_b \mid w_p), P(w_c \mid w_p)$.

5.5 comRAT-C Experimentation and Results

To evaluate the performance of the comRAT-C, the normative data from Bowden and M. Jung-Beeman [11] has been used. The results (see Table 5.4) show that out of the 144 items used in Bowden and M. Jung-Beeman's test, 64 are answered correctly[5] by the proposed system. Out of these, for 47 of all given queries all three items were known. These refer to the three expressions needed to answer the query - $E_1 = c_1c_x$, $E2 = c_2, c_x$, $E3 = c_3, c_x$ - where c_1, c_2 and c_3 are the given query words, and c_x is the correct answer from the normative data. The accuracy of the system is thus 97.92% when all three expressions are known, without using any frequency data or complex activation mechanisms, based on associative convergence principles alone.

Table 5.4: Analysis of comRAT-C's performance in relation to known items.

Number of Expressions known =>	0 E	1 E	2 E	3 E	Total
Correct Answers	0	0	17	47	64
Plausible Answers	2	11	12	1	26
Not solved	4	23	27	0	54
Total	6	34	56	48	
Accuracy			30.36%	97.92%	

We called some of the answers obtained "plausible answers", as they are not the given correct answers in the normative data, however they could be considered as interesting or good enough answers from the human perspective. Table 5.5 shows such plausible answers. Some such plausible answers arise from data regularity, converging upon items which are common to the three query items and possibly to many others, for example adjectives like *great*, *big*, *small*. Other plausible answers are more interesting, surprising

[5] Correctness in this case is considered as the exact answer provided by the system on its first try.

and can be considered more "creative" from the human perspective; they offer as a response a noun or another word which is indeed a specific remote associate of this particular 3 words tuple, rather than a word which might be a common associate to multiple tuples (e.g. words like easy, small, black, etc).

A more rigorous description of the two cases might be that interesting items are items with which the 3 elements in the query form new concepts, while the "regular" items are attributes which are perhaps characteristic of many items (or form with the second element an attribute-concept pair). In this case taking into account the frequencies of such items or their part-of-speech tag might endow the system with the ability to differentiate between surprising and regular plausible answers.

Table 5.5: Some of the plausible answers obtained by the computational RAT.

No.	w_1	w_2	w_3	$Answer_1$ [11]	$Answer_2$
1	High	District	House	SCHOOL	STATE
2	Health	Taker	Less	CARE	RISK
3	Cat	Number	Phone	CALL	HOUSE
4	Chamber	Mask	Natural	GAS	DEATH
5	Self	Attorney	Spending	DEFENSE	BILL
6	Fight	Control	Machine	GUN	POLITICAL
7	Off	Military	First	BASE	PAY
8	French	Car	Shoe	HORN	COMPANY
9	Cry	Front	Ship	BATTLE	WAR
10	Change	Circuit	Cake	SHORT	DESIGN
11	Child	Scan	Wash	BRAIN	BODY
12	Mill	Tooth	Dust	SAW	GOLD
13	Home	Sea	Bed	SICK	WATER

In order to accurately assess the performance of the system, the knowledge in the KB-comRAT needs to be compared to the knowledge required to solve the items in the normative data [11] test. Figure 5.4 offers such a visual analysis, showing the overlap between comRAT's performance (solved, plausible, not solved queries) and the number of known query items. For some queries in Bowden's data, the system simply did not have enough knowledge to respond.

As Table 5.4 shows, in the cases where comRAT-C had all 3 items in its database, its correctness of response when compared with normative answers was at 97.92%, while when comRAT-C only knew two of the given expressions, it was finding the correct answers in 30.36% of the cases. This is a bonus since humans are normally assumed to know all the three items when answering a RAT query correctly, or to at least be able to verify whether the 3rd expression is a valid, meaningful one.

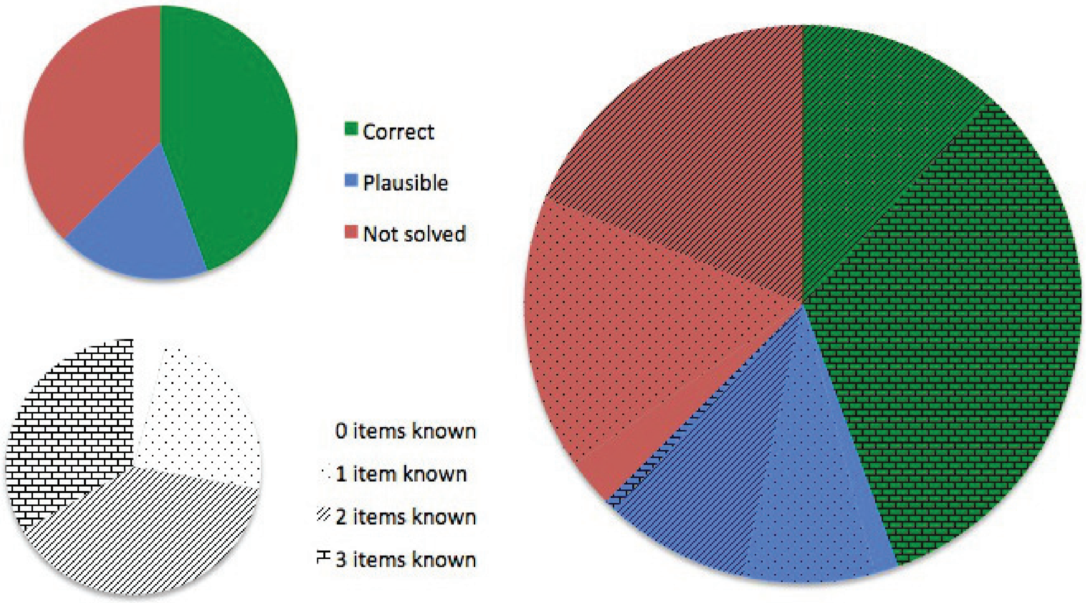


FIGURE 5.4: comRAT Results and their relation to the knowledge base: a) Left up - Correct, Plausible and not answered items; b) Left down - Number of known items per query; c) Right - Distribution of knowledge items over items answered

5.6 Preferred convergence - empirical analysis

This section presents results on whether the items preferred by humans as an answer match the probability of answer (calculated as shown in Section 5.4) based on frequency data from the corpus.

Four queries from the normative dataset where answered correctly and had multiple interesting answers. Items where other correct answers where very common (like *little*, *great*, *only*, *big* etc.) where put aside. These queries and their correct answers from the normative data where the following:

1. High District House. *Answer:* School
2. Chamber Mask Natural. *Answer:* Gas
3. Self Attorney Spending. *Answer:* Defense
4. Back Step Screen. *Answer:* Door

Table 5.6 shows the frequency-based probability for each answer of the four queries, calculated as shown in equations 5.2 and 5.3. Results have been rounded. The answers are arranged in decreasing order of their frequency based probability (with the maximum probability item to the left side). In all four cases, the first answer (A_1) which offers the highest probability is also the one which is considered correct in the normative data.

This shows that items with highest frequency might be the ones preferred by humans, and such a hypothesis is testable (see section 5.10).

The contribution of the three items to the preferred responses calculated as shown in Section 5.4 is shown in Table: 5.7. The highest contributing item is shown in bold.

TABLE 5.6: Frequency-based probability for the multiple answers of four queries

Query	A_1	A_2	A_3	A_4	A_5	A_6	A_7	A_8	A_9	A_{10}	A_{11}
High District House	School	Court	Historic	U.S.	Officials	Office	Water	State	Suburban	Light	Church
Answer Probability	0.1850	0.0306	0.0069	0.0061	0.0046	0.0034	0.0033	0.0027	0.0012	0.0012	8.8E-4
Chamber Mask Natural	Gas	Death									
Answer Probability	0.1162	0.0240									
Self Attorney Spending	Defense	Bill	Personal	Private							
Answer Probability	0.0767	0.0146	0.0059	0.0056							
Back Step Screen	Door	Porch									
Answer Probability	0.0485	0.0063									

TABLE 5.7: Contribution of the three items to various answers

Query	Answer	Item 1	Item 2	Item 3
High District House	School	**0.60**	0.40	0.00
High District House	Court	0.07	**0.83**	0.10
Chamber Mask Natural	Gas	0.24	**0.43**	0.33
Chamber Mask Natural	Death	0.45	**0.50**	0.05
Self Attorney Spending	Defense	0.25	**0.47**	0.27
Self Attorney Spending	Bill	0.32	0.03	**0.65**
Back Step Screen	Door	0.34	0.02	**0.64**
Back Step Screen	Porch	**0.66**	0.19	0.14

Contribution of items, calculated as shown in equations 5.5 and 5.6, can help further manipulation of preferred answer. When the first item strongly contributes to a particular response, and the two responses are close in probability, changing the order of the three items to show the strongly contributing items to one response or another first might help change the answer which is given by human participants.

5.7 Correlation with difficulty in human data

A correlation between the frequency based probability of results for the queries in table 5.6 and the difficulty of the RAT query in Bowden's normative data was observed (see Table 5.8). The number of participants that could solve a particular test item decreased with probability based on frequency to trigger that item. The time taken to solve a query by human participants increased the lower the probability for comRAT-C to find the answer item based on frequency data.

TABLE 5.8: Frequency-based probability for the multiple answers of four queries.

Query	Probability	% of participants solving (15s)	Mean Solution Time (s)
High District House	0.1850	55	5.59
Chamber Mask Natural	0.1162	53	5.86
Self Attorney Spending	0.0767	4	8.42
Back Step Screen	0.0485	0	-

After this observation was made, more data was analysed in order to check for this correlation on all the queries which fulfilled the following three conditions: a) comRAT-C could answer them correctly; b) comRAT-C had knowledge of all three expressions formed by the RAT query items and the correct answer and c) normative data was available in the Bowden paper. 48 such items were found.

The probability that an answer will be found by comRAT-C given the frequency data correlates positively with human data on how many people can solve the test and negatively on how fast they can solve it. Table 5.9 shows a summary of correlations and p values for all the 48 correct answers, for participants being given 7, 15 or 30 seconds to solve the problem.

TABLE 5.9: Correlation between probability based on frequency and human data, and its significance. MST stands for Mean Solution Time, and % PS stands for Percentage of participants solving.

Measure	% PS 7s	% PS 15s	% PS 30s	MST 7s	MST 15s	MST 30s
Correlation $P(w_x)$	$r = 0.45$	$r = 0.41$	$r = 0.49$	$r = -0.39$	$r = -0.3$	$r = -0.52$
Significance	$p < 0.002$	$p < 0.004$	$p < 0.002$	$p < 0.007$	$p < 0.04$	$p < 0.001$

Upon further analysis, this correlation was due to the first two terms - $P(w_x \mid w_a)$ and $P(w_x \mid w_b)$, with the third term $P(w_x \mid w_c)$ not being correlated to human performance. Table 5.10 shows all three such correlations, together with the correlation between the added probabilities of finding the first two query items.

TABLE 5.10: Correlation based on $P(w_x \mid w_a)$, $P(w_x \mid w_b)$ and $P(w_x \mid w_c)$. MST stands for Mean Solution Time, and % PS stands for Percentage of participants solving.

Measure	% PS 7s	% PS 15s	% PS 30s	MST 7s	MST 15s	MST 30s
Correlation $P(w_x \mid w_a)$	$r = 0.38$	$r = 0.33$	$r = 0.4$	$r = -0.29$	$r = -0.25$	$r = -0.33$
Correlation $P(w_x \mid w_b)$	$r = 0.40$	$r = 0.44$	$r = 0.53$	$r = -0.43$	$r = -0.26$	$r = -0.33$
Correlation $P(w_x \mid w_c)$	$r = -0.11$	$r = -0.18$	$r = -0.07$	$r = 0.11$	$r = 0.04$	$r = 0.05$
Correlation $P(w_x \mid w_a) + P(w_x \mid w_b)$	$r = 0.47$	$r = 0.45$	$r = 0.51$	$r = -0.41$	$r = -0.30$	$r = -0.41$

5.8 Generative abilities of comRAT

A system like comRAT, which can find convergences between given items of a query, their known expressions and possible RAT answers, can also reverse-engineer this process to propose queries which should be solvable by humans.

This can be done by checking for all convergences between all 3 items possibilities, thus taking w_a, w_b and w_c as variables, and replacing them with all the words in the corpus, and saving as potential RAT queries the items which have at least one convergent term w_r, to be the RAT query response item. This process is computationally exhaustive. Its costs depends on the initial size of the knowledge base (n), with a full run amounting to specifically $n*(n-1)*(n-2)$, thus approximately n^3. Then all these generated queries might need to be checked to remove very common attributes (like *little*, *great*, *only*, *big* etc.), or the entire process could be restrained to nouns.

However, with comRAT;s type of knowledge organization, this RAT query generating process can also be done by checking the items linked to each item after the knowledge organization has been performed. Thus, one could check the Concepts by considering them potential response items w_r. Whenever a w_r has more than three links, these can be considered as items $w_a, w_b, w_c, w_d..., w_n$. Queries can then be made out of various combinations of these items, obtained via the links to w_r, with the cost of one pass through the entire KB (n).

Some queries thus obtained are shown below:

1. **Answer:** Star **RAT Query Items:** movie, rock, pop, neutron, formation, basketball, power, football, witness, film, system, clusters, cluster, player, track, tennis, shooting, guest, anise, child;
2. **Answer:** Glass **RAT Query Items:** doors, door, windows, window, ceiling, wall, beads, case, plate, window, wine, bowl, water, bottles, jar, walls, shot, jars, panels, cases, martini;
3. **Answer:** Silver **RAT Query Items:** medal, lining, sterling, bullet, hair, screen, medalist, tray, spoon;
4. **Answer:** Table **RAT Query Items:** breakfast, pool, card, water, night, dressing, operating, side, bargaining, end, dining-room, corner, buffet, tennis, defense, top, lamp, salt, manners, oak;
5. **Answer:** Box **RAT Query Items:** office, ballot, dialog, boom, lunch, press, jewelry, music, glove, shoe, metal, jury, deposit, cigar, litter, set, tackle, office, spring, plastic, toe.

More examples can be seen in Table A.3 of Appendix A.

This technique can further use the frequency data to generate, for each answer item, queries with different probability (as weighed by the first two terms). This can be used to generate RAT queries fast to check whether the correlation with between difficulty of query for humans and the probability of the first two items holds over a larger body of data. Generating RAT queries with comRAT and then gathering human data on them can be used to further check this correlation.

Furthermore, in such an experiment one could measure whether indeed the frequency of the first two expression plays a decisive role independent of the frequency of the answer item w_r. This is because one can yield multiple queries with the same response item, keeping w_r as a stable variable, and only manipulating query items via their frequency.

The first presented technique will need to be applied in order to generate tests with multiple correct answers, of different probabilities. This then can be used to check to what extent the preferred answer can reliably be predicted using frequency data.

The semantic domain of the query items might play a role in the difficulty of the query, and in making the query more interesting, or the answer to be considered as more creative. Thus, in the second example of the list of queries generated above from answers (answer: Glass), items like “door” and “window” or “martini” and “wine” taken together are part of the same semantic domain, triggering the same interpretation of the response word “glass”. They might thus not qualify for a *convergence across semantic domains*. A more interesting query in the context of the same example would be “door”, “wine”, “case”. Such experimentation would need knowledge of semantic domains to be formalized and automatized.

The general premise of the RAT test deals with the principle of "remote" association. "Remoteness" could be understood in a variety of ways, including as difference of semantic domain. However, remoteness could also be expressed in our current data as a low amount of frequency of expression. Thus RAT items with lower probability to be answered might not just be harder for human participants, but also considered more creative by them. A set of such queries could be generated to check this hypothesis as judged by human observers on some designed scale, and compare these items to objectively high frequency and medium frequency items. This would shed light on whether such quantitative means of assessing frequency correlate with qualitative judgements of creativity, due to the originality component of creativity evaluations.

In summary, such generative techniques enabled by the comRAT allow further manipulation of new Remote Associates tests, thus constituting a great tool to enable the cognitive scientist, psychologist or linguist to further experiment with the task and disseminate the processes which take part in its solving. Some possibilities for such further work are, but are not restricted to:

- Verifying on a larger scale whether difficulty of answer is correlated to the probability of the first two query terms. Also checking if this is independent of the answer term, by keeping the answer the same.
- Gathering further data on the probability based preferred item hypothesis.
- Checking to see whether lower frequency items make for what is considered more creative RAT queries and answers.
- Determining the impact semantic domain has on solving such queries.

5.9 Expanding the Remote Associates Test to the visual domain

An important research question is whether such processes as the ones used by comRAT could be explored in a domain which is not linguistic. This would bring about a variety of advantages, including the following:

(i) The ability to dispel some fears in the literature that performance in the RAT might reflect language fluency performance more than creativity, by providing a way to reliably differentiate between the two components of such performance;

(ii) The ability to study a cognitive process in different domains, thus ensuring both domain independence and an ability to study domain influences;

(iii) The ability to give a creativity test in two different domains (such a test currently does not exist; though test batteries like the TTCT have sections which address visual creativity and others which address language, a test that can transfer across domains is not yet present in the literature);

(iv) Ability to deal in a more unified manner with creative processes, thus make stronger cross-domain and more refined intra-domain claims about process.

However, a visual version of the Remote Associates Test did not exist in the literature, thus we had to create our own. After this, comRAT was expanded to respond to such a test. The next sections describe this as follows: the steps taken to use our previous formalization to create a visual variant of the Remote Associates Test (vRAT) are explained in section 5.9.1. The set up of a study with human participants to deploy the visual variant of the RAT is described in section 5.9.2. The adaptation of the knowledge base of comRAT in order to make it a visual RAT solver (comRAT-V) is described in section 5.9.3. Results with human participants in vRAT and with comRAT-V for the same queries are detailed in sections 5.9.4 and 5.9.5.

5.9.1 Expanding RAT to vRAT

In order to expand the RAT to a visual domain, the previous formalization was used. Thus given a 3 item query in which w_a,w_b and w_c are the query terms, and w_x is the answer term, three items (w_a, w_x), (w_b, w_x) and (w_c, w_x) or their reverse - (w_x, w_a), (w_x, w_b) and (w_x, w_c) - must exist and be known to the solver[6] in order for the query to be valid and answerable.

Starting from this, we replaced query terms w_a,w_b and w_c with visual representations of objects and scenes, so that w_x is a visual representation of an object which can be given as answer. The idea was to count on experience with said objects and visuospatial schemas of the participants to trigger associates and converge upon the answer object. In this context, order of visual entities may be irrelevant in the same terms in which it mattered in language[7].

A visual query constructed on these principles is shown in Figure 5.5. Thus items HANDLE, GLOVE and PEN are given, and the answer expected, associated with each of these objects, is HAND.

FIGURE 5.5: Example of a visual RAT question. This first training query shows the participants visual entities HANDLE, GLOVE and PEN. The answer is HAND

We considered each initial object of the query to have a variety of visual associates in the mind of the participants, as language terms would have word associates in the original language-based RAT. In the example in Figure 5.5, visual associates of entities (HANDLE, HAND), (GLOVE, HAND) and (HAND, PEN) are necessary in order to solve the

[6]Two out of three items known might be enough for a human solver if they can still discover w_x and then assess whether the third term and w_x form a meaningful construct.

[7]However spatial position of items may not be irrelevant. This will have to be settled in future work.

query. In the next section, the application of these principles in a study with human participants is described.

5.9.2 Study with human participants

In order to run the newly designed vRAT variant with human participants, 22 such queries were composed (two were used as training queries and 20 as main test queries). A process of cognitive knowledge acquisition meant to inform the knowledge base of the computational solver (comRAT-V) was set up, by asking participants in this study to also provide visual associates to the objects in the test. If they solved a query including those objects, participants could be biased towards providing certain associates (or providing them first when they would not have otherwise). For this reason, measures needed to be taken so that the participants give associates to queries they haven't solved. To ensure this, the study was split in two parts, and the participants were assigned in four random groups. In the following, the two parts and the four group design are explained.

Part 1 - Training and Test

The 22 queries each showed 3 visual stimuli each, be it objects or scenes. Both objects and scenes where provided in the training queries (the two training queries are shown in Figure 5.5 and 5.6). Thus 5 objects and 1 scene where presented in training, and 54 objects and 6 scenes in the test itself.

Figure 5.6: Second training vRAT query showed to the participants items bathtub, glass and beach. The answer is water.

Participants were instructed that they will be presented with three objects or scenes and required to provide a fourth element related to each of them. In the context of the two training examples, they were then instructed to assess how they first perceived the answer; they could choose between (i) Visual imagery (if they assessed they imagined the answer), (ii) Word (if they perceived the answer verbally) or (iii) Other (case in which they had to specify).

They were then instructed to provide an assessment of each query's difficulty, on a Likert scale ranging from 1 (Very Easy) to 7 (Very Hard). After these instructions where provided in the context of the training examples, the participants where directed to 15 of the 20 visual RAT queries. The objects in the remaining 5 queries (different for each group as will be explained below) were meant to be used in the knowledge acquisition phase.

Part 2 - Knowledge Acquisition

In the second part of the study, the participants were asked to contribute visual associates to a set of 15 objects (5 unseen queries * 3 objects). The task was explained in the following manner:

> *"Visual associates are things you see when you imagine a particular object. These might be other objects, which are situated next to the object that you are imagining in some circumstance, or specific parts of the object you are imagining."*

Examples of various visual associates were then provided for some objects:

> *"For example, visual associates for "glove" might be: hand, thorns, snow, scalpel, hot pan, bike, dirt. Visual associates for "pen" might be: paper, notebook, letter, test, form, cheque, desk, ink, drawing, writing, pen holder, ear, pen case, pencil, etc."*

The instruction for the participants when given an object was to *"Imagine each item, and then write the visual associates that come to mind"*.

In order for all objects to be given visual associates to, while also having a good number of participants answering each of the queries, the test was set up to be administered in four groups, via four different Google form surveys. The participants selected the group themselves by using a coin randomizer[8], in which the participants would flip two Euro coins and thus settle on a heads or tails position combination. The image thus obtained via the randomizer was used to guide the participants to one of the four forms of the surveys.

In terms of the group design, the 20 test questions where split in four 5-question groups, as presented in Table 5.11. Each of the four groups was shown the two training queries, was asked to solve 3 sets of questions (15 queries) and to provide visual associates for the objects in the remaining 5 queries. These objects were presented in an alternate order, thus not to trigger the convergent associate which would be the answer.

Thus, visual associates were provided by human participants to all objects and scenes in the vRAT. These visual associates were further used by the knowledge base of comRAT-V.

[8] https://www.random.org/coins/?num=2&cur=60-eur.germany-1euro

Table 5.11: The four groups and their assigned tasks. "Q" denotes a question, and n the number of participants in each group.

Study items	**Group 1** $n = 8$	**Group 2** $n = 15$	**Group 3** $n = 8$	**Group 4** $n = 12$	**Answers per item**
vRAT Training Examples	Yes	Yes	Yes	Yes	Shown to all
vRAT Q1-5	Yes	Yes	Yes	**No**	Gr. 1, 2, 3 ($n = 31$)
vRAT Q6-10	Yes	Yes	**No**	Yes	Gr. 1, 2, 4 ($n = 35$)
vRAT Q11-15	Yes	**No**	Yes	Yes	Gr. 1, 3, 4 ($n = 28$)
vRAT Q16-20	**No**	Yes	Yes	Yes	Gr. 2, 3, 4 ($n = 35$)
Visual associates for objects in questions	Q16-20	Q11-15	Q6-10	Q1-5	all objects across groups

5.9.3 From comRAT to comRAT-V

In the previously described implementation of the comRAT-C solver of compound RAT queries (5.3), n-grams (specifically 2-grams) from a language corpus were used to generate the template (Expression) knowledge and form the associative links between concepts. Furthermore, frequency data from the same corpus was used in a probability based algorithm (5.4) in order to select the preferred answer in cases of multiple possible responses, and this correlated with difficulty from human normative data (5.5).

In the visual expansion version - comRAT-V - the visual associates provided by human participants were used in the same way as n-grams in comRAT-C. Thus visual associates for the 60 objects were used to provide an equivalent to the "Expression Templates" in comRAT-C, informing the KB of comRAT-V, which again organized its knowledge in Concepts, Links and Visual Templates[9] (which replaced Expression Templates).

The frequency with which the participants provided a certain visual associate was used as a base for the same probability algorithm in order to break possible ties, and check for correlation with difficulty. This amount of data is of course too small to draw strong conclusions, and different ways to extract larger amounts of such data will be discussed in Section 5.10. However, the current expansion provided satisfactory results in terms of adapting the RAT to a visual version. The results with human participants and with comRAT-V will be presented in the following sections.

5.9.4 Results with human participants

A total of 43 participants completed the study, 30 male and 13 female. The age of the participants ranged between (btw.) 20 and 60 years old (y.o.), as follows:

- 6 btw. 20-30 y.o.
- 19 btw. 30-40 y.o.
- 14 btw. 40-50 y.o.
- 4 btw. 50-60 y.o.

The English proficiency level of participants was (as declared by participants):

[9]Visual Templates can also be seen as a form of visual context.

- Intermediate - 9
- Advanced - 21
- Proficient - 10
- Native - 3

Human participants solved on average 63% of the vRAT, as shown in Figure 5.7. The performance on queries varied between 6.45% (Q5) and 97.1% (Q20). Queries can be classified in different levels of difficulty based on the performance, with Q5, Q13 and Q16 being the most difficult, and Q8, Q18, Q20 the easiest.

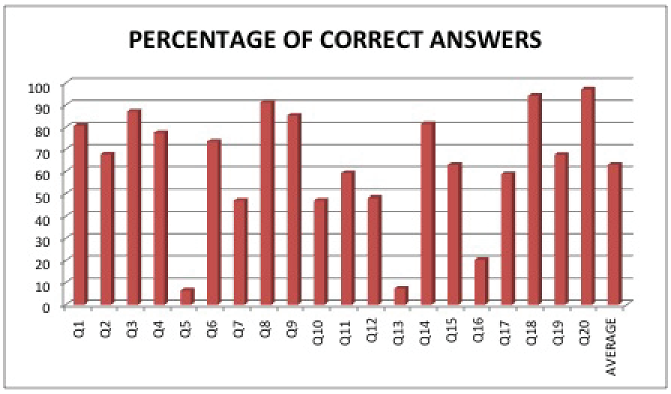


FIGURE 5.7: Percentage of correct answers per query, as solved by the human participants.

In terms of self-appraised perception of answer, as it first appeared, participants considered they perceived the answer mostly visually (56.6%) or as a word (38.9%), with some participants choosing the Other category. Out of the Other category, some participants specified they perceived the answer via a different sense modality (0.16%), for example *perceiving the feeling of heat* when the answer was *fire*.

The responses on how the answer was perceived per query item are shown in Figure 5.8. Thus the last 7 queries where perceived as much more visual on average than queries Q5, Q10 and Q13.

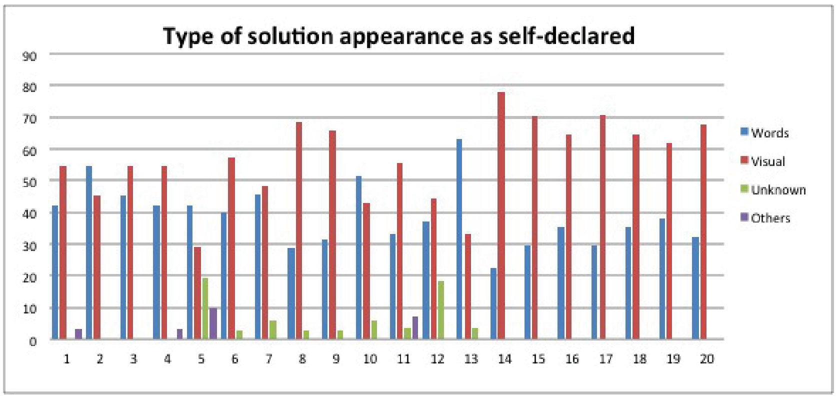


FIGURE 5.8: Type of solution appearance as self-declared by participants per query.

Participants were asked to rate the difficulty of the problems on a 1-7 Likert scale. The results of this rating are shown in Figure 5.9, together with the standard deviation (SD) of the ratings. Participants rated problems at an average of 3.41 difficulty on the Likert scale. They rated problems Q5, Q12 and Q7 as being the hardest, and problems Q18, Q14 and Q19 as the easiest, in the respective order.

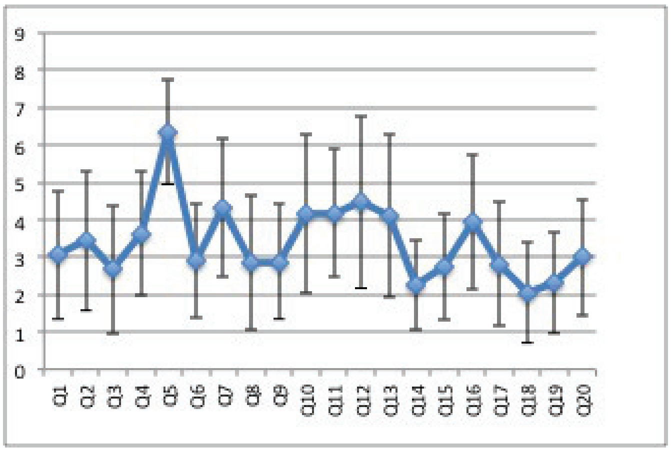


FIGURE 5.9: Difficulty ratings for the 20 problems, as expressed by the human participants.

Perception of difficulty might be individual or biased by intrinsic experience, and thus not reflect the actual average difficulty of the problems. To check whether the average of subjective difficulty ratings was related to actual average difficulty of problems as expressed by percentage of participants solving the problem, a correlation between these two types of values was run across the 20 problems. A negative high correlation of -0.78 with significance of $p < 0.001$ was found between percentage of solvers and difficulty ratings. Thus the more participants solve the problem, the lower the expressed rating. Thus it seems participants can on average estimate difficulty of a visual query quite reliably on a Likert scale, perhaps as a function of their own performance.

5.9.5 Results with comRAT-V

As explained before, the visual associates provided by the human participants to objects in queries which they haven't seen were used for the knowledge base of comRAT-V, with the knowledge organization and process of query solving being similar to that of comRAT-C. In this context, with no use of frequency, comRAT-V was already solving 63.64% of the query items. After calculating frequency, the accuracy of comRAT-V responses as related to knowledge items existing in its KB is shown in Table 5.12. Thus comRAT-V answered correctly 16 out of 22 queries. Most of the correct answers (13) were found via 3 items convergences, no answer was found in the case of only one useful visual associate being known, and 3 correct and 3 plausible answers were yielded in the case of 2 useful visual associates being known.

A few queries encountered 2 or more possible answers. For example, for Q8, two answers were possible in the 3-item convergence - CHEESE and MEAT. In the case of Q21 - (COMB, RAZOR, SHAMPOO) - a larger set of 4 possible answers is found via convergence from the

TABLE 5.12: Analysis of the accuracy of responses considering knowledge coming from visual associates in comRAT-V.

	1 item known	2 items known	3 items known	Total
Correct	0	3	13	16
Plausible	0	3	0	3
Not solved	2	1	0	3
Total	2	7	13	22
Accuracy	-	42.86% (85.71%)	100%	72.73%

3 query items (WATER, BATHROOM, HAIR, MIRROR). The correct answers are chosen in both cases using the frequency-based likelihood.

To correctly answered items, comRAT-V also offered other plausible solutions, which for simplicity we did not include in Table 5.12. This table includes only the highest probability-based items, and plausible answers when no correct answer was found. A total number of 10 other plausible answers appears in comRAT-V's solution spaces.

The amount of knowledge in comRAT-V's KB is a powerful influencer on performance. As shown in Table 5.12 and presented in a visual manner in Figure 5.10, current performance when all 3 items were known was 100%. Note that this is not necessarily the case, as other plausible items might have a higher frequency. Also, it is reasonable to believe that this level of performance is likely to decrease when aiming to answer computationally a larger set of queries, with a larger knowledge base.

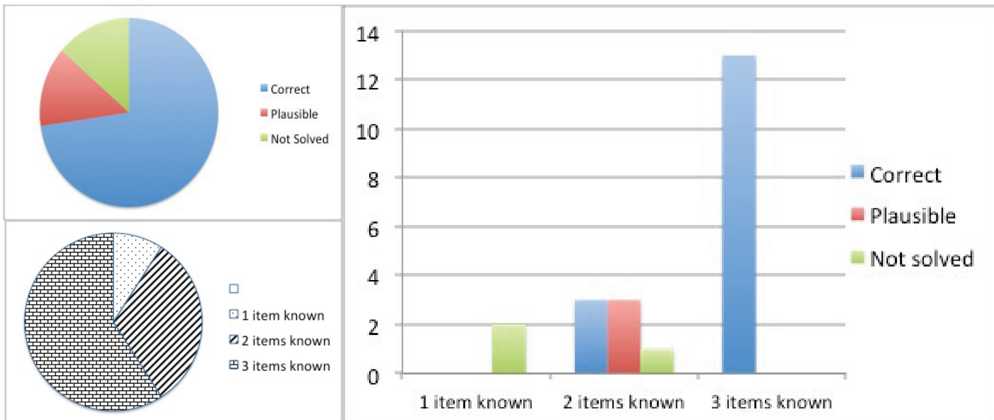


FIGURE 5.10: Visual representation of the influence of knowledge on answer accuracy.

A correlation between the likelihood that comRAT-V would find an answer and the difficulty ratings of vRAT queries as provided by humans was observed. A moderate-high negative correlation $p = -0.64$ with moderate-high significance $p = 0.01$ was observed between the two values. Thus, the more likely comRAT-V is to solve a query, the lower the difficulty expressed by human participants when rating the same query. The percentage of solvers showed a positive yet non-significant correlation ($r = 0.41$) with comRAT-V's likelihood of finding a solution, and more data is needed to check whether this could become a significant relation. However, altogether these results show that comRAT-V's likelihood algorithm and the CreaCogs convergence by association process captures something about the difficulty of the process of solving these queries, in the same manner in which the results of the same algorithm, applied in comRAT-C, showed an interesting relationship to human data.

5.10 Discussion and Further Work

In this section, the discussion is focused on explaining the following aspects: (i) the place of comRAT in CreaCogs, cognitive processes implemented and artifacts of implementation; (ii) comRAT-C performance and limitations; (iii) preferred item selection hypothesis and correlation with human data on difficulty; (iv) application of process with visual stimuli and (v) comRAT perspectives including using different data and generative abilities

(i) place of comRAT in CreaCogs, cognitive processes implemented and artifacts of implementation

This implementation is a step further towards the automation of CreaCogs specifically the use of associative links for problem solving via convergence, and the upward search mechanism proposed in Section 4. The system proposed here models a convergent way of finding an answer, with a pop-up effect of such an answer. Thus, the query elicits the knowledge of the agent, an implicit search over that knowledge base happens, and the answers come up as a result of convergent activation from different initial conceptual points.

This process is not a classic problem-solving search process. Rather it is a form of search in which the next possible states are proposed via association. These states are the items associated with the objects offered in the query - which is taken to represent the initial problem state. The problem space becomes the cognitive space of all the associations the agent can find to the initial problem state in its knowledge base. In this case, three different lexical items find the fourth element (answer) because they converge on it by associative power. The initial items can act as initial constraints of the search, because of the way the knowledge base of the system is organized.

In RAT the pop-up or the “aha!” effect is the “sudden” appearance of the solution item (or a possible solution item) in the attention of the agent. The comRAT-C assumes that this pop-up happens via a convergence of the associative mechanism. CreaCogs posits that this is what happens at much higher levels of complexity, and with much deeper constraints, in insight problem solving.

The set-up of the knowledge base in the proposed system and the stimuli used are symbolic. This is not a commitment that cognitive processing in such cases would take part on a symbolic level alone, but an artifact of this particular implementation. The proof of concept presented here uses lexical symbolic information because of ease of access to both training data (lexical corpuses) and human performance data in the literature (the RAT normative data). The principles used in comRAT-C are assumed to be applicable to other types of data, as discussed in point (iv).

(ii) comRAT-C performance and limitations

After the initial implementation of comRAT-C, its performance in answering compound RAT queries when given enough knowledge was high (97.92%), even if frequency was not used to select best answer. This suggests the type of knowledge, knowledge representation and convergence processes used are enough to automate such a task. Furthermore, comRAT-C proved robustness when dealing with incomplete knowledge, by finding the answer in some cases in which only two expression terms were known.

The limitations of comRAT-C are related to the amount of knowledge in its knowledge base. Also, in the case of knowing two items, humans can check whether the third item "fits" the answer converged upon with two items. The automatic solver has no mechanism to decide whether such an answer is absurd or can work in the context of the third item.

The comRAT system has an ability to generate different plausible answers or multiple correct answers. This ability creates the opportunity for further study into what answers are preferred by humans (iii) and what answers are considered as more creative or what queries are considered as more interesting. Regarding the plausible answers, some of them are interesting from a cognitive perspective. Part of them are semantically-related to the "correct" answer offered by Bowden and Jung-Beeman [11], like items 1, 2, 3, 11, 13 in Table 5.5, either by semantic similarity (11,13) or opposition (3) between correct and plausible answer, between one expression and the plausible answer (2) or just semantic neighborhood (1). This points at a possible inherent structure of the associative data which requires further study.

The system was not built to specifically answer this normative data: as mentioned before, its knowledge was compared to the knowledge required to solve this set of normative queries only post-factum. The system was built in a general enough manner as to be able to attempt to answer any other normative datasets of queries on similar tests which are given to human participants. The only restrictions come from the nature of the associations made by the system - thus structural associates queries will have a higher likelihood to be answered - and from the limitations of the knowledge base. Any other n-gram corpuses can be implemented as a source for comRAT-C's knowledge base.

(iii) preferred items selection hypothesis and correlation with human data on difficulty

As comRAT-C can come up with multiple results for a RAT query, a frequency based mechanism of exploration for the most probable answers was proposed, as to check whether this explains the answers preferred by human participants, or considered correct in the Bowden normative data.

The highest probability results coincided with the answers preferred by people in all four multiple answer cases with 3 known expression terms. More data is necessary to validate or falsify this probability based preference hypothesis, however these initial results are promising. Further data was obtained on the contribution of each item in the RAT queries to each answer. Complete data on these contributions and probability for the 49 correct items is given in Table A.2 of Appendix A.

The generative capabilities of the comRAT can be used to devise more RAT tests for which there are enough multiple answers in comRAT-KB as to allow for the preferred item hypothesis to be fully verified in a statistically significant manner. More language data can also be added on lower frequency items, or from other corpuses, to allow the comRAT to give multiple answers to more queries, thus allowing for further validation.

A moderate correlation with strong significance was observed between the frequency of answers in the language KB and the percentage of participants solving the respective queries. An inverse moderate correlation with strong significance was observed between probability of item selection and response times. As observed in Table 5.10, this correlation was mainly due to the probability of the first and second terms of the query.

This correlation is not strong enough to enable us to build a predictive mechanism of human response times and general query difficulty based on frequency. However its significance points to it being a contributing factor in the future building of such a predictive mechanism. Thus the current comRAT-C can be used as a tool in further cognitive modeling of the compound RAT. Other RAT queries can also be generated with comRAT and then given to human participants, in order to check if this correlation holds in other experiments.

(iv) application of process with visual stimuli The transfer of the comRAT process to visual stimuli, including the formalization and construction of a visual form of the RAT test had the purpose to check: a) whether a creativity test can be applied on multiple modalities and b) whether the CreaCogs convergence process can be applied independent of modality.

Based on the current results, humans can solve such queries, and different levels of difficulty can be envisaged. The difficulty of queries can be reliably estimated by humans. Future work related to the visual RAT will relate to creating a larger set of queries, testing such queries on a larger number of participants, gathering response time data and difficulty data. However, the initial small set of queries in vRAT shows promise in terms of administering the RAT test in two different modalities. This can further be used in order to isolate performance influences on the RAT which are due to verbal fluency or visual abilities. This is the only creativity test to date to have been given in two different modalities, as the visual or language creativity tests that exist (in TTCT) are different in content and do not aim to account for the application of the same process. The ability to investigate this process further across modalities will offer cognitive psychologists the possibility to understand this process further.

The comRAT-V system's performance was promising, despite the limited amount of visual associates data. In the future, more such data needs to be gathered, either from human participants or by setting up a mechanism to extract such visuospatial relations from existing data - for example from images depicting scenes. However, the initial correlation of comRAT-V's results with human difficulty shows that comRAT itself might be successfully applied in both domains, with the process it embodies representing some significant similarities to that employed by humans when solving such queries.

(v) comRAT perspectives including using different data and generative abilities

The comRAT perspectives discussed in this section refer to four major topics: a) comparison and transfer to other categories of RAT problems; b) analysis of items judged to be creative or interesting by human participants; c) analysis of semantic influences and d) generative abilities of comRAT, modeling and enabling further hypotheses about and human solving.

a) comparison and transfer to other categories of RAT problems

The comRAT can easily be used with other corpuses. However, other types of RAT tests could also be solved by comRAT in the future. The functional Remote Associate Test (FRAT) could be solved when given enough function associates data - perhaps from using functional data extracted from ontologies (category relations, part-of relations, etc).

If context plays a role in the organization of knowledge or the strength of connective paths between different knowledge items[10], then this test should be adaptable to different sensory domains. For example, in the visual RAT test, the stimuli are aimed at testing context based associations of visual items. The visual RAT can further be enhanced by controlling for and removing verbally connected items. Such investigations could throw further light on the influences of context on memory organization, and on possible different memory stores (different context organization based on sensory modality) for different sensory items, that can be tapped into with modality-specific stimuli. This type of test could benefit empirical studies of human performance in a direct fashion as well, as no such studies exist to our knowledge on visual associative memory (or other types of sensory associative memory), which might play a role in various domains of creative problem solving and scientific discovery.

Thus tests carefully controlled to study structural versus semantic items, and language/visual interplay could be modeled using the comRAT and enrich our knowledge about principles of convergence and associations in the context of the Remote Associate Test.

b) analysis of items judged to be creative or interesting by human participants

It is well known that one of the evaluating factors when humans judge creativity is originality. The ability of comRAT to find other plausible answers enables future work on what constitutes a creative or interesting answer from the human perspective. Further studies in this direction can be based on both low versus high frequency comparisons, and use of related or far apart semantic domains. The ability to find other plausible items also makes comRAT a likely assistive companion for humans when solving RAT queries or for triggering convergence processes in general.

c) analysis of semantic influences

The frequency of expressions might not be the only item having an impact on the memory of RAT solvers. A second possibly contributing factor is the membership of

[10]Context is not assumed to be the only element that plays a role.

two or all three of the query items to the same semantic category, or conversely, the lack of semantic category overlap. Part of the collected data could be parsed to give some answers to this question in the future.

d) generative abilities of comRAT and modeling of further hypotheses
The generative abilities of comRAT are yet to be fully explored and have great potential in creating Remote Associate Tests controlled on various variables, like: number of multiple answers; different queries with the same answer; same frequency of query words+answer, changing frequency of only one item, etc.

Further analyses on what makes RAT problems difficult using these tools could help integrate quantitative (frequency factors) and qualitative principles (semantic and ordering factors). This could enable comRAT to automatically categorize different levels of problems. Such a categorization, and control over query variables, could enable modeling and prediction of cognitive difficulty.

5.11 Conclusions

The comRAT-C implements a previously formalized upward search process in CreaCogs. This process is used to solve the compound Remote Associate Test (RAT) automatically using a knowledge base of language data.

The experimental results showed that out of the 144 items used in Bowden and M. Jung-Beeman's test [11], using the COCA corpus, 64 items are answered correctly - that is provided by the system as an answer on its first try. Moreover, over 20 of other response items are plausible answers - that is responses that a human may deem viable. The accuracy of response of the system is at 97.92% in the cases where the system had all 3 items in its knowledge base, and 30.36% in the case in which the system only knew two of the given expressions. Humans are normally assumed to answer correctly the queries for which they know all three items, so this proved that associative principles can add robustness to the system and help find solutions even in the cases in which knowledge is lacking.

A preferred answer hypothesis has been put forward, based on frequency of expressions in the knowledge base. Promising first results where obtained towards this hypothesis, however a full validation is still required.

A moderate, statistically significant correlation has been observed between probability to find the answer and cognitive difficulty in solving queries, as expressed by response times and percentage of participants solving the queries.

A visual version of the RAT test was created and given to human participants. Visual associates where gathered from human participants as to be used by a computational solver - comRAT-V. Human participants solved 63% of such queries and declared they perceived the answer visually in 56.6% of the cases. Participants showed an ability to reliably estimate difficulty of queries on a Likert scale. The comRAT-V adaptation using visual associates in its KB solved 72.73% of queries, and showed a moderate-high correlation to difficulty of query as expressed by human appraisal. More data is needed to make any strong claims on comRAT-V's ability to correlate to human performance.

The successful solving of the RAT test shows the principles posited by CreaCogs are valid and worthy of further investigation. The comRAT system has great potential for becoming a tool for cognitive modelers to further investigate the human cognitive processes used to solve the Remote Associates Test. Furthermore, comRAT-C can be used with other corpuses, and its principles can be transferred to other types of data (functional RAT, visual RAT, etc.).

The main contributions of this chapter have been:

(i) to show how upward search from CreaCogs can be applied to automatically solve a creative human test - the Remote Associates Test;
(ii) to provide a cognitive modeling tool for further study of the RAT task, with comparable results;
(iii) a moderate correlation with human difficulty has shown processes implemented here are not just computationally feasible ways to automatically solve such creativity tests, but will play a role in the modeling of the cognitive process involved in such tasks;
(iv) the foundations for a study of human answer preference in RAT in the case of multiple possible answers have been set;
(v) initial steps in the direction of making the RAT a multimodal task, which can be computationally explored in its various forms with the same comRAT process have been accomplished.

Chapter 6

A cognitive system for Object Replacement and Object Composition (OROC)

In the CreaCogs theoretical framework for creative problem solving, certain types of *knowledge organization* were posited to help the creative process, thus enabling artificial cognitive systems to propose creative solutions to various problems. This type of knowledge organization takes into account similarity of objects and concepts on different types of features, the structure of these concepts and the problem templates they engage in. Such knowledge organization is meant to allow for processes similar to those encountered in human creative problem solving, like replacement via similarity, restructuring, re-representation and convergence. While similar results to normative data for a human creativity task have been shown for convergence processes in the previous chapter, similarity and restructuring will be discussed here in an object domain. In this domain, the aims of the system (CreaCogs-OROC) are to use knowledge organization and creative processes in a way which enables it to replace objects that it needs with other objects present in the environment, and to compose objects.

However, such knowledge organization raises a few problems. Various objects in an everyday object domain are **similar**, over different types of features:

- a *spoon* is similar to a *bucket* along a *concavity* feature.
- a *surfboard* is similar to a *tabletop* along a *thickness* feature.

Still, some *tabletop* is similar to a *door* along a *shape* feature. However, these objects are dissimilar in terms of inclination and context.

Human creative thought and problem solving seems to employ such relations. However, semantic and ontological approaches do not cover (and do not automatically classify) this kind of similarities and relations (on multiple feature spaces), or how various types of subgroups of features make things similar (on multiple granularities).

At a higher level of reasoning, similar objects can have different roles depending on the **context** within which they are encountered:

- a *tabletop* on legs of lower height, with a couch nearby, is generally not used for working, but has coffee table affordances;

- a *tabletop* on legs of a higher height, with an office chair nearby and a computer on top is probably used for working;

- a *tabletop* that is somewhat higher and has a coffee machine on it is probably found in a kitchen and used as a preparation table for cooking.

These conjunctions of contexts are again not easily represented, or parsed from a set of object features, though such relations are essential to understanding the affordances, roles, uses and sometimes the very nature of everyday objects.

Finally, some objects have complex **structure**, which cannot be expressed via a single shape. However, knowledge of such structure could greatly benefit a system which aims to be able to compose objects on its own.

A custom-made approach for such knowledge organization, its implementation and analysis are thus necessary. In the following, first steps towards this are done as we introduce OROC - an **o**bject **r**eplacement and **o**bject **c**omposition system. Matters of cognitive knowledge retrieval and encoding in OROC are presented in section 6.1. These include: multi-feature object recognition (6.1.1), an approach to analysing multi-feature similarity (6.1.2) and a short discussion on the various feature spaces obtained (6.1.3) and how they could be further organized. First experiments with OROC are presented as a proof of concept for the use of feature matching, similarity and structure in the domain of everyday objects. The uses such an implementation can have for creative cognitive systems are summarily demonstrated in object replacement (section 6.2.1) and object composition (section 6.2.2). The evaluation of part of OROC's capabilities is done in section 6.3. Here, OROC's answers to a human creativity test - the Alternative Uses Test - are evaluated with the same tools with which human answers are usually evaluated. The difficulties and advantages of the proposed approach, together with the implications on the modeling of creative problem solving and empirical validation with human data are discussed in section 6.4. As future work, we consider this approach to also be viable for representing context.

6.1 Cognitive knowledge retrieval and encoding

Knowledge retrieval and encoding has special properties in human cognitive systems. These include the ability to recognize an object when other features than its name are presented, or have a guess at what the object might be when only part of its features can be observed or are known. The way these cognitive abilities are implemented in OROC is presented in section 6.1.1. Encoding similarity on various features brings about complexity; ways of describing such multi-similarity spaces are characterized in section 6.1.2. The various feature spaces obtained after such knowledge organization are discussed in section 6.1.3.

6.1.1 Multi-feature object recognition

Humans can recognize objects by a variety of features. Thus the same concept *ball* can be triggered in a human mind via a variety of sensory modalities. However, sometimes more than one feature is necessary to extract the exact object, and guesses can be made at what the object is when various features are presented to the conceptual memory of the subject.

In the following, the subject will be an artificial cognitive system, called OROC, and will bring to bear knowledge from its database KB. Let's assume that OROC lives in environment E. Various situations are possible in this environment ($Env_x \in E$). Agent OROC has to do its best to understand any of Env_x presented using its knowledge base KB and making inferences.

Perception in OROC works in the following way: OROC receives a feature or set of features from the environment. These can be a name (if OROC receives verbal input), shape and color (if it receives visual input), material (from touch and vision), affordance (if OROC sees someone doing something with an object, or does something with an object itself).

This means that by just hearing a name, seeing an object shape or a type of motion in E, OROC should retrieve the type of object implied from its KB, or a subset of objects which are candidate hypotheses retrieved from KB for what objects might be present in Env_x. The hypothesis (or hypotheses) built by OROC from eliciting knowledge from KB to understand Env_x is stored in the working memory of the system - WM (see Fig. 1). This process is shown in Fig. 6.1. The working memory seems to be displayed in Fig. 6.1 a separate, smaller knowledge base. However, this is only for visual clarity purposes. Working memory is to be understood as the bounded activation of a set of features or objects in KB. Only such a limited subset can be payed attention to at one time (working memory generally has constraints in natural cognitive systems).

Thus, a few examples of possible given stimuli in a variate Env_x, and the knowledge retrieved in the WM of the agent from its KB are presented in Table 6.1.

The hypotheses made by OROC on what the object might be elicit its entire knowledge base. For example, when something of paper is touched (and no other information is present), OROC hypothesizes that it might be touching: (a) a book, made of paper, with thick rectangular shape, with covers, the affordance of which is "to be read"; (b) a newspaper, made of paper, with thin rectangular shape, (larger but thinner than the book), the affordance of which is "to be read"; (c) a paper towel, made of paper, which can have different rectangular or square shapes, and different degrees of softness, the

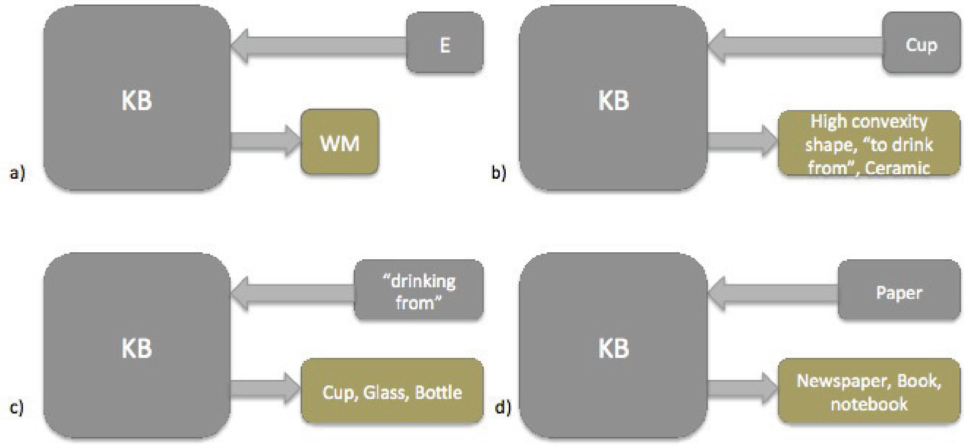


FIGURE 6.1: a) The E - KB - WM cycle and b) - d) examples of it in action.

Stimuli from E	**Concepts ellicited in** WM
Paper	Book, Newspaper, Paper Towel, Wallpaper
Long Narrow Rectangular	Shelf, Surfboard, Table top
Wood	Shelf, Table, Desk
"to wipe with"	Sponge, Towel
Sharp	Blade, Pen
"to write with"	Pen, Pencil, Chalk, Marker

TABLE 6.1: Results for multi-feature object recognition

affordance of which is "absorbent", "to wipe with"; (d) wallpaper, large very thin and generally rectangular, used for decoration.

The elicited knowledge and a need for differentiation (as to understand exactly what object is being sensed) can help guide future behavior, by guiding the senses of the agent to retrieve a new property. The most efficient property (or subset of properties) to be retrieved as to minimize the number of hypotheses the agent comes up with (ideally reducing it to 1), can be determined in advance; we would call this *the maximum discriminant*. This maximum discriminant could generally be calculated based on the knowledge present in the KB of the agent, and the feature set which has already been given. Thus the maximum discriminant would be individual for each system. It is possible that regularities in the maximum discriminant exist for agents which inhabit similar spaces. Once the maximum discriminant has been calculated, the behavior of the agent can be guided to retrieve that feature data point, allowing for a mapping of the object in the environment to a smaller set of objects in the KB, and in some cases to one object, and its recognition.

6.1.2 Multi-feature similarity

Triggering associated possible objects from the KB on one or more noticed features in Env_x helps OROC hypothesize about what the perceived object is, by exploring its feature spaces (FS) - concept (C) links. However, the same link between concept and its anchoring in feature spaces can be used to determine similar objects. This brings about the following consequences:

a) similar subsets of concepts can be determined on each feature map, for each feature point (see Table 6.2) Thus concepts similar on that FS are all n concepts encoded in that point or nearby. In the future we would also like these relationships to be partially ordered, like: - $Chair < Table < Wardrobe$ on Feature: *Height*;

Objects classified as close or similar	**feature space**
Book, Newspaper, Magazine, Notebook	Material
Cup, Glass, Bottle	Affordance
Cup, Bucket, Flowerpot	Shape
Wardrobe, Door	Height

Table 6.2: Object similarity on different feature spaces

b) a concept can be similar to other concepts on *each* of the feature spaces it is encoded on. Thus *book* is classified as similar on a *material* feature space with *newspaper*, *magazine*, *notebook*, on the *affordance* feature space in point "to be read" with *newspaper*, *electronic book*, *website*, *memorial plaque*, on the *shape* feature space with *notebook*, *chopping board*, etc. Moreover, a concept can be similar to other concepts on two or more feature spaces, with a match on all feature spaces meaning identity for the given agent.

Various feature spaces can be envisaged for objects: size (height, depth, width), orientation, color, material (primitive or composed), shape (primitive or composed), name, etc. The more such feature spaces, the more groupings of similarity can be yielded (assuming γ to be a variable which represents the number of such similarity connections in a particular similarity type group, see Table: 6.3).

FS no.	**Sim 1 FS**	**Sim 2 FS**	**Sim 3 FS**	**Sim 4 FS**	**Sim 5 FS**
2 FS	2*γ	Equivalent	-	-	-
3 FS	3*γ	3*γ	Equivalent	-	-
4 FS	4*γ	6*γ	4*γ	Equivalent	-
5 FS	5*γ	10*γ	10*γ	5*γ	Equivalent

Table 6.3: Similarity degrees and their combinations

Therefore the number of similarity groups, depending on the KB, can be calculated as a function of x, where x is the number of feature maps and k is the number of feature maps similarity is searched on (this constantly increasing until it reaches the concept equivalence case of similarity on all feature maps):

$$f(x) = \frac{x}{k!} + \frac{(x*(x-1))}{(k+1)!} + \frac{(x*(x-1)*(x-2))}{(k+2)!} .... + \frac{(x*(x-1)*(x-2)*...1)}{x!} \quad (6.1)$$

Also, remember that each such type or group of similarity connections will have a variable number of mappings (parameter γ), depending on the KB and the concepts represented. Thus, for 6 feature maps, the number of concepts would be a function $g(x)$:

$$g(6) = \frac{6}{1!}\gamma + \frac{(6*5)}{2!}\gamma + \frac{(6*5*4)}{3!}\gamma + ... + \frac{(6*5*4*3*2*1)}{6!}\gamma \tag{6.2}$$

For 6 feature spaces, this yields 120γ possible similar items with range of γ between 0 and the size of the particular feature space being considered.

Due to the CreaCogs knowledge organization, these subsets of similarity relations can easily be retrieved as a function of spatial arrangement. Thus, any or all these sets of similarity relations can be retrieved by going down the anchoring links or up the context links in this framework.

This allows inference of affordance for concept or object replacement (see Section: 6.2.1) based on whatever the functional properties of the object are, and object composition (see Section: 6.2.2) based on previous knowledge of structure.

6.1.3 The various features spaces obtained

When being presented with objects, OROC learns their properties and organizes them in its feature layer. Thus after learning a set of objects, OROC's feature space of known materials will contain, for example: "Ceramic, Paper, Plastic, Porcelain, Wood, Glass fiber, unknown, Wax, Metal, Cardboard, etc ...". These features can be reorganized based on similarity metrics - thus "ceramic" can be moved next to "porcelain", "cloth" next to "paper", etc. If these features are spatially reorganized, the pointers of the Concepts to the feature space (which ensures concept anchoring) will be moved too. A possible improvement to the current prototype system would be to obtain such similarity metrics data. This can be done using sensory science data or setting up a form of knowledge acquisition. Contextually, various material features can be grouped together in various ways (e.g. in groups like "can burn","texture", "absorbent", "resilience", "breakable"). This happens implicitly in OROC, due to the links the various objects have to affordances. Thus if an object with certain properties can do something, other objects with similar properties are inferred to be able to do it too (i.e. if the fact that a ceramic cup has been broken is registered, a general inference can be made about all the other ceramic objects that they are breakable).

6.2 Implementation of OROC

The prototype OROC system takes as knowledge base an .xml file in which 200 object concepts have been defined on various feature spaces. Some of these are complex object concepts which have other objects as parts. The various features in the knowledge base are organized on feature spaces. This allows us to use features as search keys in the various feature spaces.

Insertion
For each new concept C_x in the input, the feature spaces are checked to see if its features are already known, so that the concept can be linked to them. If they are not known, features can be inserted in the maximum similarity point that can be determined.

Recognition
The recognition of a concept in OROC is done by finding the concept with most matching features, as shown in Table 6.4.

TABLE 6.4: Concept recognition in OROC

Algorithm OROC.1 Concept recognition in OROC

```
int maxFinder = 0
for all f_x : C_input
    for all f_y : KB
    if f_x == f_y
        do f_y.activate()
            f_y.parent().setActive(), f_y.parent().activity++
     end for
end for
for all C_x : KB.getActiveC()
     if C_x.activity > maxFinder
        maxFinder = C_x.activity
        answer = C_x
end for
return answer
```

Thus from object recognition to object replacement there is only a step, as follows: instead of searching for matches, on all features, a search with a looser threshold is applied, accepting (i) matches on some features and similarity on others, or (ii) accepting matches or similarity on a subset of features that is relevant for the affordance at hand[1]. This is the topic of the next section.

6.2.1 Object Replacement Experimentation and Results

Various types of questions could be answered by a system able to perform object replacement. In the following, we will discuss 3 such question types, and present results which OROC provides to some of them. It is worth noting that the answer to all these questions can be given in OROC (and CreaCogs) by using a small set of algorithms and principles of search.

[1]Currently similarity of concepts based on matching of features is implemented, as feature similarity would require either cognitively acquiring such metrics, or a subsymbolic layer. This is above the scope of this current prototype, which aims to test whether processes of the theoretical framework can be implemented with results that are creative, and comparable to human results.

Question type 1
A possible question type would be to give OROC a known affordance, a set of objects in the environment, and ask which of the given objects can be used as replacement for specific affordances.

An example of this would be the following: given the affordance *to tie with*, which of the following objects could you use for it - *a sponge, a hammer, an electric chord*?

This can be solved under the CreaCogs paradigm by going from the specific affordance to known objects to embody it - thus let's say objects like *strings, rope* have been used for tying and are known to the KB of the agent. Common properties of these objects can then be searched for, to generalize what properties seem essential for that affordance based on experience of affordance-property co-occurence. The properties of the given objects are then searched for, and the most similar object (in terms of this particular affordance) is thus chosen (in this case, the electric chord, which is also thin, long, bendable). The algorithm in Table 6.5 shows an example of how this is implemented in OROC.

TABLE 6.5: Algorithm for finding the objects to which affordance applies from a restricted set

Algorithm OROC.2 Finding objects to which affordance applies creatively

$aff_x.active()$
for all $C_x : KB.getCwithAff(aff_x)$
  for all $F_x : C_x.getFeatures()$
    do $F_x.active()$, $F_x.activity++$
  end for
end for
for all $F_x : F.getActive()$
  if $F_x.activity > threshold$
   for all $C_y : C_{input}$
     if $C_y.has(F_x)$
      do $C_y.answerValue++$
      if $C_y.answerValue > threshold$
        do add C_y to AnswerSet
    end for
end for
return AnswerSet

Question type 2
A second type of question would be to give OROC an object, and find all the objects in its knowledge base that are similar to it, on it's different features, or that are of a certain given degree of similarity (degree 2 for 2 feature spaces, degree 3 for three, etc.). Thus, given object a, find all objects which could replace a for each feature space f_x or with a degree of similarity n.

In human terms, such a question would be phrased as the following: given a cup, find all objects that are similar to a cup in terms of it's various properties.

In the CreaCogs framework, OROC would go down from its knowledge of the concept c_a representing object a into the features on which such knowledge is represented. Then it would search for mappings of all the other objects in that feature, or in its neighborhood. The algorithm in Table 6.6 shows an example of finding objects that have a matching feature. The same can be adapted when searching for objects with a similar feature, using F_x^i, where i stands for a distance in the feature space.

Table 6.6: Algorithm for finding objects similar on various feature spaces

Algorithm OROC.3 Finding objects similar on various feature spaces

for all $F_x : C_x.getFeatures()$
  $F_x.active$
  do $C.List = F_x.returnConceptLinks()$
    for all $C_y : C.List$
      do add C_y to AnswerSet
    end for
end for
return AnswerSet

In OROC, such a question produces results like the ones shown in Table 6.7.

Table 6.7: Finding objects similar on various feature spaces with OROC

Given object	**Similar objects**
Cup	sim to Bowl on material sim to Flowerpot on material sim to Can on shape sim to Candle Holder on material sim to Container on shape
Coat brush	sim to Bucket on material sim to Toothbrush on material sim to Toothbrush on shape sim to Shoe brush on material sim to Shoe brush on shape [...]
Table	sim to Shelf on material sim to Wedge on material sim to Desk on material sim to Desk on affordance sim to Doorstop on material sim to Hammer Handle on material [...]

Question type 3

A third type of question which could be answered with OROC under CreaCogs is what kind of other affordances might apply to a particular known object.

Thus given a KB and a particular object a, make loose inferences about what aff_x you can creatively use a for by learning from the other objects and their similarities.

This inference of affordance mode output is more likely to correspond in its current form to the Alternative Uses Test [60, 61], a test of creativity which asks its participants to yield as many alternative uses for an object as they can think of in a certain amount of time (e.g. 2 minutes).

The Object replacement algorithm in loose inference affordance mode simply selects the $2nd$ degree similarity matches on shape and material. The algorithm in Table 6.8 shows the application of this in OROC. This can also be done with the $1st$ degree on shape, or any other combination of features considered to be relevant[2].

Table 6.8: Algorithm for finding new affordances for objects

Algorithm OROC.4 Finding new affordances for objects

FList = $C_{input}.getShapeFeatures() + C_{input}.getMaterialFeatures()$
for all $F_x : FList$
  $F_x.active()$
  do $C.List += F_x.returnConceptLinks()$
end for
for all $C_y : C.List$
  if $C_y.material.isActive()$ AND $C_y.shape.isActive()$
  $C_{input}.inferAffordances += C_y.getAffordances()$
end for

Some results of OROC can be seen in Table 6.9, with Table B.1 in Annex C presenting a longer list of such generated examples.

Table 6.9: Object replacement in a household domain

Object replacement proof-of-concept with OROC
Maybe Cup can be used to carry water
Maybe Cup can be used to put flowers in
Maybe Cup can be used as food container
Maybe Cup can be used to hold earth and plants
Maybe Cup can be used to cook in

Figure 6.2 shows how this mechanism of loose affordance inference fits into the CreaCogs framework. Thus an object, which is a concept in the CreaCogs framework, triggers its known properties in the KB. These, in their turn (especially the shape and material ones) trigger other concepts anchored in them (or similar properties in the neighborhood can trigger other concepts). In the next step, OROC infers that the affordances of these objects might also apply creatively to the initial given object.

The results yielded by using this approach for a set of objects in OROC will be evaluated in section 6.3, but first object composition and proof of concept results are presented in the next section.

6.2.2 Object Composition Experimentation and Results

The second part of OROC uses the structure of known objects and their similarity in order to generate new objects [3].

[2]Relations between functional property and affordances could be also determined via co-occurrence in a larger data set. However, in the object domain, shape and material seem to be particularly important features for affordance, as will be shown in section 6.3.5.

[3]This could be also used to generate new structures, and hypothesize about their composed affordances.

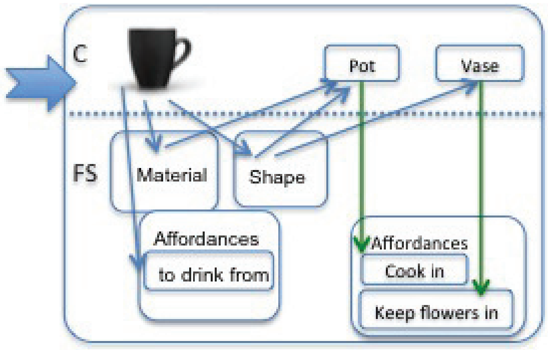


FIGURE 6.2: OROC's loose inference mechanism in CreaCogs.

In the following, we will discuss three types of questions that could be asked about object composition, the processes they reflect in CreaCogs, and present results of the prototype OROC for the wider question type 3.

Question type 1

This question is of the type *"Given a set of objects, what other objects could you make from them?"*. In this type of question, the composing parts are known, there is an unlimited projection to the composed forms known in the KB of the agent, and a set of composed objects is expected.

This translates in CreaCogs to the following: given a set of concepts $c_1, c_2, ..., c_n$, applying templates of known composed concepts $cc_x \in KB$, infer what new composed concepts can be created. In the restricted case of this domain, the concepts which we refer to are objects, and the complex concept templates are objects composed of multiple parts.[4]In this case, the templates to be applied are not given, they must thus be triggered from an identity or similarity relationship to other object parts.

For example, in human form, this question would look like the following. Given a bar, a piece of string, a bottle and a paperclip, what objects could you make of them? The search in CreaCogs would proceed as follows: associationist processes would start a search from each of the given concepts, into the known object templates. Thus objects that contain a bar and a piece of string could be convergently yielded by such a search - for example a fishing rod. With the fishing rod template, one would then need to search the given objects for a hook. This could involve a downward search of overlapping properties - thus the paperclip could be determined as the closest thing coming to a hook that exists in the room.

A more restrained form for such a question would be the following: *"Given a set of objects, which of these composed objects could you make from them?"*. This would involve merely comparing properties of parts of objects in the complex objects with the properties of the given objects.

[4]Templates for objects composed of multiple parts are anchored in the set of parts that create them, the relations between those parts and the affordance of the composed object in the same way in which problem templates are anchored in objects, relations between objects, actions and solutions, as explained in Section 4.

The algorithm in Table 6.10 shows how this question takes process form to be answered in OROC.

TABLE 6.10: Algorithm for composing a new object from given objects

Algorithm OROC.5 Composing a new object from given objects

for all $C_x : Env$
  $PTList1 = C_x.PTLinks()$
  for all PT_x in $PTList1$
    do $PT_x.setActive()$ AND $PT_x.activity++$
  end for
  add PTList += PTList1
end for
PT_z = PTList.getMaxActive()
partsFilled=0
for all $C_y : PT_z.getConceptParts()$
  for all $C_x : Env$
    if C_x sim C_y OR $C_x = C_y$
      do $PT_z.replace(C_y, C_x)$
      partsFilled++
      return
  end for
end for
if partsFilled==$PT_z.countParts()$
  return PT_z

Question type 2

This question is of the type: *"Given an object, what objects that you know of could you compose it from?"*. In this case, the object to be made is known, the object parts are unknown and must be retrieved from the knowledge base. In a restrained form, this question asks: *"Given a set of objects, can you make a specified object out of a subset of them?"*.

This type of question translates in CreaCogs to the following: given a cc_x, the parts of which are known, thus which can act as template PT_x, what set of other known objects $c_1, c_2, ...c_n$ can be mapped to it? Thus a search can start from the PT_x to the set of its parts, and then further proceed to finding replacement of those parts as known objects with similar properties. This is shown in an algorithm in Table 6.11. Similar objects can be found via property based replacement, as explained in the previous section.

Question type 3 Given all known objects, what new objects can you compose? This is a loose inference form of the questions above, which asks for all projections of objects from the KB into the composed objects in the KB. This question encompasses questions 1 and 2, constituting a directed search based on every object or on every template (whichever set is smaller should direct the search). If the templates are guiding the search, this is for replacement parts based on similarity. If the initial known objects

TABLE 6.11: Algorithm for composing a specific object from known objects

Algorithm OROC.6 Composing a specific object from known objects

$PT_z = PT_{input}$
partsFilled=0
for all $C_x : PT_z.getConceptParts()$
  get $C_y = KB.getSimC(C_x)$
  do $PT_z.replace(C_y, C_x)$
  partsFilled++
endfor
if partsFilled==$PT_z.countParts()$
  return PT_z

are guiding the search, this is a search for templates these objects (or objects similar to them) have been part of, then a search for other objects to fill in that template.

Examples of object compositions obtained with such a search are shown in Table 6.12.

TABLE 6.12: Object composition in a household domain

Object composition proof-of-concept with OROC
Use sharp stone and branch to make a knife with handle.
Use salad tongs and hairband to make a slingshot.
Use tree stumps and shelf to make a table.
Use jar and candle to make candle with support.

In loose inference mode, the number of composed objects created is equal to the number of known structures times the number of variable replacements combinations in that structure. Thus the larger the knowledge base, the higher the number of composed objects and the object replacements that can be performed with composing object parts, the larger the list of results. However, our current knowledge base has a very limited amount of composed objects, thus we used this question to show a proof of concept of creative compositional results.

Theoretically, a set of questions of type 4 is also possible - this involves using both disassembly and assembly techniques. Thus, given a set of objects which in turn can be regarded as composed objects with various parts, what objects can be made using knowledge of their parts. The same processes would be applied in OROC to solve such questions.

The object composition capabilities of OROC could be used in their current form in empirical comparison to an object composition test given to human participants. A creativity test for evaluating this ability doesn't exist in the literature, but could be designed. An algorithm could be written taking advantage of the system's knowledge of object structure to give answers comparable to those in the Wallach-Kogan test [28, 156], which asks its participants to come up with as many possible items which contain a specific component.

6.3 Evaluation of performance with the Alternative Uses Test

In order to evaluate the performance of OROC and further illuminate cognitive creative processes, a creativity task normally given to humans that could be solved by OROC needed to be found. The tasks that came to mind were the Alternative Uses Test [61], and the Wallach-Kogan [156] creativity task. What follows is an account of OROC's performance in solving the former. The rest of the section is organized as follows. Section 6.3.1 describes how the evaluation procedure was constructed and deployed. Section 6.3.2 discusses results of this experimentation and evaluation with human judges, together with other observed correlations which followed from data analysis. The viability of the metric used is analysed in Section 6.3.3. Evaluation using human data from a think aloud protocol is discussed in Section 6.3.4. Finally, the importance of property use in human answers to the Alternative Uses Test is discussed in Section 6.3.5.

6.3.1 Constructing an evaluation procedure

The Alternative Uses Test [61] is a creativity/divergent thinking test as described in section 2.4.1.1. The participants to this test are given a certain amount of time and an object, which they are supposed to come up with alternative uses for. Then, the uses are scored on Fluency, Flexibility and Originality or Novelty (sometimes also on Elaboration).

We assumed OROC was able to come up with answers to this by using its ability to make loose creative inference of affordance. Thus, given an object x, OROC will check it's known properties $(f_1, f_2, ...f_n)$. These properties are then inspected for other objects anchored in them - e.g. objects y and z have property f_1 and f_2 respectively. If a set of significant features are the same or similar between the given object o_x and objects o_y and o_z, then affordances of o_y and o_z will be inferred to possibly apply to o_x. Thus OROC could propose those affordances as alternative uses for x.

Concerning the evaluation procedure applied to human answers, Fluency and Flexibility could be assessed manually: Fluency by counting the number of alternative uses proposed, and flexibility by counting the number of different semantic categories these alternative uses span over. However, Originality could not be assessed as this metric requires comparison of a particular answer to the answers produced by a population of other agents in order to qualify answers as original or highly original if they have been produced by a small amount of the population (e.g. 5% and 1% respectively). Normative data from human participants for a specific set of objects was not available, thus we opted for using the Novelty metric instead.

Novelty is assessed using human judges which give their answers on a Likert scale. For comparability to assessments of human answers from Gilhooly et al.[58], a 1 to 7 scale was chosen, with 1 representing a use considered *"not at all novel"* by the judge, and 7 representing a *"highly novel"* use.

In order to further investigate OROC's answers in terms of human assessment, two other metrics were chosen - a Likability metric and a Usability metric. These were implemented on the same scale. These metrics were also meant to ensure that judges will not give a low Novelty assessment because of interfering judgements of Usefulness, or because of a preference for a certain object. Details of the experimentation procedure are presented below.

6.3.2 Experimentation and evaluation with human judges

Five objects from the household domain were given to OROC to make inferences of alternate uses for. These objects were: Cup, Newspaper, Toothbrush, Carpet and Dental floss. Objects were chosen as not to overlap in shape category, thus producing alternate use answers that did not overlap. Thus, for example, the object Vase was not chosen, because of its high-convexity shape which overlapped with that of the object Cup.

An online survey was set up using Google forms to evaluate OROC's answers[5]. The survey contained two initial examples of alternative uses to be rated. Each alternative use was presented as a sentence, followed by the three rating choices which the judge had to make. This looked as follows:

Sentence: "A shoe may be used for putting a nail in the wall"

Novelty Rating: *not at all novel* 1 – 2 – 3 – 4 – 5 – 6 – 7 *highly novel*

Likability Rating: *I do not like it* 1 – 2 – 3 – 4 – 5 – 6 – 7 *I like it a lot*

Usability Rating: *not useful at all* 1 – 2 – 3 – 4 – 5 – 6 – 7 *very useful*

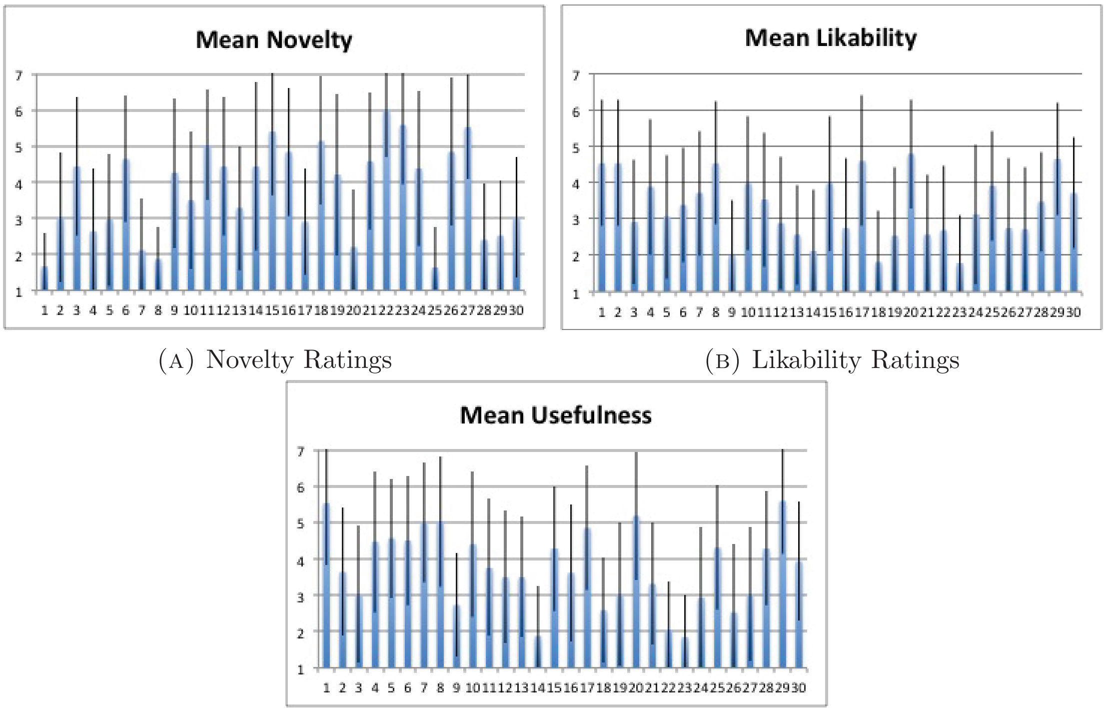
30 alternative uses produced by OROC on the 5 objects were thus rated by 34 participants - 24 male and 10 female (ages 20-70). To ensure no bias on the judgements the participants made by their opinions on machine creativity in general, participants were not informed that the answers they were rating were produced by an artificial system.

Figure 6.3 shows the ratings human judges made on all three factors - Novelty, Likability and Usefulness - across the 30 alternative use statements. Mean Novelty appraisal for all uses was 3.79, with a mean (across statements) standard deviation (SD) of 1.69. Mean Likability appraisal for all uses was 3.31, with a mean SD of 1.68. Mean Usefulness appraisal for all uses was 3.77, with a mean SD of 1.7. The mean of these judgements as expressed numerically per sentence item can be seen in Table B.2 in Appendix B.

Over all items and uses, the highest ratings on each of the three metrics were obtained by the following statements:

- Highest Novelty: *"Dental floss may be used to hang clothes to dry"* (statement no. 22, mean rating = 6)

[5] http://goo.gl/forms/snaqh4b0LH



(A) Novelty Ratings

(B) Likability Ratings

(C) Usefulness Ratings

Figure 6.3: Ratings on a Likert scale (1-7) across 30 object use statements.

- Highest Likability: *"A cup may be used to keep objects in"* (statement no. 20, mean rating = 4.79)
- Highest Usefulness: *"A cup may be used to hold a candle"* (statement no.29, mean rating = 5.59)

The highest Novelty and Usefulness combined score and Novelty (N), Likability (L) and Usefulness (U) combined score were achieved by the following use: *"Dental floss may be used for sewing"* (statement no. 15, $\frac{N+U}{2} = 4.85$, $\frac{N+L+U}{3} = 4.56$).

Table 6.13 shows an overview of the evaluation per object, including Fluency, Flexibility, Novelty, Likability and Usefulness. Average Fluency over all 5 objects is 6; average Flexibility is 4.4.

The participants in the study of Gilhooly et al.[58] come up on average with 27.25 alternative use responses for the Think aloud group and 26.43 responses for the Silent group, for 6 objects. This is currently comparable to OROC's total Fluency rating of 30 for 5 objects. However, this might change with the addition of more objects to OROC's KB if no time-sensitive mechanisms are put in place. Unfortunately, Gilhooly et al.[58] do not present object normative data or Flexibility accounts.

Ratings per object group are shown in Figure 6.4. Thus the alternative uses for Cup received the lowest Novelty ratings, while the alternative uses for Dental floss received the highest Novelty ratings. This might be because Dental floss is relatively a newer invention, while people have had much more time to be creative about the uses of cups.

TABLE 6.13: Evaluation of OROC on Fluency, Flexibility, Novelty, Likability and Usefulness.

Item	Fluency	Flexibility	Novelty		Likability		Usefulness	
			Mean	SD	Mean	SD	Mean	SD
Cup	7	5	2.61	1.47	4.30	1.72	4.80	1.76
Newspaper	7	5	3.34	1.72	2.84	1.50	3.61	1.61
Toothbrush	5	3	4.29	2.08	2.85	1.80	2.98	1.83
Carpet	6	5	4.00	1.71	2.86	1.64	3.60	1.63
Dental floss	5	4	5.32	1.56	3.25	1.75	3.53	1.71

However, the alternative uses for Cup were rated highest on the Likability and Usability scale.

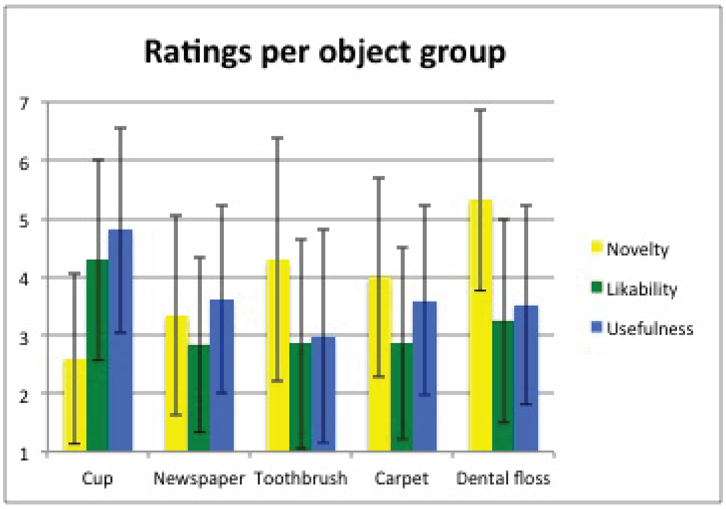


FIGURE 6.4: Ratings per object group.

A positive correlation with strong significance was observed between the ratings on Likability and Usefulness of all judges. This indicated that the more judges the considered an alternative inference to be useful, the more they liked it. For all items, the mean correlation between Likability and Usefulness was 0.63, $p < 0.005$. This correlation ranged across statements between 0.35 and 0.93, as shown in Figure 6.5. Thus for statement no. 24 — *A cup may be used to cook in* — the Likability-Usefulness correlation was at its highest (0.93), while for statement no. 21 —*A carpet may be used as a bed cover* — it was at its lowest.

6.3.3 Validity of human evaluation metrics

In order to check whether the human judgement offered a useful, generalizable metric, two measures pertaining to the validity of this evaluation were analysed: a) the inter-agreement of judges measured as the mean correlation between judge ratings and b) the correlation of individual ratings to mean ratings.

Inter-agreement of judges is shown in Figure 6.6. Take p_x to be the number of the participant and $c(p_a, p_b)$ the Pearson correlation between the ratings of two participants for the 30 uses on one of the 3 metrics. The inter-agreement was measured as follows:

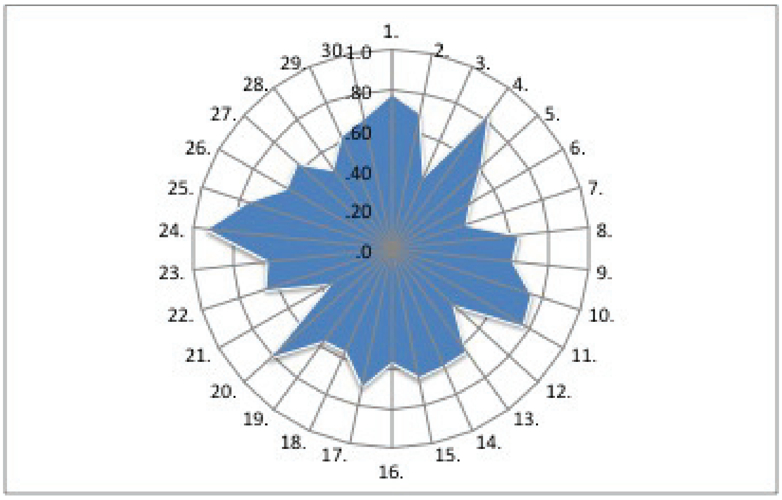


FIGURE 6.5: Correlation between Likability and Usefulness for each item. The 30 alternative use statements are shown clockwise around the dial. The center of the dial represents no correlation (0.0), and the edge of the dial a perfect correlation (1.0).

1. The correlation of each subject's ratings with the ratings of all other participants was established. Thus for all $p_x, x \in \{1, 2, 3....34\}$, a correlation set c_x of 33 items was obtained. E.g., for $p_1, c_1 = \{c(p_1, p_2), c(p_1, p_3), c(p_1, p_4)...c(p_1, p_x)\}$;
2. The mean of these correlations was calculated per participant. Thus for all $p_x, x \in 1, 2, 3....34$, k=34, mean of correlations of each participant with all the others was:

$$\mu c_x = \frac{\sum_{n=2}^{k} c(p_1, p_n)}{k-1}; \tag{6.3}$$

3. The inter-agreement measure was set as the mean of all participants' correlation means. This was calculated as:

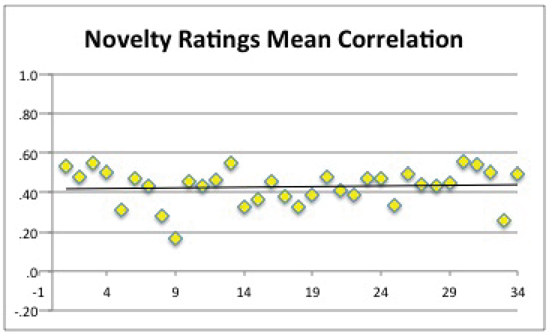
$$\frac{\sum_{n=1}^{x} \mu c_n}{x} \tag{6.4}$$

Thus, for Novelty Ratings (6.6a), participant no. 30 shows the highest mean correlation with all the other participants (mean r = 0.56), while participant no. 9 shows the lowest (mean r = 0.17). The inter-agreement on the three types of ratings was: a) Novelty – r = 0.43 ; b) Likability – r = 0.24 and c) Usefulness – r = 0.3.

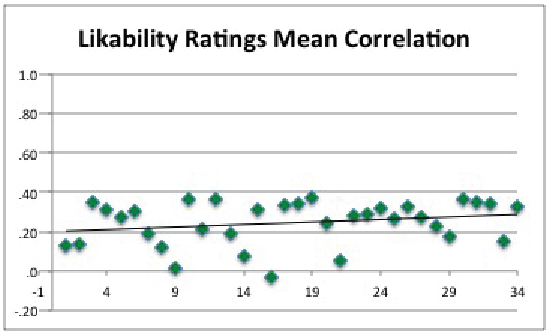
To check whether the mean of the ratings was representative for the group, the correlation of each answer to the mean was calculated. The average correlation of all participants' ratings to the mean was:

a) for Novelty - $r = 0.68$ ($n = 34$, $p < 0.001$);
b) for Likability - $r = 0.55$ ($n = 32$, $p < 0.01$) and
c) for Usefulness - $r = 0.58$ ($n = 34$, $p < 0.001$).

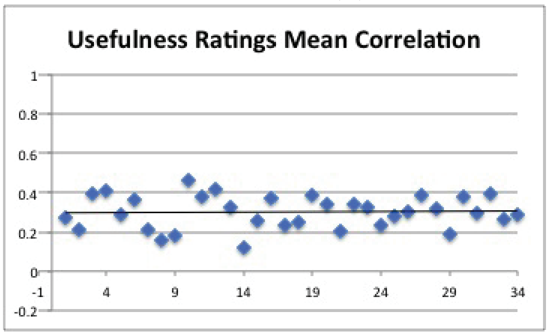
The inter-agreement of judges and the correlation of individual ratings to mean ratings have thus shown that using human judges for evaluation was a reasonably reliable measure.



(A) Novelty Ratings Mean Correlation



(B) Likability Ratings Mean Correlation



(C) Usefulness Ratings Mean Correlation

FIGURE 6.6: Inter-agreement as mean Correlation of ratings. The x-axis represents the participant's number. The y-axis represents the mean correlation (r) of a participant with all the others.

6.3.4 Evaluation using human data from Think Aloud protocols

The results of the think aloud coding scheme by Gilhooly et al. [58] can be compared to the processes used by OROC. Think aloud protocols use standard protocol analysis [37, 152] and are transcribed into short phrases (called segments). The resulting segments are then classified into categories. As the paper from Gilhooly et al. [58] provided an interesting analysis of the Alternative Uses Test, we decided OROC can further benefit from an analysis of its processes as compared to Gilhooly's analysis.

Gilhooly et al. built 18 categories in their first experiment. These are treated as describing different processes. A residual "Other" category accounting for less than 1% of the segments is also built. The first 15 categories with a frequency above 1% are then detailed.

In the following, the categories of most interest to OROC are listed. Note that we kept their original number as provided by Gilhooly et al. [58], who arranged them in decreasing frequency:

- Disassembly Uses (no.6) - States a way of decomposing the target item and using the resulting components. For example, *Remove laces from shoe and use them to tie your hair up.* 80% of participants, 5.5% +/-1.3% of segments.
- Property (no.8) - States property of object. For example, *Bricks are heavy.* 55% of participants, 3.4% +/- 0.7% of segments.

- Property Use (no.11) - Explicitly indicates property which enables the stated use. For example, *A pencil is sharp so can be used to poke holes in paper.* 48% of participants, 2.9% +/- 0.7% of segments.
- Context (no.14) - Mentions context in which target object is often found. For example, *You often see tires in garages.* 40% of participants, 2.9%, +/- 1.2% of segments.

The rest of the segments and their corresponding categories are not as informative when trying to understand the processes humans use to solve such tasks. For example, these are: Unmediated use (mentioning a possible use without an explanation) – 33% of segments, Item naming (repeating the name of the item - perhaps to enhance search activation processes) – 11.66%, Episodic Memory use (remembering previous creative use, so not novel to their experience) – 9.2%, Use query (Re-asking themselves what else the item could be used for) – 5.9%, etc.

The categories of Property and Property Use are both reflected in OROC's processes. Properties and their use are the equivalent of features in OROC. Thus both of these categories can be interpreted to use feature match of some form in order to generate alternative uses of objects.

The Disassembly category refers to the ability of decomposing the object in specific parts and using those parts while thinking about alternative uses, or thinking of objects as having a potential role as an object part. This is reflected in OROC's compositional capacities. Note that the Disassembly strategy frequency has been shown to make an important contribution to novelty.[6]

The Context category reflects a use of context for the initial object in the creative alternative use process. Though not yet implemented in OROC, *CreaCogs* posits the use of context, defined implicitly by the templates in which objects are used. A spatial neighborhood in the real world might also determine associative links and context.

6.3.5 Human Alternative Uses answers

The evaluation survey in which 34 participants made judgements on the Novelty of OROC's alternative uses of objects had a second part. This part was meant to provide the judges with an opportunity to express their free answers, in the style of the Alternative Uses Test. This part can be used to further understand the processes humans use to answer this test, and compare these to OROC's processes.

This free part was two-fold:

1. After rating each statement, the judges were asked *"What other objects would you use for this purpose?"* (with the purpose being implicit from the sentence);

[6] This is further motivation to put together a type of evaluation which includes OROC's compositional capacities. It might be that the objects created using these processes, or both processes in tandem, would be rated as the highest in Novelty. Such a rating might reflect a higher appreciation for the cases in which two processes are used to make such a inference: (i) composition/decomposition, used to transgress object boundaries, and (ii) creative replacement.

2. At the end of the evaluation of the 30 uses, a page asked for each of the 5 objects *"What other uses would you find for this object?"*.

As not to encumber participants which were in a hurry, or felt uncreative, discouraging them to finish the evaluation, these parts of the form were made non-compulsory.

This part of the survey links each 30 uses to other objects, and each 5 objects to other uses. Table B in Appendix B shows the other uses humans came up with for the 5 initial objects of the test. These uses were grouped according to how unique or frequent they were. A summary of the most frequent and some of the most unique alternative uses proposed by the human participants is presented in Table 6.14.

For example, for the object Cup, 9 of the alternative uses given by the participants involved putting stuff in the cup (pencils, brushes, pens, sauce for mixing), and 7 uses proposed involved amplifying sound (using the cup as a speaker, headphones, musical instrument, or to hear through a wall). One use of Cup referred to using it as a shovel (specifically to dig earth with) and another one to use it as a mace, in order to smash garlic using the basis of the cup.

Table 6.14: Frequent and rare alternative uses proposed by participants for the given five objects

Object	**Frequent use**	**No. times proposed**	**Rare use**	**No. times proposed**
Cup	to put things in	9	as a shovel	1
	to amplify sound	7	as a mace to smash garlic	1
Newspaper	to make shapes and origami	10	as oven gloves for protection	1
	to wrap something	8	wrapping a mommy - fancy dress	1
Toothbrush	to clean with	16	as a nail on a sundial	1
	to brush with	4	weapon	1
Dental floss	fishing line	4	macrame	1
	jewellery part	4	keyring	1
Carpet	damping noise/vibrations	2	to protect against wind	1
	keeping fire lit	2	make new shoe soles	1

This data grouped by uses was analysed in order to find out:

(a) what properties are relevant for humans when connecting an object to a possible affordance, and
(b) whether feature similarity, a principle which OROC's processes use, is relevant when coming up with creative answers.

The results of this analysis follow. Table 6.15 shows how often properties of shape and material were important when humans came up with a new affordance for the given 5 objects. For example, for the object Cup, participants came up with a total number of 26 different other uses (some of these occurred repeatedly, as explained above). Out of these uses, the shape, material or shape and material properties together of the given object were relevant to the new uses in 21 cases. Thus the percentage of shape and material relevance amongst unique uses was 80.77%. On average, shape and/or material properties were relevant for 85.67% of the new uses human participants came up with.

Out of these, shape was sometimes relevant on its own, material relevant on its own or both properties were relevant together for the ability to create a new use. As Table 6.16

TABLE 6.15: Human participants' reliance on shape and material properties when coming up with new uses for the given five objects

Object	**Total unique no. of other uses**	**Total unique no. of uses with shape and material relevance**	**Percentage of uses with shape and material relevance**
Cup	26	21	80.77 %
Newspaper	25	24	96 %
Toothbrush	18	17	94.45 %
Dental floss	28	20	71.43%
Carpet	28	24	85.71%
Total	125	106	84.8 %
Average per obj.	25	21.2	85.67%

shows, for the unique alternative uses for which shape and material mattered, shape and material were relevant together 51.15% of the cases, Shape was relevant on its own 19.32% of the cases and material for 29.53% of the cases.

TABLE 6.16: Relevance of shape and material properties itemized for the other uses provided by participants to five given objects

Object	**Total shape &material**	**Shape**	**Shape %**	**Material**	**Material %**	**Shape & Material**	**Shape & Material %**
Cup	21	9	42.86 %	4	19.05%	8	38.1 %
Newspaper	24	0	0	14	58.33%	10	41.67%
Toothbrush	17	2	11.76 %	5	29.41%	10	58.82 %
Dental floss	20	5	25 %	1	5%	14	70 %
Carpet	24	18	16.98 %	38	35.85%	50	47.17 %
Average			19.32 %		29.53 %		51.15%

6.4 Discussion

OROC shows a good comparability to humans in both results and process when answering the Alternative Uses test. However, OROC has not been purposefully designed to answer the Alternative Uses test, and its abilities encompass a larger area than answering this one creativity test. OROC can further be investigated using the Wallach-Kogan test, object composition tests (which need designing), or elaboration tests starting from one object part or feature.

An interesting knowledge organization property of OROC is that each object in the KB is anchored in a set of features. To recognize an object uniquely, a determinant set of features is needed, otherwise a set of objects is given as the possible object. This can depend on what features exactly are provided, thus on the upwards mapping of various features in certain concepts. For example, to recognize object O_{14}, when given the name, the full existing knowledge can be retrieved unambiguously. When a general description of the shape is given, this maps to 6 possible objects. When material is given, this maps to 10 objects. When material and shape are given, this maps to 2 possible objects, etc.

This sets us up for an ability to model shortest discriminant description of an object, given the other objects in the KB, and the way ambiguity grows or diminishes when adding more objects and features (cognitive economy would indicate that it is mostly discriminants that are retained). As mentioned before, these descriptions, as implemented in OROC, might be different for different systems with different KB. This is probably a cognitively valid emergent property. However, in the context of OROC, changes in the shortest discriminant description could be calculated as a function of learning, thus providing a good setting for experiments on various measures of information entering a KB - coherence, informativity and generativity [120].

A valuable result is that the hypothesis of creative processes modeled by OROC is falsifiable, as its computational underpinnings transform into the following empirically testable assumptions.
We can increase people's ability to be creative by:

1. increasing their ability to see the way objects are structured
2. enhancing their ability to notice similarities between objects or object parts
3. increasing their ability to notice similarities between structures
4. generally giving them a larger number of object templates and types to know/-choose from (this would be like learning more items for the KB, therefore the capacity for transformation applying these principles should grow)
5. encouraging them to destroy and construct object/ generally cross over what the gestalt of an object is perceived to be.
6. encouraging fluidity of transfer between different parts/templates.

These assumptions could be proven or disproven using specifically designed alternatives of the aforementioned tests. Such design could include a condition in which each of the assumptions mentioned above are tested.

The Likability–Usefulness correlation provides an interesting point of further investigation. Previous computational creativity evaluation models generally deal with novelty. An implicit assumption seems to sometimes be made that aesthetic appreciation (part of which is measured here by Likability) would be correlated with Novelty. However, according to the results described above, in an object domain, Likability and Usefulness are correlated. This can have interesting implications for usability in design, and for the more complex investigation of aesthetic appreciation of creativity as pertaining to object domains.

The contributions of this chapter are the following:

(i) A prototype system capable of object replacement and object composition was implemented, expressing and testing part of CreaCogs' principles;
(ii) A prototype knowledge base in the household object domain which specifies properties and object parts was designed for this system;
(iii) A more concrete description of types of similarity spaces in such a knowledge base was explored;
(iv) The system was shown to offer results comparable to the Alternative Uses Test. A methodology for evaluating such systems in a manner comparable to the evaluation of human answers was put in place;

(v) More complex metrics for such evaluation have been explored, including ratings on Likability and Usefulness in the human judge rating. Likability and Usefulness ratings have been shown to correlate;

(vi) Humans where shown to use similar processes and properties as OROC.

Various points are open for future work, including the following:

- Modeling shortest discriminant description of object. Checking what empirical inferences can be made from the model;
- Testing assumptions relating to creativity processes as pertaining to structure and similarity of features empirically, through adding new conditions to creativity tests;
- An implementation of the various feature spaces in subsymbolic maps;
- Obtaining object similarities from humans or from sensory data science;
- Devising a human test for creative object composition;
- Implementing larger databases of objects, adding knowledge from ontologies to the current scheme.

As OROC is currently a proof of concept system, further work to improve it will involve the development of the similarity metric, which can be done using qualitative shape descriptions [40] or approaches based on the conceptual space theory [52], like the approach proposed by Chella et al. [16]. Learning can be used for the acquisition, recognition and categorization of knowledge in OROC using various computational approaches [42, 69, 142].

Chapter 7

Practical Insight Problems

The account of creative problem solving wouldn't be complete if the mechanisms of the proposed CreaCogs framework weren't tested on some insight problems. In this chapter we opted for the further study of practical object insight problems, as the knowledge involved in solving such problems, involving objects, affordances and spatial relations, will be easier to model in the future than knowledge in problems which involve abstract concepts.

Empirical insight problems are generally considered very different from each other, as a different insight is required to solve each insight problem. Insight problems can also lose their insight problem status after being solved once, if the participant still remembers the type of restructuring or re-representation which triggered the insight. Thus once a participant has acquired the insight about how to solve a particular problem, the same problem cannot be used a second time with the same participant.

Though such problems are one of a kind (in terms of solution) and with the caveat that "insight" is not present on a second round of solving the same problem, this work started on the assumptions that: (i) data can be gathered on human participants as long as it is taken into account whether or not they have seen the problem before (ii) different problems will address similar processes, though the knowledge required to solve them and the solution itself might be different (iii) different problems can be created as long as one has a working assumption about what insight is. Our working assumption is that insight requires re-representation, restructuring of the initial interpretation of the problem space, and that creative problem solving processes like the ones posited by the CreaCogs framework will be encountered in the human problem solving of insight problems.

The rest of this section proceeds as follows. Empirical insight problems which will be used for testing the framework are described in Section 7.1. Some of these problems are classical and some are made by the author. The principles of creating such problems are described in Section 7.1.2. A think aloud protocol with human participants was run with these problems. The encoding strategy and codes deployed to analyze the data from this think aloud protocol are described and explained in Section 7.2. Two case studies of human participants solving the problems in this think aloud protocol are described and analysed in Section 7.3. The codes utilized to analyse the solving process are discussed in the context of CreaCogs in Section 7.4. The order of the processes is analysed in Section 7.5 to enable the future modeling of such problems in CreaCogs. Some of the aforementioned problems are then analysed in the context of CreaCogs in Section 7.6. A discussion and future work directions are provided in Section 7.7). Conclusions close the chapter with Section 7.8).

7.1 Setting up the practical insight problems

Five classical empirical insight problems have been selected from the literature by the author. Some of these came with classical illustrations, some required the author to create the stimuli from the description of the problem in the literature (sometimes by its creator). The creation of the scenes of such problems required also the addition of various other objects, as described below. Three other problems were created by the author in the spirit of classical insight problems and object composition. Some of these were meant to provide multiple solutions and to be used in an empirical setting to study the process of forming a solution, selecting salient objects and re-representing the problem. Some were meant to require "insight" in the classical sense.

A list of these problems is presented below, with abbreviation C being used for a classical problem, and abbreviation N for a new problem:

1. The Candle Problem (C) [36]
2. The Two Strings problem (C) [101]
3. The Hat rack problem (C) [101]
4. The loop problem (C) or The paperclip problem [36]
5. Attach the pendulum problem (C) or the weight problem [36]
6. Johnny dusting (N)
7. Lost teddy (N)
8. Jack and Jill - weight problem (N)

7.1.1 Practical object insight problems

The Candle Problem [36] is stated as follows: *You are given a candle, a box of thumbtacks and a book of matches (see Fig. 7.1). You are supposed to fix the lit candle unto the wall in a way that doesn't allow the wax to drip below.*

The solutions that human participants come up with for this problem are varied in the literature. Some participants melt some of the candle to then use wax as a gluing agent. Some use the thumbtacks to pin the candle to the wall. Obviously, this is not enough to make the wax not fall below[1], which is why some participants attempt to make a small

[1] Some formulations of the problem include a table next to the wall onto which the wax is not supposed to drip.

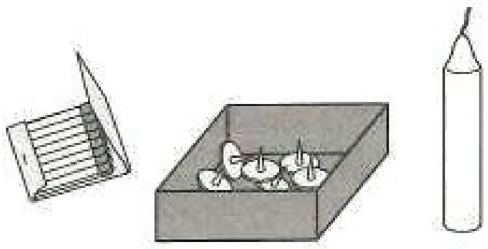


Figure 7.1: The Candle Problem

bridge or support under the table from thumbtacks[2]. However, the solution considered as "correct" for this problem is to use the thumbtack (or nail) box as a support, to pin it to the wall with thumbtacks (or nails), put the candle in it and light it. It has been shown that human participants are better able to come to this solution if the thumbtack box is already empty, and the thumbtacks are presented outside of it. It might very well be that while the thumbtack box is being used as a container (and full), human participants do not consider its other possible uses or affordances. The solved Candle Problem is shown in Figure 7.2.

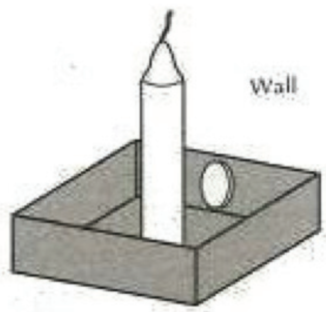


Figure 7.2: The Candle Problem Solved

The Two Strings Problem [101] is stated as follows: *A person is put in a room that has two strings hanging from the ceiling. The task is to tie the two strings together, but it is impossible to reach one string while holding the other.* The depiction of this problem is shown in Fig. 7.3.

The participants make various attempts at tying the two strings, including getting on the chair thinking this might enable them to pull one of the strings further, and thus reach the other. The correct solution to this problem is considered to be using one of the strings and a heavy object from the pile of objects scattered on the floor (like the pliers), to create a pendulum. The creation of the pendulum allows the solver to set one

[2]This is sometimes made of nails, as some formulations of the problem give a box of nails rather than a box of thumbtacks. A nail might be a better tool for pinning a thick object (like the candle) to a wall, thus leading the participants on a wrong representation path.

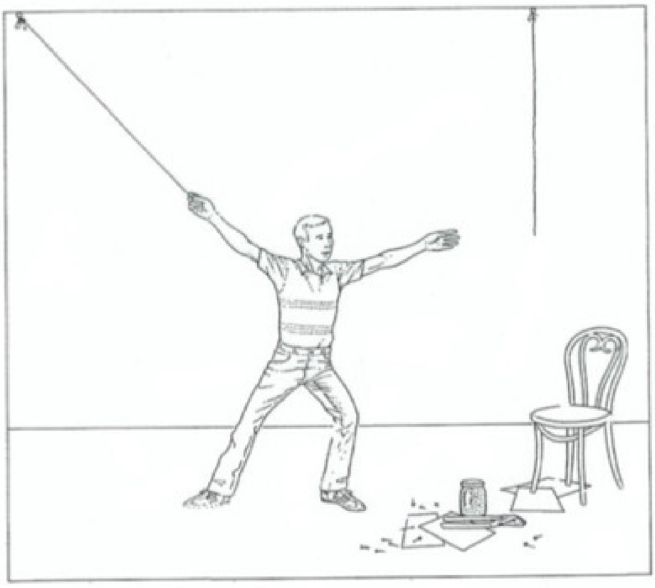


Figure 7.3: The Two Strings Problem

of the strings in motion, so that the string comes towards the solver. This allows the solver to grab onto the other string and catch the one set in motion.

Some participants struggling to solve the two strings problem are helped to come to this solution by the investigator, which brushes past one of the strings, setting it in motion. The affordance for pendular motion of the string is thus triggered. However, though more successful in solving the problem in this condition, participants report most of the time not being aware that the investigator has helped them, or that they have seen the string set in motion by her [101].

The insight in this problem is about switching the representation template from trying to reach the other string to trying to make the string come to the participant. The second creative step is the construction of a pendulum out of the given objects (see Fig. 7.4). This is were both object composition and object replacement procedures can help.

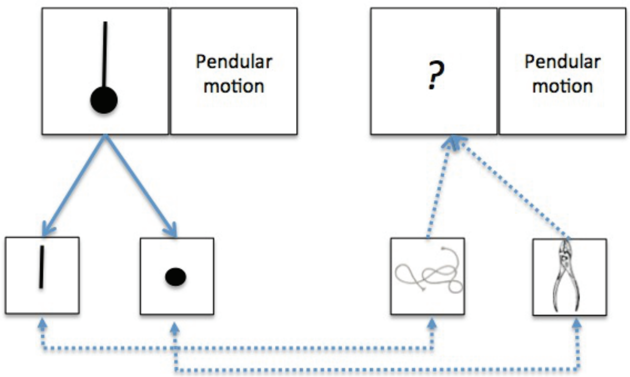


Figure 7.4: Composing a Pendulum, a subpart of the String Problem

The Hat rack problem [101] is stated as follows: *You need to make a hat rack (a rack to put your hat) in the room shown below; on the floor they are two planks and a G-clamp. What do you do?* The hat rack problem is depicted in Figure 7.5 - with measurements adapted from the original (in inches), to cm[3] - as to be suitable for participants more used to the metric system. This adaptation was made because the hat rack problem seems to be amongst the hardest practical insight problems in the literature.

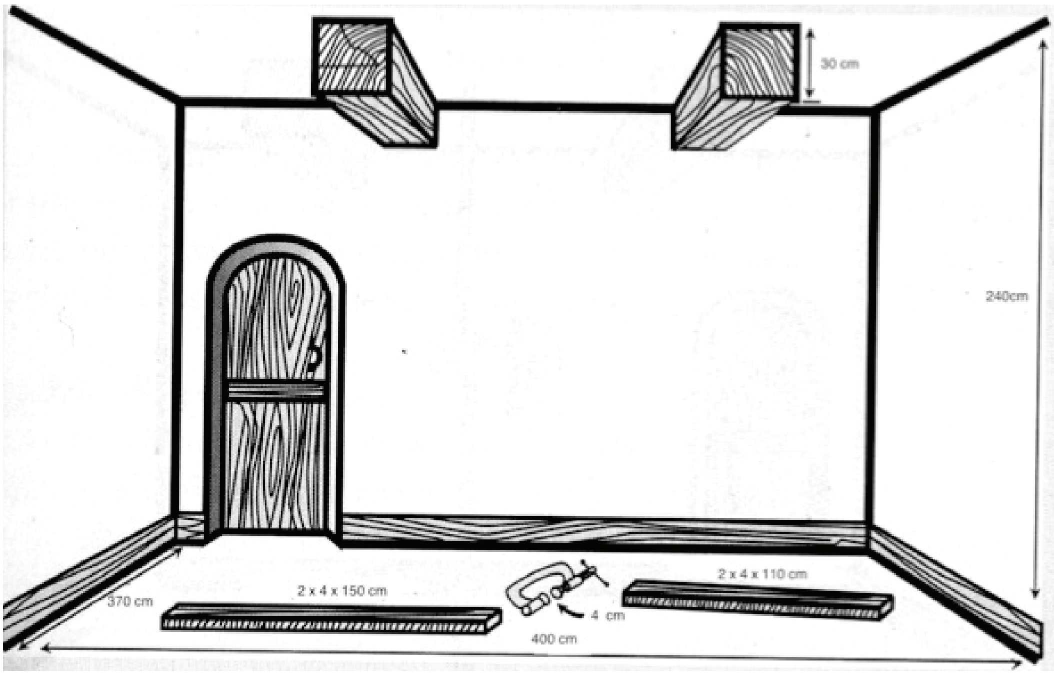


FIGURE 7.5: Depiction of the Hat Rack problem with metric measurements

The solution to this problem is to use the two planks vertically and clamp them with the G-clamp while overlapping 20 cm of their length, as to match them to the height of the room. Then the G-clamp, because of its shape, can also be used as a hook for a hat. Thus the planks together form something like a tree hat rack with the knob of the clamp being the only hook.

In our opinion, two main difficulties are presented by this problem. The first one is the lack of resources - in opposition with other problems where the main difficulty might be selecting the best suited object or set of objects amongst many, and memory might be overloaded as a function of this. However, in the hat rack problem very few objects are present - two planks and the G clamp, together with two boards that are attached to the ceiling (and which serve no purpose in reaching the correct solution, however they might be considered red herring objects).

The second difficulty of this problem is the ambiguity of the goal - forming a hat rack begs the question which kind of hat rack, and what the hat rack looks like. Depending on which kind of knowledge would thus be brought to the fore by the solver, this can

[3]This was an adaptation, not a direct translation of original measurements, as not rounded measurements might have encumbered the solver with more information in the metric measurements variant.

be horizontal (shelf-like), or vertical (tree-like). The latter template obviously has more chances in triggering the right solution.

Besides needing to bring the right kind of template to the fore, the hat rack problem involves two insight parts: a composition element and a double use element. The composition element requires the insight that the two planks on the floor, though longer together than the height of the room, can be thought of in terms of adjustable height - thus depending on where one overlaps the planks and puts the G-clamp, the height of the two planks can be made to match the height of the room (despite an initial mismatch). This insight can probably be triggered by the measurement of 4 cm on the opening of the G-clamp, being the sum of the widths of the two planks. However, the G-clamp in itself is a tool the width of which can be altered (to a limited degree), thus participants might miss this cue when seeing the tool under its adaptive nature rather then as a fixed point to start building the problem solution from. The second insightful part of the solution consists in realizing that the G-clamp can be used not only for its clamping affordances, but also, because of its shape, as a hook.

The Cardboard and loop problem was taken from Duncker's *On problem-solving* [36], where it is called *the paperclip problem*[4], and came without an illustration. The cardboard problem is stated as follows: *You are asked to help the experimenter attach this piece of cardboard to the loop in the ceiling. How do you proceed?* We represented the problem for empirical investigation as in figure 7.6, adding as other objects a hammer and nails on a table. The cardboard to be attached to the loop has four pieces of paper attached to the four corners with four paperclips - as per Duncker's formulation. The solution to this problem is to get one of the paperclips out of it's position in holding the piece of paper, bend it and turn it into a two way hook, then use one side of the hook to attach to the loop, and another to pierce through the cardboard (in a corner, to also hold the piece of paper in place, if necessary).

The difficulty in this problem is presented in our opinion by: a) seeing the paperclips in two functions - as holding one of the pieces of paper attached to the cardboard and as a bendable object which can be detached and used for hooking and piercing, and b) piercing through the cardboard, an action which might be perceived by the participants as destroying the cardboard and thus yield resistance.

There is perhaps an added amount of difficulty in our presentation because of similarity of affordance between attaching to loop and attaching to wall, and fixing affordances pertaining to nails. In fact an interesting second condition here would be to present this problem with different objects in the context, the affordance of which would have less of a chance in interfering with the one of the request. This would probably yield a much lower chance for an imperfect mapping of the request to different objects with similar affordances (the nails), and make the participants less likely to perceive those objects as salient and fixate on them as useful for the solution.

[4] We have not used the original name here because the name contains the object used for the solution.

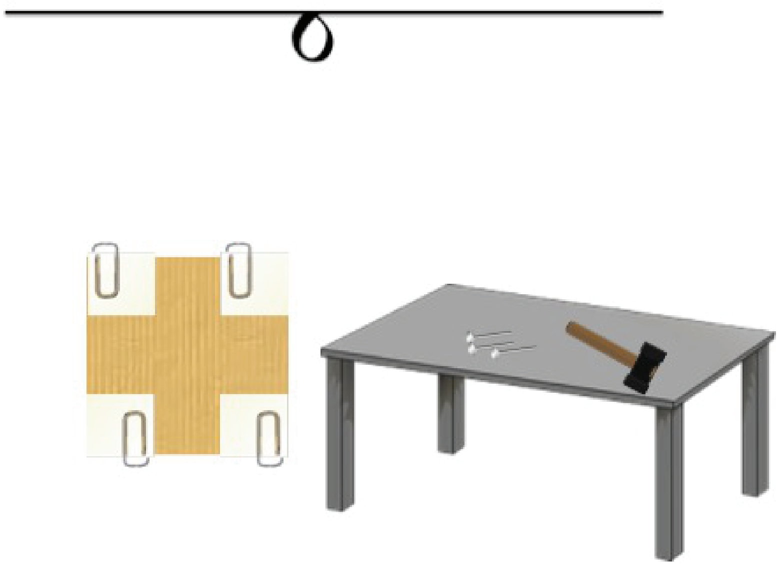


Figure 7.6: Author's depiction of the cardboard problem

Attach the pendulum problem This problem was taken from *Duncker's On problem-solving* [36] - where it is called *the weight problem*[5] - and came without an illustration as well. The problem is stated as follows: *You are to help the observer set up the room for an experiment. You need to attach the pendulum to the ceiling. What do you do?* We represented the problem for empirical investigation as depicted figure 7.7, adding as other objects the red sock, the glasses, the table and the ladder. The solution to this problem is to use the pendulum head as a hammer to put the nails in the ceiling, before attaching the pendulum.

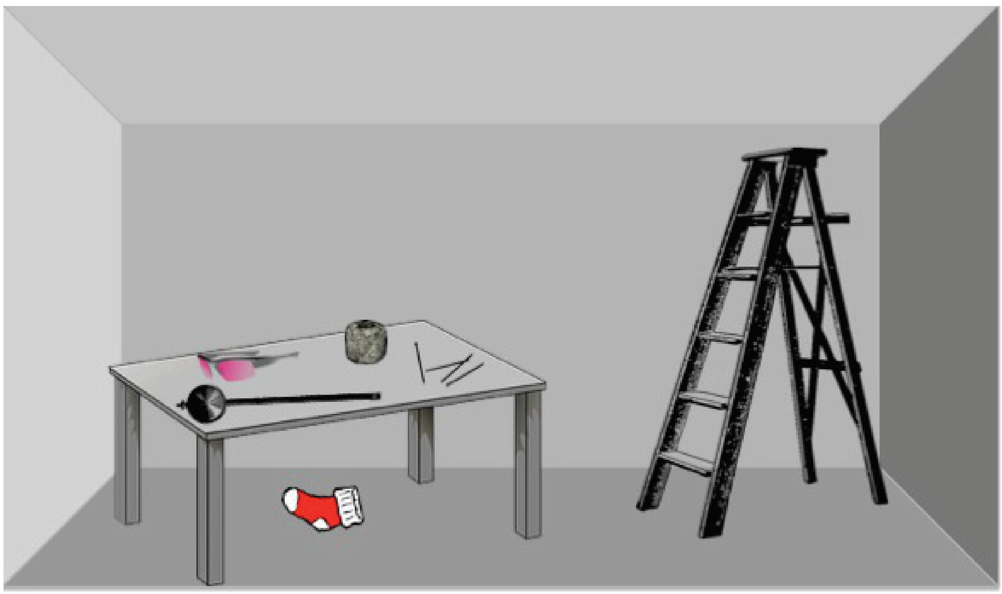


Figure 7.7: Author's depiction of the pendulum problem

[5]We have not used the original name here not to confuse this problem with the Jack and Jill problem

The difficulty in this problem resides in seeing the pendulum in two functions - the thing to be attached, and the hammer replacement. The nature of the problem, or the stumbling point in attempting it might not be clear to the participants initially. Participants might thus take a while to realize that the inherent problem - making a hammer - is not formulated in the problem description, but comes as a consequence of one of the steps.

Dusting the clock is a new problem created by the author, and meant to elicit multiple solutions. The problem is stated as follows: *Johnny is cleaning a room. How can he reach to dust the clock?* Figure 7.8 depicts this problem.

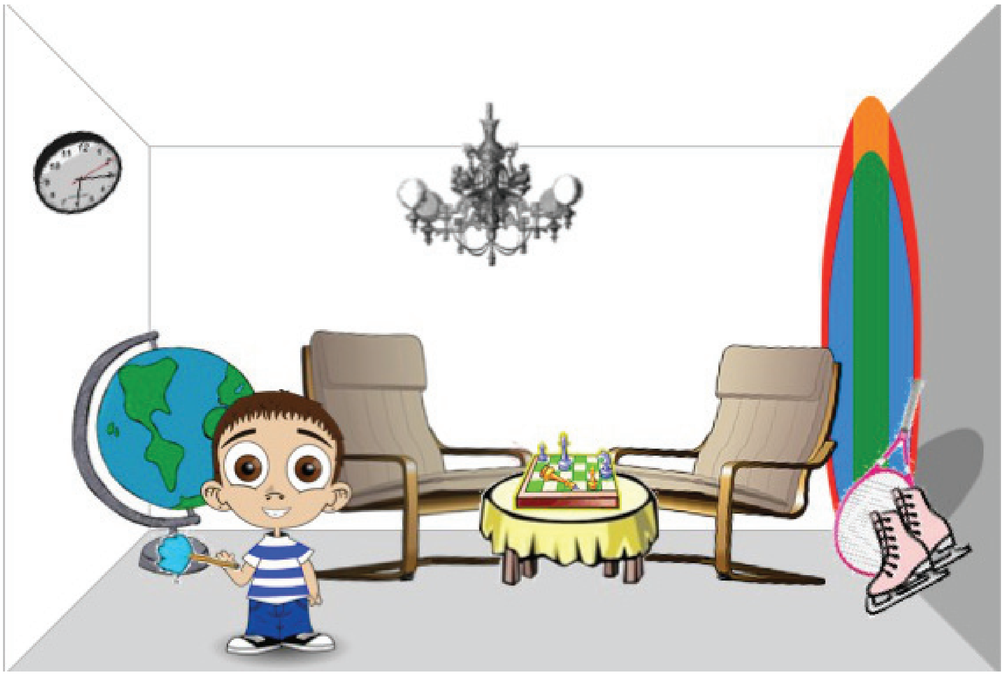


FIGURE 7.8: Dusting the clock problem

A large amount of constructions and solutions are possible in this problem, due to the large amount of objects presented. The author was thus looking to observe the process of construction of various solutions here, rather than one particular solution. An interesting part of the problem was that some solutions could be perceived as dangerous. One possible solution, for example, was using the surfboard on the table as a seesaw and putting the globe on the other side, as this involved bringing knowledge about a new object to structure some other objects in the given environment. The difficulty in this problem thus consisted in the multiple objects present and multiple possible solutions (which might make participants stuck and unable to see other possible ways of structuring the problem), coupled with the ambiguity in terms of stability and safety of the solutions.

Blown away teddy is a new problem created by the author. The problem is stated as follows: *The wind blew your son's teddy bear from the clothesline into your neighbour's garden. The neighbour is in holidays and the fence is too high to climb. How can you* *retrieve the teddy?* Figure 7.9 depicts the problem. The solution to this problem is to construct a fishing rod, using the mop, the clothesline and the bended clothes hangers.

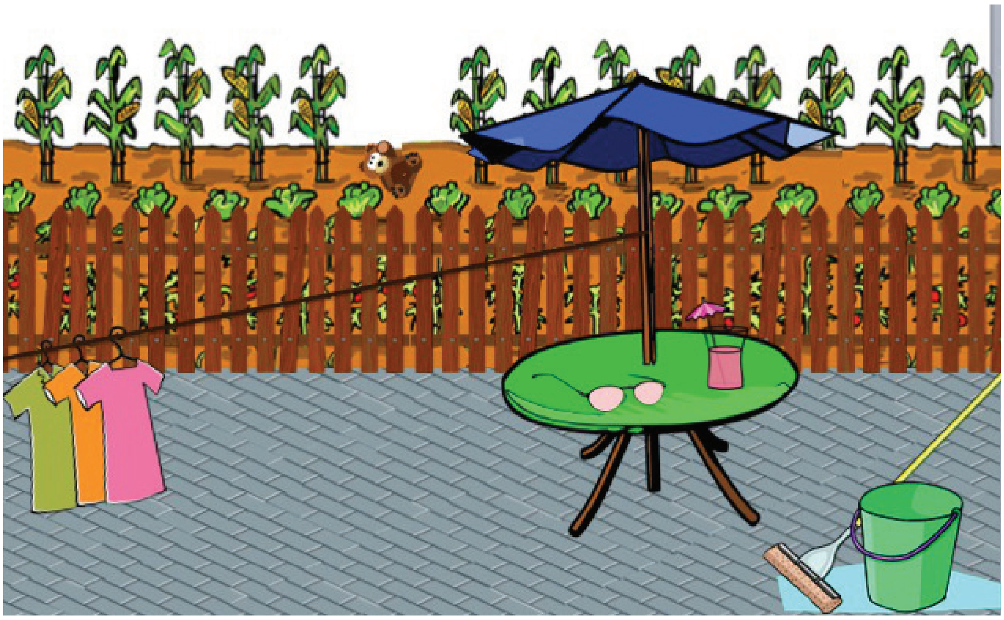


Figure 7.9: Blown away teddy problem

The difficulty in this problem can reside in seeing objects out of their normal context and affordances: a) seeing the mop out of it's cleaning context (which is why the mop was put in this context using a bucket and water) and b) seeing the clothesline and clothes hangers out of their context of being used for drying clothes. However, this might not be as hard an insight as when an object shares two uses out of which both seem required for the problem at hand. In terms of insight, this problem requires the solver to realize a fishing template would be useful to "catch" and drag the teddy over the fence. In terms of object composition, this problem requires the solver to map various objects as parts of a fishing rod. The exact distance to the teddy is unclear to the solver. Thus the observing experimenter can intervene at various object construction or strategy deployment points and state the object might not be long enough to reach the teddy, thus requiring the solver to come up with another solution, and sometimes a new way to see the problem.

The Jack and Jill weight problem is another new problem created by the author. The problem is stated as follows: *Jack and Jill are arguing about whom weighs more. What could they do to find out for certain?* Figure 7.10 shows the problem.

The solution to this problem is to create a seesaw out of a borrowed surfboard and the bucket in order to weigh Jack and Jill comparatively.

We consider this problem as the closest to a classical insight problem. An object which exists in the picture in a different context, is already in use and is not salient, is (re)used for a construction which the solver has to bring to the fore as appropriate from their knowledge base. The second object used as a pivot (the bucket) is also full of sand (in a similar way with the thumbtack box being full with thumbtacks - though in this case

FIGURE 7.10: Jack and Jill weight problem

the representation is not accessed necessarily to use the contained object - i.e. the sand. These constitute sources of difficulty, together with the fact that the problem only allows one correct solution.

Furthermore, the inflatable swimming pool can be taken as a red herring and Archimedes' principle for measuring mass rather then weight deployed. Similarly, appearance of the two people can be taken as a red herring.

Several other problems were created, on the same principles, however for the sake of brevity they won't be depicted here. These eight problems (5 classical and 3 new) were the ones employed in an empirical investigation of the creative problem-solving process, as explained in Section 7.3. However, the strategy of creating new problems will first be discussed.

7.1.2 Strategy for creating new problems

The strategy used for creating new problems was to start from a form of a practical problem involving objects, with an easy solution, and then switch to a creative form. This was done by hiding the objects needed for the solution or obscuring the solution itself, with various processes, like the following:

(i) making the objects less salient, through putting them into a different affordance context;

(ii) making needed objects occur under a different form - a different object representation;

(iii) decomposing the solution into (object) parts and hiding the parts in other structures;

(iv) adding more salient possible solutions and red herring objects (the inflatable pool)

(v) using an object for a rare or remote affordance which had no salient association with it, so that the useful problem template needed to be found first, before discovering the possible useful objects.

This strategy could also be automated by the CreaCogs template by, for example: (a) replacing objects of a given problem with other objects which have the same particular affordance, but for which that affordance is less salient and (b) decomposing the solution into various objects and putting such objects in a non-salient context in the environment.

This strategy was used when depicting classical insight problems as well, in the process of making a choice for other objects to add to the problem[6]. While designing problem stimuli, an interesting difficulty encountered was that adding virtually any object to a scene introduces multiple possibilities of interaction with other objects in the problem, multiple new possible problem paths, problem representations, and sometimes new solution paths. As the intention was to explore the complexity of restructuring and re-representation, salient objects that could lead the solver on different paths and multiple solution paths have been added in some problems.

7.2 Encoding strategy and Codes

A think aloud experiment was set up with the aforementioned problems. In accordance to think aloud protocols, in order to analyze the answers and the problem solving process of the participants, the recorded verbal data needed to be transcribed and the transcription segments needed to be coded. A set of codes thus needed to be created. In order to usefully analyse to what extent the processes posited by the theoretical CreaCogs framework are present in the solving of such problems by human participants, a relation between the transcript and the theoretical model of processes needed to be established.

To this purpose, upon inspection of the pilot answers and according to the CreaCogs framework, a set of codes was constructed. The pilot protocol on which these codes where established will from now on be referred to as P0. Some such codes pertain directly to the CreaCogs framework and formalization, while others are part of the larger issue of (creative) problem solving.

In the following section, these codes will be listed, together with a short description and examples of how they can look in think aloud protocols. Some such codes didn't have a suitable example in P0, however we posited them anyways, as a relevant part of the CreaCogs framework. Segments corresponding to these codes were later found in the protocols of other participants. In this case, we shall give examples for them from those participants. In the case of each example, the anonymous participant code is mentioned (e.g. P0, mb8, fb6), together with the name of the problem.

[6]Some classical insight problems are depicted in the literature by describing the main objects that are necessary to solve the problem, with no mention of what the "filler" objects where.

Problem solving general process codes (PSP)

PSP - Reading the problem This encodes both initial reads and complete re-reads of the problem. In the case in which only the key requirements are read again, this corresponds to code **PSP - Defining key requirements of the problem**.

PSP - Comprehending This can appear in transcripts through moments of re-reading the problem, pauses at various points when reading, and verbal cues like *"So let me understand this ..."*.

PSP - Defining key requirements of the problem In these segments, the participants focus on extracting the main requirements of the problem, thus they scan through the problem statement to synthesize such requirements. We hypothesize that this then allows strategies of search based on the key requirements, and also enables future evaluation using those said requirements. This code might correspond to reiterating key parts of the problem statement, like *"It needs to be attached to the ceiling" (P0, Attach the pendulum problem)*, or to actual statements about what the key requirements are - for example: *"So, let's redo the... the logical assumptions here, and these are that the fence is too high ... Yeah, that is actually the only one that is to be taken into consideration"* (P0, Blown away teddy).

PSP - Mapping problem formulation to objects This code describes looking at the objects in the problem while reading the problem, as to anchor the verbal formulation of the problem into visuospatial input, or visuospatial representation. The two presentations are somehow bound together - the Environment problem depiction to the Problem formulation, and then participants proceed to reason about it. Looking at objects is not always obvious from speech. Sometimes, notes on this have been made by the experimenter that was observing. At other times, speech segments point to it, for example: *"I have to get teddy, so that is the teddy over there"*.

PSP - Taking stock of problem objects This code reflects statements in which the participant seems to run an inventory of the objects in the room. Sometimes such an inventory is run in conjunction with affordances (or might trigger such affordances). For example: *"So, what do we have? There, we have a chair and some... some bowl. And we also have some... some old objects that could look like some pieces of paper, and some things on the ground [...] Maybe some... some very, very small nails."* (P0, Two strings problem). Sometimes this strategy appears later in the process of solving (after at least a way of solving the problem has been already tried). This might help the solver switch focus on other objects, and build solutions around them. Thus we assume this is used to both *select* useful objects in a fast broad manner and to *trigger* associations of uses, which might be unconscious or not vocalized.

PSP - Proceeding on path Once a path has been set (starting with some objects or a problem template which will be used intuitively as a heuristic), the participant then proceeds on this path. This is a complementary code to switching path or template.

PSP - Backtracking This code refers to going backwards on a solution path, and picking things up from an earlier state. This can involve going back to a crossroad decision point. This is sometimes done explicitly, like in the following: *"Okay, sorry, wait, let me... let me come back on that"* (P0, Dusting the clock). At other times, this is done implicitly, by turning back fast from a hypothesis that was being considered; this can sometimes be followed by **PSP-Defining key requirements** again, for example: *"And we... we will tie that left end of the rope to the fence... No, we will not do that. So, you... you cannot climb the fence"* (P0, Blown away teddy).

PSP - Evaluation In these segments, participants evaluate a particular solution to the problem. This can be more general than comparing solution states to constraints (though not necessarily). For example: *"so I would have to go with this solution, although [...] maybe five percent certain that this solution would work"* (P0, Attach the pendulum). Also, this might involve expressing satisfaction or dissatisfaction with the solution, in both objective or emotional, intuitive and aesthetic terms.

PSP - Running through consequences This describes segments in which the participant thinks about the consequences of moving objects, or doing things in a certain way. For example: *"And we will have, after this action will be performed ... so we will have that piece of paper nailed to the ceiling by three or four nails, and will have that piece of rope left and on top of that piece of paper, and right under the ceiling ..."* (P0, Two Strings problem).

<u>Affordance related segments (Aff)</u>

Aff - Determining object affordance This can range from actually listing the affordance of various objects, to listing more creative affordances, or affordances for which objects are not generally used (like in the Alternative Uses Test). In the latter case, we generally also use code **OU - Object used in novel way**. Examples of determining object affordance can look like the following: *"The matches could be there just to [...] light the candle ... and maybe to melt the candle"*(P0, Candle problem). It is useful to remark upon the fact that affordances in this context can be related to another object (they can show ways of acting *upon* the other objects), thus acting as links to build higher compositions of solution chains, which can be matched to various existing (known) templates.

Aff - Inferring more affordances This refers to inferring new affordances that are not explicit, as well as developing upon direct object affordances to infer what other affordances might be present. Such inferences generally make use of common sense knowledge, and can prepare the object for use within a specific template. For example: *"so those two wooden objects out there seem to be of the same width and length [...] it looks like a square. So that means that actually the lower width ... width is also 30 centimeters as the vertical width there."* (P0, Hat rack problem). However, such inferences are to be differentiated the mentioning of unusual or creative affordances with existing objects.

Aff - Determining lack of affordance This code stands for stating or determining that a certain object can't be used in a certain way. Such a determination can initially begin as a statement of affordance, which then turns negative - a form of affordance rejection (in which the participant prompts himself to stop considering an affordance as being enabled by the object). For example: *"The thumbtacks would .... couldn't possibly be used for nailing the candle to the wall"* (P0, Candle problem).

Aff - Determining template affordance If a certain template is being used consciously, or the participant has access to meta-reasoning tools about the template used, this code marks segments in which affordances about templates are being used - for example: *"I could construct a platform but that's not going to be any good, what I need is [...]"*.

Problem template use category (PT)

PT - Requirement-based search of template This code implies searching for a template with the constraints of the problem. For example: *"So, how can you... how can you fix something up near something [...] Oh yes, you can provide some sort of stable platform for... for it."* (P0, Candle problem). Sometimes this overlaps with **Determining PT to use**, at other times determining PT to use is a less specific code, as it is not clear how the template to be used was reached. This code is also part of the **Search** codes.

PT - Determining PT to use This code describes segments in which the participant is choosing what template could be suitable for the problem. These segments correspond to moments of structuring the problem in a certain way, using that specific template, which will probably guide the future steps until either a solution is found, or an impasse is reached, and the participant decides to let go of the template, or a new template "pops out", intersecting current solving. Such a new template could appear from already made associations which converge or form a new template/way of solving things. Examples of segments in which the PT to use is determined are the following: *So, of course, there is no way for him to reach that clock, yes, which is on the left wall. Okay, so once again we would have to provide some steady platform for... for Johnny to be able to dust that watch.* (P0, Dusting the clock) or *"by looking at it... by looking at it... It seems to be a very straightforward application for the Archimedes' principle"* (P0, Jack and Jill weight problem).

PT - Adaptation of PT to problem A chosen problem template is adapted to fit the constraints of the problem (or to work with other templates). Sometimes this adaptation can occur when determining a PT to be used. For example: *"So, how can you... how can you fix something up near something, or in this case, to the wall?"* (P0, Candle problem). This is also a **Creative Adaptation** code.

PT - use to search for suitable objects An abstract template that would be suitable has been found (or the participant estimates it is suitable). Now this template is used to select objects that could participate in realizing it in the given problem environment. For example: *"So, the only thing that could be provided as a stable platform in which to place the candle is of course that box, that it couldn't be something else."* (P0, Candle problem). This code is also part of the **Search** category.

PT - Adaptation of problem template to objects An existing problem template is adapted to properties of the objects. For example: *"If you put it [...] on a horizontal position, then you would need just two thumbtacks on each end of ... it to nail them to the wall, and in this case to really fix, to link the box to the wall by using thumbtacks, which would provide a stable horizontal platform for the candle, in which you could place the candle"* (P0, Candle problem). In this example, after the platform template is applied to the objects, a modification is observed: the candle is not *on top of* the platform, but *in* the box that has initially been used to fill the platform template, which is actually upon inspection also a container. This code also belongs to the **Creative Adaptation** category.

PT - use of PT construct This code marks segments in which a problem template is being used to organize objects in an obvious manner. This code is also used when the same template is being used again immediately or a participant comes back to it after trying out different paths - however, the objects used to populate the template might differ. This is also a **Composition** code.

PT - use of PT construct with reaching solution path This code marks segments in which a problem template has been used successfully to reach a solution.

PT - Rejecting template In the segments encoded under this category, the participant decides against using a template, or makes statements about how a certain template would be inappropriate. Sometimes, such a template is rejected out of hand on initial assumptions, without running through the consequences of using it, just because a certain template does not seem to fit, because of some of its affordances or requirements coming in conflict with constraints of the problem, or not being enabled by the objects in the problem. A PT could also be rejected because it simply seems that affordance-wise it comes short of getting the job done. Examples of this are *"but unfortunately, here we have to... to establish if some.. some sort of differentiation can be obtained from weighing, and not from... not from just calculated... calculating volume"* (P0, Jack and Jill weight problem).

PT - Template Switch This reflects segments in which the participant switches from a pre-existing or used problem template (or way of structuring things) to a new one. Such template switches might ensue during or after the process of restructuring the problem elements. For example: *"So, instead of ... instead of fixing the candle to the wall in the most regular way, you could just provide a platform for it on which it could stand."*. (P0, Candle problem)

<u>Assessment category (A)</u>

The Assessment category generally refers to partial assessments, rather than end of solving Evaluation segments.

A - Checking joints in plan This code reflects segments in which the participant considers how the various objects fit together, in the overall attempt at solving the problem. This might involve references to particular parts of objects fitting with other objects, in the general context of the plan.

A - Checking object against constraints This code pertains to checking an object against problem constraints or template constraints. Subsequently, the object could be integrated or found to be lacking, which would make the participant discard it or adapt the problem template to this issue by adding other objects to the problem space. For example: *"Okay, but right now Johnny is... Johnny is still very small to be able to get on that... that platform"* (P0, Dusting the clock)

A - Comparing solution state to constraints In these segments, the participant compares directly some state that has been reached in solving with the constraints or requirements given by the problem. For example: *"which will make him a little bit higher and maybe able to place himself and... and now climb on [...] that platform, from which he ... he can easily dust that clock. "* (P0, Dusting the clock)

Focus changes

F - Focusing on object This reflects a segment in which the participant focuses on a particular object (or objects) and builds solutions around it, or tries to use it in every solution for a while. For example: *"So, obviously, we ... we would have to use that rope in some way to reach the... the teddy"* (P0, Blown away teddy)

F - Switching to new object as focus This reflects segments in which the focus is switched from an object or a set of objects (and implicitly their affordances) to another object or set of objects, thus allowing for a new type of solution to emerge, around those objects. Sometimes this is a fresh start, equivalent with structuring the problem starting from that object and its affordances. At different times, it happens when the participant notices a new object, which then can be integrated. For example: *"[...] and the box would be fixed to the wall by using thumbtacks. But why that box of matches there? "*(P0, Candle problem)

The equivalent of this focus and switch of focus in problem templates are codes **PSP - Proceeding on path** and **PT - Template switch**.

Creative problem solving process specific

Composing fuller results based on previous exploration If affordances of various objects were previously just triggered, or new creative uses of some objects assessed, in this case a fuller, more detailed result is assembled based on these initial "hunches", the mechanism of which the participant didn't yet run through (at least verbally). It is sensible to assess that after making previous fast and wide searches of solution affording objects and templates, the participants take, at this stage, more time to deploy in detail a solution which seemed plausible.

Insight marker expressions This code is assigned to segments or expressions which can be reflective of insight. For example, this code refers to utterances like *"Ah!"*, *"I see!"*, *"I know!"*, *"Aha!"*, *"I got it"*, *"I have a new crazy idea which might just work"*, especially when such utterances come after a long break in verbalizing or in new ideas, when they seem to come out of nowhere, or intersect a previous (coherent) line of thought. These may or may not be reflective of actual insight, and further proof of a new restructuring is necessary to deem such expressions as actually reflecting an insightful moment of problem solving.

Making assumptions With insight problems and problems which require creative problem solving, a decent amount of ambiguity comes naturally. Participants seem to contend with this by setting up assumptions of their own. Such segments may but must not necessarily start with *"I'm gonna assume that.." or "Can I assume that..?"*. For example: *Okay, assuming that Johnny can... can easily move on... on top of the table* (P0, Dusting the clock) or *"So, assuming that you... you in no way are able to disembowel that... that table"* (P0, Blown away teddy). These assumptions may or may not be valid or helpful.

Stuck or functional fixedness This code reflects segments in which the participant can't come up with anything new, and is either silent, voices that no new idea is being found, or keeps on iterating previous ideas.

Forcing solution This code is allocated to segments in which the participant is trying to force a certain solution to work, despite evidence to the contrary or already declared estimations that it wouldn't work. Some such solutions can be far fetched, and can be seen as a way to trying to close the gap between problem space and solution state, with very low thresholds on what can be done with the objects, and sometimes applying quite complicated attempts at solving the problem. For example, P0 forces the solution to the Attach cardboard to loop problem by attempting to nail the table to the wall, in such a way that a table leg is placed under the loop, in order to be used as support for the cardboard which also now touches the loop. Such forced solutions might appear after being stuck in functional fixedness for a long while, and possibly being frustrated with the inability to solve the problem in any feasible way.

<u>Object (O), Object templates (OT) and object use (OU)</u>

O - Disassembles object An object is split in pieces **or broken**, possibly to extract parts which can be used for their affordances. For example: *"take the shoelace or the lace of one of the skates there"* (Mb8, Dusting the clock) or *" pull the legs off the table"* (Mb8, Dusting the clock). The code is also part of the **Disassembly** category.

O - Property-based search of object This code stands for segments in which a participant has already formulated what kind of property is essential for fitting an object into a problem template and is searching the objects in the room that could yield the corresponding property (or affordance). For example: *"so wow now I can take the clothesline because it's a long wire"* (Fb6, Blown away teddy). This code is also part of the **Search** category.

O - Adaptation of objects to template An object is fitted into a problem template by changing properties or main uses of the object. This sometimes comes as a consequence of how the object is seen (object template) or of needing certain properties of the object as required by the template, though those properties are not necessarily salient. For example, properties of the object "paperclip" need to be changed for the object to become a hook. Physically, the object needs to be unbent. Paper sheets can be folded to use their length and bendability properties, under a Chaining template, etc. This code is also part of the **Creative Adaptation** category.

O - Object used to search for template Starting from a given object, the participant is trying to extrapolate what template it could be part of, or find a template that is suitable. The constraints of the problem can simultaneously be used in this search, overtly or covertly. This is partly why sometimes affordances are developed, and initially explicitly stated. For example: *"different sorts of construct, but all of them would imply that... that rope some...somehow, because we need to ... to make that pendulum moving, and we can do that by only...by only linking... tying that one end of that rope to the upper side of the pendulum".* (P0, Attach the pendulum) This code is also part of the **Search** category.

OT - Object template use An object template is used to re-create the object out of parts or other objects. Thus parts of other objects or full other objects are adapted to an object template. For example: *"Okay, to use the right rope for tying down the neck of that bowl right there, then swing it and the weight of the bowl will just make the rope act like a pendulum."* (P0, Blown away teddy) or *"So, that means we will actually use... we will actually use that table as some sort of prerequisite step for him to be able to gradually move... move up the... the ladder up on.... on that platform"* (P0, Dusting the clock). In this example, the table is used as a step of the ladder. This is also a **Composition** code.

OT - Object template adaptation An object template is adapted to the parts at hand. For example: *build a scale of sorts [...] But you do not have anything to support it on except for the bucket.* (Mb8, Jack and Jill weighting problem). This code is also part of the **Creative adaptation** category.

OT - Object template rejection An object template the use of which has been considered for a brief or long period of time is rejected. For example: *"It's not like you can build a scale"* (Mb8, Jack and Jill weighting problem).

OU - Object used in novel way This code marks when an object with a set of familiar affordances is used in a novel way, similar to the answers given in the Alternative Uses Test. For example: *"maybe we will use some of the matches to further prevent the candle from dripping down"* In this example the matches are used as a miniature dam, or a drip stopper. (P0, Candle Problem).

<u>Meta-cognitive</u>

Meta - remark on problem nature This code reflects segments in which participants make meta-cognitive comments or reason at a meta-cognitive level about the nature of the problem they are confronting, or the nature of such problems in general. For example *"so those objects put there in the right side of the room, obviously we will have to... I will have to give them some purpose in order to help me to make this person able to reach both strings"* (P0, Two strings problem).

Meta-remark on own process This code reflects segments in which participants make comments about their own perceived process of solving the problem. For example: *"I have a few solutions that come to mind quickly. I can't really iterate them or I can't really verbalize them that quickly. I got a couple of different ones coming. You could [...]"* (Mb8, Blown away teddy) or *"Okay, right now I'm just looking at all these different things, trying to figure out how... which combination can be of any help."* (Fb6, Dusting the clock).

Other codes

Other - affective state The participant expresses an affective state about the problem at hand, be it directly (telling the experimenter about it - for example *"I am getting frustrated with this now"* or *"That's interesting!"*) or indirectly (tone of voice, giggles, gestures, etc.) like joy, interest or frustration.

Other - talking to audience or observer These are statements in which the participant addresses the observer directly or talks as if having an audience.

Other - talking about self action The participant describes an action she has done, like moving to the next slide, or picking up the glass of water, etc.

Other - talking about previous experience The participant relates the current problem template used or object use to a previous experience or a memory.

Other - distraction The participant distracts themselves from the problem. Possibly an indication of encountered difficulty, or need for rest/refocus.

Other - talking to self This might show up in the form of boosting one's own process by directing it in a certain way or another, be linked to evaluating a certain way the participant is proceeding or performing, as well as a variety of other cases. For example: *"Okay, not forget, don't forget"* (Fb6, Attach to loop) or *"Okay, keep talking"* (Fb6, Attach to loop).

Creative adaptation processes (CA) **PT - Adaptation of PT to problem**, **PT - Adaptation of problem template to objects** ,**O - Adaptation of objects to template** and **OT - Object template adaptation**.

Composition and Disassembly **PT - use of PT construct**, **O - Disassembles object** and **OT - Object template use**.

Search **O - Property-based search of object**, **PT - use to search for suitable objects**, **O - Object used to search for template** and **PT - Requirement-based search of template**.

Insight relevant This includes insight moments, as expressed in insight marker expressions, sudden moments of attempting a new strategy and restructuring the problem.

7.3 Two Cases Studies

The codes described in Section 7.2 were constructed to analyze the think aloud protocols of participants solving the eight problems described in Section 7.1. These problems were given to 32 participants, 16 male and 16 female. The participants were asked to provide an assessment of their problem-solving and creativity skills before and after solving, on a 1 to 7 Likert scale (7 being excellent), and an assessment of their performance. 10 minutes solving time were allocated for each problem, except for the Hat rack problem, which was the hardest and for which 15 minutes were allocated. Solving time was observed, and voice recordings were made of the problem solving think aloud sessions.

In the following, the codes from Section 7.2 will be used to provide a descriptive narrative of the think aloud protocol of two participants in this think aloud study. These participants were the best performing participants in their gender group - mb8 in the male group, and fb6 in the female group.

7.3.1 The case of mb8

Participant mb8 is a male Entomologist graduate student, with native level English skills. He rated his problem-solving and creativity skills at 5 on a 1 to 7 Likert scale (where 7 is excellent), both before and after the session. The participant solved in the expected correct way 7 out of the 8 problems, and provided multiple plausible solutions to the 8th (Dusting the clock). He rated, on good grounds, his performance at a 7 (excellent) and considered he had plenty of time.

P1 - Attach to loop problem - solved in 4m 25s, difficulty as rated by participant 1-2.

The participant read the problem. Then he took stock of problem objects. He then returned to determining key requirements of the problem, refined this as attaching the cardboard to the ceiling, and tried to determine what template to use by asking the experimenter how the solution would look, which would allow him a PT search:

> *"How do you want to attach it to the ceiling? Do you want to attach it flat like the broadest surface to the ceiling like that or do you want to hang it?"*

He then focused on the paperclips objects, and started building solutions around them and the nails. In this process, the *bendable* property of the paperclips was used multiple times, to bend paperclips around the nails. The nails were then used to attach the cardboard to the ceiling. The observer prompted the participant to the initial requirements of attaching the cardboard to the loop. The participant adapted his initial solution to using a nail to hold the paperclip in place, then using the paperclip to make the connection to the loop. While talking about these solutions, the participant mentioned object properties (*"paperclips are light"*) and object parts (*"the round end of the paperclip"*).

The participant kept on applying the same template even when confronted with the constraint that the cardboard might be too heavy to be supported by one paperclip hanging from the loop. He attempted to get around this by adapting the same template to multiple paperclips, and making more complex constructions with nail supports. After using multiple times the nails to pierce the cardboard, he realized that the nail could be skipped (Discarded object), and the paperclip used more directly:

> *"You could always just skip the nail and stab the paperclip through the cardboard. [...] Oh yeah. If you - yeah, you could just punch the paperclips through the cardboard and then hook that onto the loop"*

He motivated this template switch, that afforded him the correct solution, with noticing the parts of the paperclip distinctly: *"because the paperclips have two open ends"*. However, his evaluation of the solution, at the aesthetic level, was not positive: *"I think that would look pretty ugly"*.

P2 - Candle problem - solved in 7 s, difficulty rated by the participant 1-2.

Participant mb8 solved this problem directly, in full form, adding to the solution the further refinement of dripping wax into the box so that he could use that to fix the candle.

P3 - Attach pendulum problem - solved in 2m, difficulty rated by the participant as 2-3.

After reading the problem, mb8 took stock of the problem objects - pendulum, string, nails. He then focused on properties of the pendulum, looking for parts of it to attach it from and observed the hole in the pendulum. He proceeded to compose a fuller result based on the string and the pendulum, by looping string through the hole. He then moved his focus on securing the pendulum to the ceiling. For this, he asked about the weight property of the pendulum, checking the object against constraints of what could be hanging from a string nailed to the ceiling. After detailing on joints of the plan - how to tie the string to both the weight and pendulum, he was asked by the experimenter how exactly he would nail the string to the ceiling. At this, mb8 finally noticed the lack of the hammer.

Mentioning he has previous experience with such situations, he proposed using either the pendulum or one of the legs of the table to replace the hammer. Thus, in this context, both objects received an alternative use. The participant however worried about damage to the pendulum, and the ability of the table to be disassembled.

P4 - Two Strings problem - solved in 1m 15s, difficulty rated by participant as 2-3.

Mb8 read the problem and proceeded to take stock of the objects - pliers, pieces of paper, nails, stool. He then focused on the nails and the chair, re-iterated the goal and made the assumption that collateral damage was not an issue. He then proposed as a first solution to climb the chair, nail a string to the ceiling, then grab the other string and bring it to the previous fixed one. Running through consequences, he verbalized the damage he was initially describing: *But then you have a hole in your ceiling.*

Told by the experimenter that he might not be able to reach the ceiling, even while standing on the chair, mb8 then asked about the strength property of the string and about the parts of the jar (whether it has a lid or not). He proceeed to empty some of the nails out of the jar to make it lighter (still worried about the strength of the string), then tied the string to the jar, and used the pendulum principle to solve the problem:

> *"Okay, so you can empty some of them (n.a. nails) out so it doesn't weigh very much, and then you could screw... screw the string so that it's - you know - kind of on the jar. Then you stand on the stool, grab your one string, hop on the stool. Then if you tied the jar of the nails to the other string, you could let it swing... And then you could grab it when it comes back to you, just kind of get your string out and tie them together. "*

P5 - Jack and Jill weight problem - solved in 6m 36s, difficulty rated by the participant as 2-3.

After reading the problem, and then making social politeness comments about Jack declaring one's weight as higher than Jill's, mb8 started taking stock of the problem objects. He then checked for access to the seawater, and depth properties of the pool, looking like he was already applying a certain unvocalized template and checking if objects would be in place to apply it. He then indeed proceeded to apply an Archimedes' principle template, on the path of which he stayed and added details for a while. This involved getting rid of the sand in the bucket, using the bucket to bring water from the sea and alternating between the two kids filling the pool and displacing water. The measurement he proposed was that of the water remaining in the pool after each kid's immersion. He correctly evaluated this solution path to lead to a volume determination, rather than weight. This made him discard the template for a while.

Mb8 then focused on the other people, asking whether they can help, then he discarded such a possible path due to subjectivity of the measurement, which might be tampered in his opinion by social politeness. After discarding a path which involved the other people weighing both Jack and Jill, mb8 returned to his previous Archimedes' principle template, and tried to realize it using different objects, specifically sand rather than water:

> *"You can do the same thing in the pool with sand. You could set one of them in the pool and fill it up with sand and then have them get out and see how much is left, but ..."*

Mb8 then started making a template switch, based on considering the requirements of the template. These requirements for certainty made him try to search for a form of a scale, which he attempted to obtain in various ways, filling in the template of a scale with initial unlikely objects. A specific template of a scale is also implied as mb8 mentions ends of a scale. He oscillated between keeping and rejecting the scale template for a while:

> *"Huh! The only way to say for certain would be to put each of them on the opposite ends of the scale and there is no way to construct a scale here...*

> *or is there? ... You can't build anything out of sand because it's not like it's going to hold up... or maybe you could. I don't know... [...] I was just thinking about what kind of options you would have if you have a bucket of sand and the shovel in play when you could build different things but I mean that wouldn't really be useful. It's not like you can build a scale. "*

Considering the template however proved useful, because mb8 then found more likely objects to fill it with: the bar of the umbrella and the bucket:

> *"so I initially thought about taking the poles from the umbrella and using that as ... as something to help build a scale of sorts because you have two ends of it that could hold... (and show you) which one is heavier. But you don't have anything to support it on except for the bucket [...] like if you put the bucket upside down and you put the bar over it"*

Mb8 then proceeded to compose the solution in more detail, run through it's consequences and evaluate it. Then he switched back to offering arguments for his Archimedes' principle solution, and evaluated that solution again. However, he noticed a new object all of a sudden *"Uh! Surfboard!"* and then proceeded to integrate it in the "scale" template (rather a seesaw as scale template):

> *"You can do the same thing. So you could scrap the pole idea and then ... and then just use the surfboard on the bucket."*

P6 - Hat rack problem - solved in 2m 30s, difficulty rated by participant as 3-4.

After reading the problem, mb8 proceeded to make assumptions: *"So it doesn't matter how it looks, as long as it holds the hat(s)"*. Then proposed jokingly to *"Put the hat on your head. The very first hat rack!"* Mb8 then proceeded to inspect the measurements in the scene, focusing on the width property. From that, he put the width of the two planks together, and proceeded to infer affordances, like *"That's probably big enough to stand on"*. Mb8 then proceeded on a path of constructing a vertical hat rack made by the two planks held together by the G-clamp, fitted in a corner of the room. He then asked the experimenter about more requirements, on whether the rack should fit one or multiple hats. He evaluated this construction, than proceeded to develop it. Noticing one of the parts of the G-clamp, he then determined it's affordance in terms of holding the hat, thus achieving the first part of insight required to solve the problem in the classical way. He returned to aesthetic evaluation:

> *"I mean it's not going to look pretty. You're not going to want your guests to see that. You want a hat rack that looks nice."*

Mb8 then switched template, to a new vertical construction that represented the second path of the classical solution of the problem: posting the planks between the floor and the ceiling, with a small overlap. He then composed the fuller solving path and described it, proposing putting the hat on the board overlap part. Mb8 then switched his attention back to the G-clamp, while integrating the object in this new vertical template, noticed its uses as a hook and achieved the full solution.

P7 - Blown away teddy - solved in 3m 58s, difficulty rated by the participant as 2-3.

Mb8 read the problem, then proceeded to take stock of objects, already regarding them as tools: *"What kind of tools do we have?"*. He then inquired about object properties - whether the clothesline is a long solid or non-solid object . He asked about the distance between the fence and teddy bear, which cannot be provided. Mb8 then made meta remarks on his own process:

> *"..so I have a few solutions that come to mind quickly. I can't really iterate them or I can't really verbalize them that quickly. I got a couple of different ones coming."*

The participant then proceeded to describe one such solution path, under the assumption that *"collateral damage is not an issue"*. This solution was based around the fence and an ability to disassemble it, though mb8 evaluated it as *"probably not the best way to do it"*. The participant then looked closer at the assembly properties of the fence, and decided to use the mop handle in a novel way (as a lever) to *"Pop off the boards"*. He then proceeded to compose further on this path. Then proposed alternative paths, like *"walking around the fence to see if there is a door"*.

The participant then focused on another object, the umbrella, and used an object template, a rake, to cast the umbrella. Immediately, he recast the same rake object template to another object filler - the mop.

> *"You could try using the umbrella like a rake in reaching over the fence to grab the teddy bear. You could do that with the mop, too."*

Mb8 then switched template again, proposing to climb on the table and jump over the fence. At the experimenter's prompting that he may not break or dismantle the fence, nor set foot in the neighbour's garden, he restated the previous path. The casting of the umbrella as a rake was so strong, that later he referred to the umbrella with the name *"rake"*, despite being a native English speaker:

> *"The rake or the mop over the fence, trying to rake the teddy bear back would be the best thing to try"*

Determining a lack of the *long enough* affordance for these previous constructions, mb8 then started focusing on other objects that could be used to lengthen that construction. Thus, the coat hangers where considered, adapted to the "lengthening" template, and unbent. The mop was also considered for its length properties. After searching for suitable objects to lengthen the construction, mb8 composed a fuller path based on previous exploration of affordances. Thus he proposed making a straight line out of the coat hangers, the length of which he estimated. Analysing the properties of the coat hangers, the bending property became suddenly apparent, and mb8 adjusted his construction to better suit the goals of the problem: *"You can put a hook at the end of it"*. Considering this construction further under the *length* lack of affordance, mb8 added to it the sunglasses, appearing to search for long objects (property search), or objects that could be adapted as to become long (e.g. by straightening them). The bucket handle was also considered.

With markers of insight (*Huh! (laugh to self)*), mb8 used the already fashioned hook at the end of his construction to switch to a new template. Thus the hook alone was kept, disassembled, and attached to the clothesline. Soon enough, this grappling hook template turned to a fishing rod template:

> *"Huh! (laugh to self) It's a little bit cliché ... but you could take the clothesline, and you could fashion a pronged hook out of the coat hanger. You could attach that to the clothesline, and then you could throw it over like a grappling hook until you get the bear. So that would be longer, but then you could tie the end of that line to the end of the mop, so you get the mop then the end of the clothesline, then some coat hanger construction whatever you want. Then you could throw it like a fishing rod."*

P8 - Dust the clock - multiple plausible solutions given in 10 m. Difficulty rated by participant as 3.

After reading P8, mb8 got quiet. Upon prompting he said he was *"thinking about the objects we have available"*. He proceeded to initially focus on the duster, and to restate the key requirements of the problem. He then asked about height properties of Johnny, which the experimenter was not allowed to provide in a quantitative manner. Without this data, mb8 proceeded to make a height estimation (which prepared him for an approach of compensating for lack of height through making a construction of other objects to put Johnny on top of):

> *"He looks like he's about there, so that's like what? ... That is that plus his height, so that puts him here, then his little arm will reach up and he can dust the face."*

Mb8 then proposed a variety of constructions to put Johnny on top of. First, he proposed to put Johnny on the table. However, as this was still lacking in the height affordance, he switched to an elongating arm approach, adapting objects to this template. Thus, the duster was tied with the shoelaces (which were disassembled from the skates) to the tennis racket, in order to elongate Johnny's reach. The participant then switched back to considering what objects he could use to fill the construction template. He considered stacking the chairs and discarded that option, because of lack of stability affordance of said chairs, estimated based on experience: *"I've stood on chairs like that before and they've just broken"*. He considered and discarded using the globe as a filler for his construction. He then proceeded on a new path, adapting the construction template to a platform template. This template was then refined to include another object, which has already been considered:

> *"You could put these two chairs on each end of the room, put the surfboard over the arms of them and stand on that or put the table on top of the surfboard and then stand on that."*

Mb8 then integrated the extending arm construction into this new solution path.

When asked by the experimenter whether he could consider other solutions, mb8 focused on the clock and asked if it could be moved. Then proceeded to search for suitable objects with the affordance of moving the clock. Objects considered where the globe, the chessboard (being thrown at the clock) and the surfboard. The skates were also considered and discarded, because of running through the possible consequence of them sticking in the wall. The participant then returned to the former template, and voiced it in terms of a table Object-Template rather then platform template, which hints at seeing the surfboard as a table surface: *"Putting the surfboard over two arms of the chair so that the arms of the chair are basically formed legs of the surfboard table, then you could stand on that..."*

Mb8 then proceeded going through his previous strategies and evaluating them, re-iterating them, and sometimes modifying them. For example, he considered the arm elongation template with a new object in - the surfboard, but discarded it in favour of the racket, because of an analysis of properties of the end part of the surfboard and previous experience:

> *"I woud've suggested tying the duster to the end of the surfboard, but I don't think that would work, because the end of the surfboard is round like that, not like a cone but it's kind of rounded, so I don't know if you've ever tried tying a string around an end like that. It just doesn't work, like the tie just slips off. But the tennis... the tennis racket would be perfect. I mean I have tied shoelaces around - I have - the end of tennis rackets before because the grip is squish, it just tightens right there."*

Mb8 then considered disassembling the table and using the legs of the table to build something long, at the end of which the duster could be attached (this is still the elongate arm template). However, this is dependent in his assessment upon Johnny's *strength* property, and will have as consequence the destruction of the table.

The participant then switched focus between different other objects, perhaps considering whether they trigger new solving templates, or at least new meaningful affordances that can be used for finding such templates, or integrating the objects with previous templates: *"I was just thinking about the chandelier, and whether or not it's possible bringing that into play, but I don't think so. It's not possible to bring it into play in an effective way"*. He then considered the skates in the context of the previous knocking down the clock template. The participant then got stuck in functional fixedness, iterating only through already proposed strategies, with the only novel improvement being his realization that surfboards have a ventral fin on which the duster could be attached in a more stable manner.

7.3.2 The case of fb6

Participant fb6 is a female Business Psychology graduate student, with advanced English skills. Her estimate of her problem-solving and creativity skills were 6 and 5 respectively pre-test, and 5 and 4 post-test. She rated her performance as 4 and considered she had enough time. Fb6 solved 5 problems, provided a partial solution to the hat rack problem, and multiple solutions to the Dusting the Clock problem.

P1 - Jack and Jill weight problem - solved in 2m 40s, difficulty rated by participant as 4.

Fb6 read the problem, then proceeded directly to a solving path which focused around the small swimming pool, involving implicitly Archimedes' principle. The solution state was then compared to constraints: *"Then they would know how much the volume is there ..."* (intonation emphasis on word volume) *"I don't know if that helps for the weight, but it should, kind of..."*. After switching attention to other objects, fb6 redefined/reiterated the key requirements of the problem, trying to find a path to a solving template. Then she made comments attempting to determine the affordance of using Archimedes' principle as a template, comparing volume of water (affordance of said template) to requirements of the problem: *"If I have a certain amount or volume of water, will it weigh as much as a certain amount of human? I'm not entirely sure"*.

Fb6 then applied the same template to other objects, showing some possible process of search for suitable objects with the same template. Still, a gap remained between the affordance of the template and requirements of the problem:

> *"Same you could do with the little shovel and the bucket like (laughs)... bury yourself in the sand an see how much sand is coming out and then weigh the ... they don't have a scale to weigh the sand, but they can see how much sand there is..."*

After comparing solution state with constraints again, fb6 continued with determining template affordance: *"But still, it doesn't mean... that just helps me to see who's... who's bigger. That doesn't help me see who's heavier"*. Discarding the template for the moment, fb6 started switching to other objects as focus. The object chosen was the surfboard, on which fb6 proceeded on a object based search of template. The initial template yielded by that search was a traditional one - standing on the surfboard. Fb6 attempted to adapt this to the context of the problem: *"Stand on the surfboard and see how far it... yeah... it goes down in the water"*. Fb6 then compared the solution state to goals of the problem, evaluating, determining template affordance, and trying to further adapt the template to the goals of the problem by putting both Jack and Jill on the surfboard. After this, using the surfboard as a focus object for a template search and to build a solution around yielded the solution:

> *"Or... I don't know if that works but like... switch the bucket around, put a surfboard on it, they both stand on a side. It might work as the - how is that called - like on a play slide?"*

P2 - Attach pendulum - solved in 8m 5s, difficulty rated by participant as 6.

After reading the problem, fb6 started taking stock of the problem objects, and determining some object affordances: *"I got a sock, this is the pendulum, I got nails. I got ... umm... glasses and what's that? A string. So I got a ladder so I can reach the ceiling. That is good already"*. She noticed the need for the hammer straight away, while checking the joints in her plan. She then proceeded to construct a partial solution, using the objects she already knew were part of the solution. She then proceeded to search for a hammer replacement based on properties (something she called "stability", but can be inferred to represent solidity/hardness of the object, as the participant is not a native English speaker). She focused on various objects, trying to use them as replacement, and showing a particular fixation with the sock. Fb6 attempted to improve/adapt replacement objects as to fit her property criteria:

> *"Maybe if ... I mean I could wrap them (the sunglasses) in this sock like help for stability, and then use that if I like fold them together and wrap it in the sock, use that to hammer in the... the nail [...] what is this sock doing there? [...] or if I ... wrap the sock around the... the ball of wire, will that be hard enough to use it as a kind of hammer thing?"*

Continuing the use the object template of a hammer: *"So let's go on with my idea to try to build a ... a hammer"*, fb6 attempted to let go of the red-herring sock object: *"I just don't understand what the sock will help me for, it's... or maybe not every object is important for me. That could be, too. I just... They're just there to confuse me, so... "*

After checking the other parts of her template construct of attaching the pendulum to the wall and re-determining object affordance in the current plan, fb6 showed all signs of being stuck for a while, with statements like: *"I feel like I can't really figure it out in another way. Or if I just... I don't know ... I don't know. I don't see another way."* and *"I am ... kind a... at a dead-end here I feel"*. Fb6 attempted to exit this state by focusing on different objects, and checking whether objects she was already using were necessary in her solution construct, or could indeed have different affordances. This helped her see the double use of the pendulum, as a consequence of the property of its material: *"I can use the pendulum if it's hard enough to hammer the nails in the ceiling. I mean it looks like it's (giggle) made of metal."*

P3 - Blown away teddy - solved in 4m 40s, difficulty rated by participant as 3.

Fb6 read the problem, mapped the problem formulation to objects (bear, garden), then focused directly on the stick of the broom and started constructing solutions around it, along it's length property. When prompted that this might not be long enough to reach the bear, fb6 continued searching for objects with the length property: *So wow now I can take the clothesline because it's a long wire.* Fb6 then proceeded to attach the clothes hanger at the end of her construction, and considered this similar to a lasso in it's uses. Then the object template was adapted to the hook of the clothes hanger: *"throw it and hope that with the hook of the cloth hanger might grab one of his arms or legs or his head and then pull it to me"*.

At further prompting that this might not be long enough, fb6 proceeded to make other constructions: using the clothesline and the broom, with the broom end "shoveling" the teddy (definitely not the traditional use for a shovel, but apparently in the participant's template). Fb6 then switched focus to other objects, by taking again stock of the objects presented in the problem scene: umbrella, sunglasses, bucket. The same shovel object template was then used with other objects, like the clothesline and the umbrella. The participant then investigated the properties of the clothes, discarded their use, and then proceeded to determine affordance and uses of objects she deemed more suitable:

> *"I got this clothes hanger which I really like where I think I would like to do something with them. So if I maybe... open up, I mean they like like they're just made from wire like metal wire. Can I open them up, tie them together somehow they're a long line, and just make a hook at the end and then grab it like this."*

This together with a comparison to goal state allowed further construction until something like a fishing rod template solution was built from the umbrella stick, the clothesline and a clothes hanger, cast as a hook.

P4 - Attach to loop - not solved, difficulty rated by participant as 5.

After reading the problem and taking stock of problem objects, fb6 proceeded on a solution path which involved putting a paperclip around the loop. She then persisted in this template, attempting to improve it with various nail constructions and then manifesting functional fixedness. She attempted to force the solution by nailing the cardboard to the ceiling. When exiting functional fixedness, fb6 had two other template switches: she attempted to build some short form of paperclip chain, or to use the hammer itself for attaching to the loop. She then attempted to force the solution again by folding the cardboard and putting it on the loop.

Finally, she admitted to being stuck and made remarks on her own process about functional fixedness and only coming up with different ways of modifying the attaching point to the loop: *"Everything that comes to my mind are almost the same things that I've already said, like just a different... where I'm framing them... to the loop in the ceiling"*. She proceeded to reiterate the paths she could think of, until the time allocated for the problem run out.

P5 - Dusting the clock - multiple plausible solutions provided, difficulty rated by participant as 6.

Fb6 read the problem, then framed the key requirements as Johnny's property of being too small to get to the clock. She then took stock of part of the objects in the scene, and determined the lack of affordance of stacking on the chairs, from what she later revealed to be personal experience. She then made a first attempt to attach the dust cleaner to the tennis racket, possibly based on their length property which translated into an arm elongation affordance, without finding any object suitable to produce such attaching.

Fb6 proceeded to search for objects to construct a platform or a high construction to put Johnny on in parallel with searching for objects to elongate his arm. She thus realized she could disassemble a part of the ice skates to use for this purpose:

> *"Okay, I can use the laces of the... ice skating shoes to attach the duster to the tennis rack. Should be possible, so I've got a longer duster, and... so that is already a little bit of... that is already closer."*

She then constructed in parallel a platform made of a chair and the table, to make Johnny taller. Fb6 then started taking stock of the problem objects again, switching between them and determining their affordance in the context of the constraints. She thus discarded the surfboard *"I'm not sure you can really climb on it"*, the globe, the chessboard. Fb6 then made meta-remarks on her own process: *"Okay, right now I'm just looking at all these different things, trying to figure out how... which combination can be of any help."*. Fb6 then focused again on the surfboard, using it in the context of a platform template, with the two chairs arm rests as support. Commenting on the new straight surface property obtained, she proceeded on inferring more affordances, and considering what other objects she could put on top.

After focusing on different objects, she proceeded on object-based searches of template - leaning the surfboard on the wall under the clock, swinging on the lamp on the ceiling using the shoelaces, which she evaluated as very dangerous and *"not good for little Johnny"*. Fb6 then got in a functional fixedness place, and continued to iterate previously offered paths, and slightly improve on some - for example using the surfboard as a platform on top of the two chairs, then putting the table on it, then the globe, made unmovable by using the shoelaces, etc.

After attempting this problem, fb6 showed some signs of tiredness, which generally manifested in her stating the goals or key requirements of the problem at hand much more often, possibly in an attempt to refresh her own memory and keep her attention processes directed on the goal.

P6 - Candle problem - solved in 3m 10s, difficulty rated by participant as 3.

After reading the problem, fb6 defined its key requirements, and proceeded directly on the path of using the box of thumbtacks under the candle to protect from drips on the floor. Thus she has seen the box as a possible container for wax drips, but not for the candle itself. She then proceeded to find a way to attach the candle to the wall, which she reiterated as a key requirement. For this, she considered using the wax, which she discarded, using the thumbtacks for their piercing affordance on the candle, which she again discarded. After searching for more objects to fit the fixing to wall requirements, she focused on the matches, on which she then composed fuller results:

> *"So there's the candle... and with the tacks and the matches I feel like I want to build a little holder to the wall, so take four of these so that they make a ... a little thing that I can put the candle in, so that the matches are around it [...]" etc*

Fb6 then proceeded to evaluate her construction, comparing it to the key requirements of the problem: *"Will that hold or will it fall out? Or would it even be too big! I don't know. It should not drip on the floor"*.

Upon returning to the mechanism which she set up for wax dripping (the thumbtacks box, which she called the cardboard in this case - possibly by appeal to a familiar template), she fully realized the solution:

> *"Yeah, there's a cardboard for that. But maybe that's not the solution. Ah! Can I attach it to the wall? Yeah, can attach the cardboard to the wall with the tacks, so that is it attached to the wall on one side, then just stand the candle in there after dripping some wax so that it stands."*

P7 - Hat rack - not solved (partial solution), difficulty rated by participant as 6. Participant fb6 read the problem, then defined key requirements of the problem, and proceeded on taking stock of the measurements offered. Returning to the requirements of building a hat rack, fb6 seemed to start looking for an object template: *"Okay, hat rack... So how is that supposed to look like?"*.

The participant then started focusing on the beams in the ceiling as a pre-existing construction, and aimed to use the planks on the floor to reconstruct a shelf object template with the beams. She proceeded on this path, considering using the walls as part of the shelf sides, and determining whether she could make the assumption of the planks on the floor being long enough to fit between the beams on the ceiling in a shelf construction. She then proceeded on an affordance based search for an object to attach the two planks, which revealed the G-clamp as the only possibility. The participant further determined a lack of affordance in using the G-clamp for this purpose on the ceiling beams, because of their size. Fb6 then further inferred that the G-clamp could be used for its attaching affordance on the planks on the floor, from the measurement of the G-clamp opening and the size of the planks. However, this lead to the further inference that only a certain type of attaching the planks was possible, thus constraining further templates: *"If I just put them like a T together (the planks on the floor), that won't work because I can't use the G-clamp then, so they kind of have to be both horizontal or vertical"*.

Switching back to the previously used template, she reconsidered her assumption over the length of the planks: *"This time I can't just assume they are very long"*. Fb6 then assumed she might be able to infer the length of the gap between the ceiling beams, and then fit her already made floor plank construction between them as to bridge the gap.

Prompted to try in a different way, fb6 switched template and considered using the planks upright, but evaluated this as not working, and then got stuck in functional fixedness on the beams in the ceiling. She tried refocusing on the measurements, however this didn't break her functional fixedness, with her bridging template becoming clearer: *"Let's assume it all comes down to just slamming planks between one of the spaces for me. I don't see another way of doing it."*. She then persisted in this template and functional fixedness, attempting to bridge under various places around and under the beams, and in the corners of the room. She considered and discarded making a hat rack that laid on the floor: *"My hat rack can't just be laying on the ground because it's a hat rack. I have to have it somewhere up..."*.

Backtracking into meta-reasoning seemed to help break the functional fixedness. First, fb6 made the following meta-remark on her own process:

> *"I'm just staring at the plank, some of the measurements, adding them altogether and trying to search for something that fits to it because I hope that that might help me to find the perfect spot for the planks..."*

This brought about a new consideration of the key requirements of the problem, this time retreating from some of the already made assumptions of what type of template to use, having a template switch and the markers of an insight moment:

> *"A hat rack. A hat rack (intonation emphasis on rack), so that is not really a hat shelf... And if I just... a hat rack is something where it hangs on. I know! If I just.... put one of those, lean it up the wall, put the clamp on it or both of them if I can so that it's fixed. Then use the end of the clamp to hang my hat on it."*

Fb6 then had just enough time left do detail this solution. She thus had part of the insight required to solve the hat rack problem - using the G-clamp as a hanger. However, she did not provide the full solution of an upright hat rack between the floor and the ceiling, making the hat rack lean against a wall.

P8 - Two strings problem - solved in 8m 30s, difficulty rated by participant as 5. After reading the problem, fb6 started on a path of using the chair to stand on to attempt to hold both ropes. When this solution was rejected, she backtracked into taking stock of problem objects. She then switched to attempting to attach the two strings to the middle of the ceiling, as to have one fixed. Fb6 thought of using the pliers as a hammer to fix a string in the ceiling (with one of the nails on the floor), thus showing some clear influence of the already solved Attach pendulum problem, in which she created a hammer out of the pendulum.

Under the further constraint that she couldn't reach the ceiling, fb6 switched to a template of elongating the strings, as a prerequisite for reaching both of them. *"Then I have to make the string somehow longer, so that I have more .... that I have at the end the opportunity to reach them both with my hands while standing on the ground"*. For this purpose she decided to use the paper sheets to make a tube and the nails to attach it.

Considering this might not make a long enough construction, she focused on the pliers, used for the ability to elongate one's arm and thus grab one of the strings. Fb6 then got stuck in functional fixedness, running through the solving paths visited before, attempting combinations of them for their various affordances and even attempting to force a solution by ripping the strings of the ceiling.

She then attempted a template switch to exit functional fixedness (attaching the chair to the string), then started considering the various objects again and attempting to find (other) ways in which she could use them (object based search of template). Then a new remark on her own process and the nature of the problem seemed to bring her close to switching to a new template:

> *"I really just feel like attaching different things that I got here to the wire to make wires longer. Maybe that's not the problem. Maybe I'm (not) supposed to make the wires... the strings longer, but... to find the possibility to reach them both, or do I even have to reach them both? Is that even necessary?..."*

After another round of functional fixedness, and considering the previous solution, fb6 finally switched template and came by the correct solution, using for the "heavy" part of the pendulum the pliers *"Put something heavy like attached to the pliers with a knot to the wire ... to string to make it swing like this [...] Then when it swings, it should at some point the pliers should reach my hand"*.

7.4 Analysis of process and codes in the context of CreaCogs

In the following, the codes and their observed functioning in the protocols of human participants will be analysed in the context of the CreaCogs framework and processes, as to bring them closer to a possible future computational model of human practical insight problem solving. Each code will be described in turn with this purpose.

Problem solving general process codes:

PSP - Reading the problem In CreaCogs, this code would correspond to a read-out of the problem environment given as input. This would be a mix of inputting the main objects and requirements of the problem statement, which would need supplementing by the objects and relations in the picture representation of the problem, as not all objects are given in the problem text. Some relations between objects would be provided either via problem text, via analogical representations (e.g. pictures) or via a mix of such means. Most importantly, the problem makes a request of what is to be done. All this of course needs to be interpreted in terms of the knowledge the agent already has. For example, the statement of the Two Strings problem could be translated for CreaCogs as follows:

Objects (or concepts): $(Person, String_1, String_2)$

Relations: $Attached(String_1, ceiling), Attached(String_2, ceiling), Hanging(String_1, ceiling), Hanging(String_2, ceiling)$

Goal: $Tied(String1, String2)$

The problem also provides the constraint that if $Hold(Person, String1)$, then $\neg Reach(Person, String2)$.

PSP - Comprehending This might correspond to building a mental model of the relations the various objects are in, and of the goals. Various stages of comprehending the problem might happen, as the relationships are understood at a deeper level. In a model of human cognition, this would correspond to mapping the problem statement and requirements to items in the KB, then loading a model of the problem in the working memory.

PSP - Defining key requirements of the problem This corresponds in CreaCogs to refining the goals and constraints of the problem. In a model of human cognition, this would mean selecting the goals and constraints to focus on from the given text, and the participant building them in the internal model of the problem.

PSP - Mapping problem formulation to objects In CreaCogs this might imply mapping concept names to positions in the image representation given as a scene of the problem. Also, at this point, some of the other objects which are not presented in the problem statement, but are present in the picture, might be implicitly integrated in the problem statement. In the context of the two Strings problem, some such new concepts and relations could be:

Objects or concepts (from picture): $Jar\ of\ nails, Chair, Pliers, Sheets\ of\ Paper$

Relations (from picture): $Contains(jar, nails)$

Spatial relations (from picture): $onFloor(Sheets\ of\ Paper), onFloor(Jar\ of\ nails)$ etc.

Other details about parts of objects could also be obtained from inspecting the picture, for example, the fact that the person is clothed, which yields new concepts, like $Shoes, Shirt, Pants$, but also new relations, like $clothedIn(Shirt, Person)$, which then require an explicit move on the part of the solver to $remove(Shirt, Person)$ in order to gain access to said objects, the affordances of which can then be used. The model of the problem can then be expanded to contain the $Shirt$ object, and it's affordances.

PSP - Taking stock of problem objects This is an iteration strategy of going over the objects in the room, until an interesting affordance is observed (which triggers a template), or in order to make sure that everything was noticed. This might yield explicit affordances or not (by explicit we mean those referred to in verbalized protocols). However, it is sensible to assume that once an object has been truly noticed, it has been mapped to a representation of the concept in the KB of the agent. Thus it is possible that affordances of the object can be activated with much more ease, and such an activation process might start covertly the moment the objects are noticed. In the context of CreaCogs, this would mean activating the concepts corresponding to the problem in the KB.

PSP - Proceeding on path In CreaCogs, this would be the equivalent of having selected a PT to build the solution around, and then trying to build it, with the given objects, until either the solution or a more complex impasse is reached. Proceeding on path can happen either instantly, with focusing on specific salient objects and affordances, or the most KB-salient yielded PT, or after having selected such objects through cycles of **Taking stock of objects, Focus, Determining Affordance, Determining template, Searching for template**, case in which the codes **PT-Use** and **Composing fuller results based on previous exploration** are more suitable.

PSP - Backtracking In CreaCogs, backtracking can happen on two levels. One is the classical problem solving level, on which a previous state of the problem is revisited, and an attempt at solving the problem proceeds forward from that place again. In the creative problem-solving paradigm, backtracking can also be seen as corresponding to abandoning a problem template, which has been deemed unproductive, and backtracking to a state in which a PT can still be chosen. The abandoning of a PT can happen through a fast assessment and fitting of existing objects, or through a thorough construction proceeding on the path or set of paths (code **PSP - Proceeding on path**) afforded by a certain template. In this case, such "meta-backtracking" would correspond to changing the state of one's working memory to a state in which restructuring, or a **Template Switch** is more easily possible. Sometimes, being stuck in a problem template for a while or seeing no possible solutions (and thus not verbalizing anything new) can also yield such a working memory state, possibly through a decline of the activation of a specific template. Sets of roles assigned to objects can also be abandoned, while backtracking to the state of deciding what to fill the PT with.

For example, let's say the PT used for solving the Dusting the clock problem is that of building a construction of a certain height. Thus a CreaCogs agent can attempt to solve the Goal: $reach(Johnny, clock)$ and Constraint: $height(Johnny) = small$ by increasing Johnny's *height* using PT: $on(construction, Johnny)$, until the *height* attribute of Johnny's arm is deemed suitable to fulfill the *reach* goal. The *construction* automatically inherits the requirement of matching $height_x = height_{clock} - height_{Johnny}$. Objects which would help match that height are required to fill in such a template; the template PT $on(construction, Johnny)$ also brings about implicit stability constraints for the *construction* object. Let's envision a CreaCogs agent which attempts to fill the *construction* element with a *chair* object. The *height* argument is not matched upon further evaluation. Backtracking in this case would be to retreat from previous *construction* arguments and choose other objects, or another object arrangement. For example, an attempt at filling $construction = chair_a, reverse(chair_b)$ can be made. However, this might not match the *stability* constraint, thus further backtracking to the abstract level and considering anew the other possible objects is required.

PSP - Evaluation

In CreaCogs, this could correspond to mapping the constructed solution to other known templates or situations, to check if, at the end of deploying a solution path, the key requirements of the problem are satisfied. Also, implicit requirements might be checked for. For example, in the case of the Dusting the Clock problem, some implicit requirement that the construction has a property of being *stable* might be analysed, because of known consequences of people falling when attempting to climb unstable constructions. Also, requirements for *height* might be analysed - in order for Johnny to reach the clock, his height plus the height of the construction plus, if the construction allows it, the height of his stretched arm plus the length dusting object he is currently holding might be taken into account when evaluating whether they match the height of the clock.

Aesthetic preferences would imply matching the construction to a problem template or object template as close as possible. Thus, the constructed *hat rack* might be compared to some held template of how a traditional or fashionable *hat rack* might look like. Other aesthetic properties might be also taken into account here - cleanliness of lines, simplicity of solution, other preferences for what objects should look like, etc.

PSP - Running through consequences This means applying a chain of affordances after building a new solution composition, and then inferring further consequences and side effects of that partial solution composition. This happens along the course of building a solution, after having put together some elements. For example, in the Candle problem, a CreaCogs agent could construct from PT $light(matches, candle, lit\ candle)$, for the side result of getting *wax* which can be used for its *gluing* properties, or could use $melt(candle, fire)$ to get *slimmer candle*, thus adjust the width property of candle so that it can fit the PT $pin(thumbtacks, o_x)$. However, for the latter, a side effect is *melted candle*, thus the requirements of the problem can't be achieved anymore.

Affordance related segments (Aff)

Aff - Determining object affordance In CreaCogs, this corresponds to explicitly retrieving an object affordance, iterating through object affordances, or applying an object affordance to another object. For example, a CreaCogs agent which has activated the object $Pliers$ could retrieve $aff(Pliers, to\ hold\ objects\ with)$. As we see from the case studies of human participants retrieving such affordances, these are not always retrieved in the abstract, but more often the affordance of an object that has gained focus is already projected through an instantiation of the object's possible interaction with another object. In CreaCogs, this would mean linking the object affordance to another object, thus already creating mini compositions of two object interactions, or the action of an object upon the other. For example, this can refer to the instantiation of the above case affordance as the mini composition $holdWith(Pliers, Sheets\ of\ Paper)$. An affordance thus becomes a mini-template for a tuple of objects, thus the *to hold objects with* affordance is expanded, when starting from the Pliers as a focus object, to $holdWith(Pliers, o_x)$, in which o_x has to correspond to some size/weight constraints to fit the template.

Aff - Inferring more affordances Inferring more affordances in CreaCogs implies interpreting the current context of objects through existing knowledge as to yield new affordances, or building longer affordance chains. For example, given that in the Two Strings Problem the relation $hangingFrom(ceiling, String_1)$ is provided, this could lead to further inferences like $attachedTo(ceiling, String_1)$. Upon consulting such further properties of PTs of Strings attached to ceiling from one's commonsense KB, a CreaCogs agent should ideally provide further inferences (which come from commonsense assumptions) $nailedTo(ceiling, String_1)$ or $attachedTo(ceiling, String_1, nail)$. This allows for further construction and use of objects, upon retrieval of their affordances. For example $aff(Pliers, remove\ nails)$ can be used to interact with the previous stated assumption $attachedTo(ceiling, String_1, nail)$. Thus, if the aforementioned $Pliers$ affordance is developed to its action template form of $remove(hard\ surface, nail, Pliers)$ by applying $remove(ceiling, nail, Pliers)$, the new state would be $onFloor(String_1)$, and the problem environment can then be updated to include $String_1$ as a non-attached, freely usable object.

Aff - Determining template affordance is generally done in the context of the goals and key requirements of the problem. Thus if a PT's affordance shows promise in matching the goal, or bringing the agent closer to applying another PT the affordance of which is the goal, that specific template might be selected. PTs can also be applied and then discarded, after the agent has attempted to bridge the gap towards the goal unsuccessfully. Productive PTs can also be discarded at a shallow glance, though in fact they might have enabled the solution. PTs can also be discarded not because of their lack of a goal matching affordance, but because of an inability to adapt them to the objects at hand.

Aff - Determining lack of affordance Lack of affordance of an object in this context might mean a lack of ability to apply said object affordance to another object.

Thus, in the case of the Candle problem, a CreaCogs agent could initially retrieve the affordance $aff(thumbtacks, to\ pin\ with)$. However, the action template of this affordance - $pinWith(thumbtacks, o_x, medium\ hard\ surface)$, would have constraints regarding the size of o_x that are depending upon the size of provided or prototype $thumbtacks$. Thus, in the context of the size of a prototypical candle, affordance $aff(thumbtacks, to\ pin\ with)$ would be rejected, as $size(o_x) > size(thumbtack\ pin)$, if o_x takes $candle$ as a filler.

Problem template use category (PT)

PT - Requirement-based search of template An initial search of useful PTs can be triggered by a CreaCogs agent using key problem requirements which have been determined. For example, if the goal G of a particular problem is to reach a particular high object, PTs which offer this affordance or have it as a side effect might be searched for, for example $PT_x|\ aff_a(PT_x) = extend\ arm$ or $PT_y|\ aff_d(PT_y) = get\ higher.$

PT - Determining PT to use This can be done in a variety of ways in CreaCogs, by object-based search, property-based search, requirements-based search, or by simply triggering the most salient templates which come to mind from the most salient objects.

PT - Adaptation of PT to problem (goals) In CreaCogs, this means modifying a pre-existing PT_x to fit goals G of the problem, be it by changing parts of PT_x, or by linking/expanding or combining PT_x with another template PT_y as to afford G.

PT - use to search for suitable objects In CreaCogs this means using a PT to search for objects similar in properties or affordance to the inital objects for which the PT was used. This might involve further refinement of various objects of the PT being used as further OT.

PT - Adaptation of problem template to objects A PT can be adapted inherently when various non-traditional objects are cast in it, because of the differences between the new objects and the objects specified by the template. However, these differences can be so large that, after adapting a PT, the agent becomes aware its realization is closer to other PTs than the PT which was adapted, or that the PT resulting after the adaptation is different enough that it can be encoded as a new example in the KB. For example, using a $platform$ PT with the box and the candle (in the candle problem) results in creating a construction which is closer to a partial container template.

PT - use of PT construct In CreaCogs this means applying or re-applying a PT to the set of problem objects. Thus, given PT_x, problem objects $\{c_1, c_2...c_n\} \in C_P$, and problem goals G, fix PT_x in various ways to problem objects C_P so that G becomes possible.

PT - use of PT construct with reaching solution path In CreaCogs this would mean reaching a point in which the solution state matches the goal state of the problem, and optionally external feedback has been gathered on the correctness of the solution.

PT - Rejecting template In CreaCogs, this would come about either after a) inferring not enough objects can be matched to the currently used PT from the given problem environment (Statement + Picture); b) determining a lack of affordance of the template; c) attempting to use the template in various ways without reaching the goal. For example, let's say an initial template PT_x is being used, and Env_z is the environment of the problem, composed of its given objects, the relations between them, etc. $PT_x = \{c_a, c_b, c_c\}$; $c_d, c_e, c_f \in Env$ However if $\nexists c_x | c_x \in Env \wedge (c_a \ sim \ c_x)$ might result in PT_x being abandoned.

PT - Template Switch A PT switch in CreaCogs might happen through: a) abandoning a previous PT, which is considered unproductive; b) a chain of previous affordance inferences or object constructions linking associatively into a promising PT; c) considering a new set of objects as the main focus, or noticing a new object; d) considering a different context for what the goal or its property might mean; e) noticing new affordances or properties of the given objects, or different ways in which these can be linked. A template switch means projecting a new PT on the existing object set, which might involve the required use of certain objects, or their saliency, with the further work of considering what other objects or actions to use to reach the full PT.

Assessment category

A - Checking joints in plan In CreaCogs, checking joints in plan is related to the simple machines example. In the simple machines analogy, motion is being passed between the different machines, and one can check whether a certain simple machine sm_1 can take said motion from a machine sm_4 and pass it further to machine sm_5. In this case, a matching of affordances between objects within a template or a solution plan is checked for. Thus object o_2 is checked for fitting the affordance of object(s) o_3, o_4, etc.

A - Checking object against constraints Objects can be checked property-wise against constraints or goals of the problem in CreaCogs.

A - Comparing solution state to constraints Comparing a solution state to problem constraints or to key requirements in CreaCogs means comparing current affordance yielded by the template used or the object construction to the problem goal.

Focus changes

F - Focusing on object In CreaCogs, focusing on an object when solving a problem would mean starting the search or construction processes based on this object, its properties or affordances, sometimes by creating chains of affordances starting from the object in question. Sometimes, the affordances of the object, and the associate PTs it triggers are the most salient to the agent, and also seem to match some direction of the required goals.

F - Switching to new object as focus means iterating this process with a new object and its associated affordances, templates and properties as the main center of attempting to derive a solution.

Creative problem solving process specific

Composing fuller results based on previous exploration After triggering the affordances of various objects, and checking whether a certain affordance chain holds to get closer to the goal, the entire solving path could be deployed in more detail, and its inferences explored. For example, triggering property $(paper, foldable)$ and the OT of a $(tube, has\ length)$ on it, together with noticing *fixing together* affordances of the *nails*, under a general PT with affordance *elongate* might motivate an agent to further explore this path in more detail.

Insight marker expressions These could be triggered in CreaCogs when a new template which matches the goal and can be deployed on existing objects has been discovered, to check for consistency with human data.

Making assumptions While matching objects to some problem template, not only other objects need to be filled in, but also other relations and properties. In CreaCogs, making assumptions is a matter of transferring such properties and relations (or other pre-existing requirements) in order to be able to apply said template.

Stuck or functional fixedness In CreaCogs, this would apply to moments in which a template or set of templates are applied over and over with different objects, with no actual progress in bringing the affordance of that template closer to the goal.

Forcing solution in CreaCogs would mean: a) applying a PT even if it is not entirely suitable; b) breaking some of the key requirements/constraints or givens of the problem, or modifying them in such ways as to fit a template that is used, rather than attempting to adapt the search for a template to them (approximating solution too low); c) making constructions which are too complicated and too far removed from the initial templates, or from the properties of the objects; d) applying various objects in an OT or PT despite them lacking some of the properties needed, or having other properties which interfere with the smooth creation of said template.

Object (O), Object templates (OT) and object use (OU)

O - Disassembles object In OROC, OTs are disassembled in the KB when attempting to make new composed objects. For the realization of this code, objects in the environment can be disassembled when only a subset of their particular parts is considered useful for the problem at hand, even if the other parts are not used and the object is broken - thus unavailable for its previous affordances. A decision to disassemble an object can follow a property-based search of the object parts.

O - Property-based search of object In OROC, this is one of the mechanisms which powers object replacement. Property-based searches can be done on both simple and composed objects, or on composed object parts, if knowledge of those parts is available to the agent. Properties are searched for in objects generally because it is assumed such properties would provide a certain affordance. Thus a property-based search is also a form of an implicit affordance search in many cases.

O - Adaptation of objects to template This might imply changing an object to fit a particular OT or PT, by either modifying properties - like length, orientation - or using the object for its non-traditional affordances. For example object *matchstick* could be used not for its direct affordance of *setting on fire*, but for it's length, width, solidity. The matchstick could also be broken, a string cut, a paperclip bent, etc. Some such physical modifications can be done with an agents' hands, some require the use of other objects. In CreaCogs this requires a set of object transformations, which can be projected from knowledge of what can be done with thin metal wires, ceramic objects, thin wooden objects, etc.

O - Object used to search for template In CreaCogs, this corresponds to the process of triggering the PT associates of a given object in the KB, and expanding that search to include the PT associates of similar objects, if necessary.

OT - Object template use The use of an object template is similar to OROC's object composition, taking objects as possible object parts of a previously known object, based on object similarity (similarity of property). This also accounts for **OT - Object template adaptation**, as using the parts at hand to compose a particular object from a previously known OT might yield a somewhat different object to the initial OT. Such an object might maintain the initial affordances for which the parts where selected; however, it might also inherit new affordances from these parts. This might produce completely new objects, with new affordances, and sometimes new OT. It is also possible that in the process of creating such an object, the construction itself might be evaluated as being more similar to another OT altogether.

OT - Object template rejection In the context of CreaCogs, rejecting an object template can be done for various reasons: a) because the object parts cannot be found; b) because the OT affordance, though initially salient, has proven not to lead to a productive path; c) because the OT doesn't fit well into the context of the larger PT applied; d) the parts are required for their other uses in different constructions, thus the OT cannot be applied anymore.

OU - Object used in novel way This is similar to OROC's object replacement processes, and also to the answers in the Alternative Uses Test. The process of using an object in a novel way can thus be done via: a) projection of property similarity from another object, which allows the inheritance of new affordances; b) implicitly by applying a specific OT, in which a specific object is matched to take the role of a specific part or c) implicitly by applying a specific PT in which the role of the object has been selected based on one of its properties, but it's not traditionally its most salient role or affordance.

Meta-cognitive

Meta - remark on own process Meta-cognitive remarks on own process could be made available in CreaCogs by simply reporting on the processes used and on the state of the problem-solving process per se.

Other codes

Other - affective state CreaCogs does not include a model of human interest or pleasure in dealing with a challenge. However, such a model could be implemented based on assumptions of what a challenge can be translated to, in computational terms. For example, use of multiple objects in a way which is far removed from their initial use but aligns well in a PT might yield excitement, joy, playfulness, or a sense of freedom. Requirements to go through multiple PTs might yield a sense of challenge through mental stimulation. Reaching a possible solution - thus aligning objects in a PT which provides an end state that overlaps all or parts of the problem requirements might yield contentment, joy at one's success, excitement. Failing to find a suitable PT even after multiple manipulations, or generally being stuck in one PT and following the same path to no avail for a long time, without the ability to switch to a more productive one, might yield frustration, or a desire to abandon the problem altogether. Agents with different personalities and reactions to different levels of challenge, and with different abilities of perseverance, flexibility in switching between templates, fluency in proposing new applications of a template, would need to be implemented to model such affective states and individual problem solving courses in a more diverse manner.

Other - talking about previous experience In the case in which CreaCogs' problem templates would not be implemented directly, but would be a function of abstracting over a number of problem situations, then a CreaCogs agent could talk about these situations as "previous experience".

7.5 Order of process for modeling in CreaCogs

As it could be seen from the analysis of the think aloud protocols with human participants, variations of the order in which the various processes happen in creative problem solving is likely. Also, some participants seem more inclined to use certain processes more than others. For example, mb8 showed a strong propensity to break objects, and a high fluency in switching between various templates, while fb6 showed a relatively high use of refocusing on new objects and object affordances to get herself on a new, more productive path.

In the context of CreaCogs, such observations are important in determining a possible order or flow of running such processes, for a future computational solver. Thus, after certain processes have been run in CreaCogs, the application of other processes should be made possible, in accordance to the empirical observations made in the think aloud protocol.

Though all processes explained in relation to CreaCogs and defined as codes seem important for creative problem solving, various process flow paths can be taken, depending on the individual cognitive agent and their propensity to rely more on a process or another, and of course the content of their KB, the objects they focus on initially (or that seem more salient to them), the OT and PT they associate to various objects.

We will present some of these possibilities of process flow in the following as a list of code implications, sketching various types of process order. The sign → should thus be interpreted in the following as *"can lead to"*. Figure 7.11 represents a non-exhaustive summary of these possibilities of process, as detailed below.

The process starts with **PSP-Reading the problem** → {**PSP-Comprehending**, **PSP-Defining key requirements of the problem**, **PSP-Mapping problem formulation to objects**, **PSP-Taking stock of objects**}. This implies making an initial model of the problem - which might be precise or imprecise, deep or shallow.

Other codes correspond to starting to build a possible solution. This can be done by: a) using initial salient templates and objects: **PSP - Proceed on path → PSP-sol, PSP-Running through consequences, PT-Rejecting template, PT-template switch**. A rejection of an initial template, or abandoning of a problem path, can lead the agent to backtrack to b) or c);

b) building from the object level, by determining and inferring affordances **PSP-Mapping problem formulation to objects, PSP-Taking stock of problem objects** → {**F-Focusing on object**, **PSP-Aff-determine object affordance**, **Aff-determine lack of affordance**, **Aff-inferring more affordances** }

c) attempting to determine a PT to use **PSP-Taking stock of problem objects, Defining key requirements → PT-requirement-based search, O - object search for template, Aff-Determine PT affordance**

An initial selection of a PT can lead to attempts to apply it or adapt it: **PT-Determining PT to use → PT-adapt PT to objects or problem, PT-use PT search for objects.** This leads to further filling in the template with objects, via **Disassembles object, O-property-based search of object, A-checking object against constraints, O-Adapt object to template, OU-object used in a new way** and to processes of partial construction and evaluation: **PSP-Running through consequences, A-comparing solution state to constraints**. If the so constructed path does not lead to a solution, functional fixedness ensues, or an attempt at restructuring by going back to previous processes of switching to new objects to build from or determining a new PT to use.

In the cases in which this leads to a satisfactory solution sketch, this yields to fuller descriptions of solution attempts **PSP-Proceed on path, PSP - Composing fuller solution**. If this is still satisfactory, a solution is obtained, and if time is left an evaluation follows. If this is not satisfactory, functional fixedness or new attempts at restructuring occur.

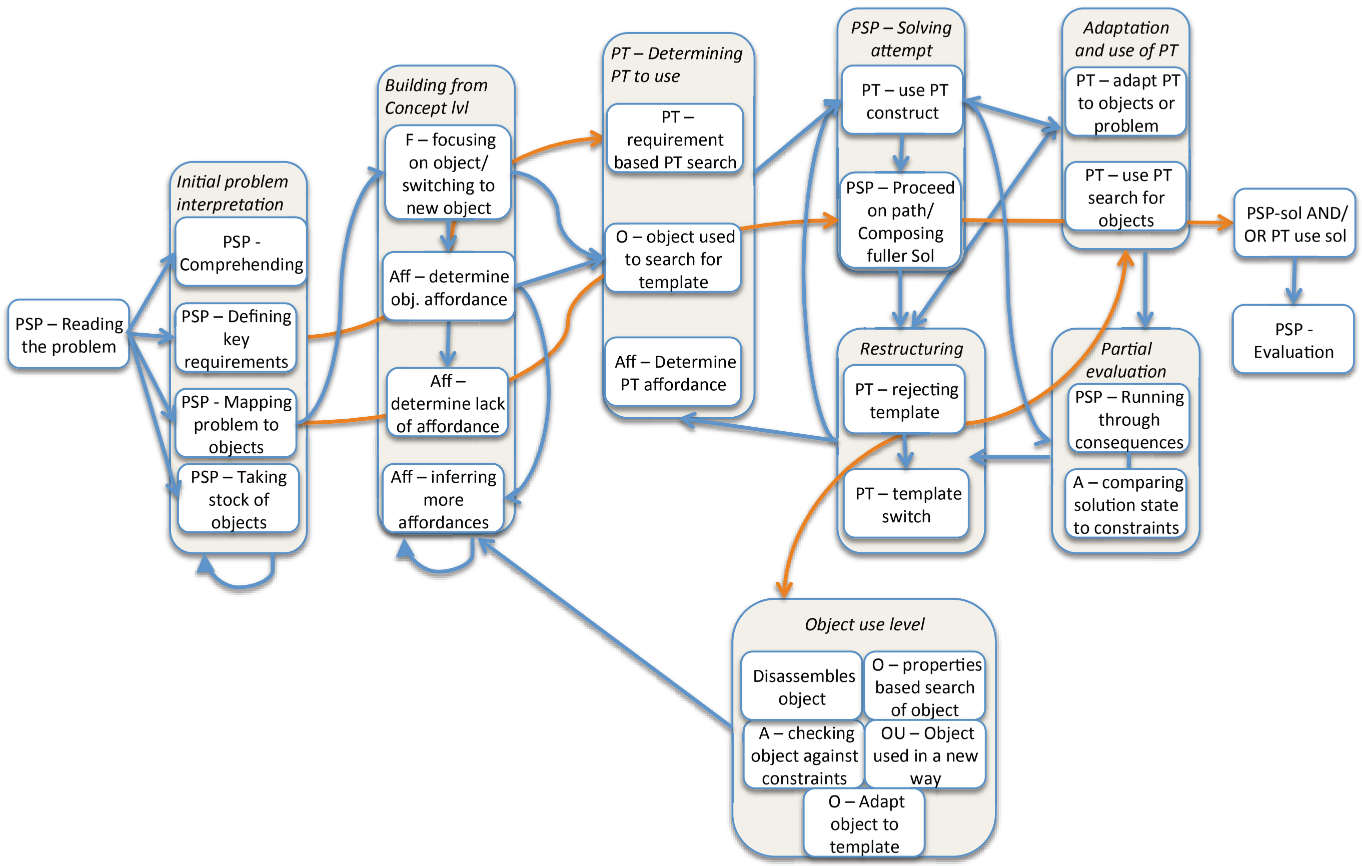


FIGURE 7.11: Summary of flow of processes. The tip of the arrows shows a potential next process. The colour of the arrows is only meant to help readability.

7.6 Towards modeling practical object insight problems in CreaCogs

In order to be able to model insight problems, knowledge pertaining to insight problems needs to be formalized as to be given to the system. A strategy for doing this is to define each practical insight problem as a scene. Each scene contains a set of objects and some particular relations between objects. The following section describes such a set-up in terms introduced in Chapter 4, and possible knowledge required by an agent in order to solve practical object insight problems in a cognitive manner using CreaCogs processes. Two problems are described: the candle problem (section 7.6.1) and the Two Strings problem (section 7.6.2).

7.6.1 Modeling the candle problem

In the candle problem [36], the initial state of the problem contains the following objects and relations (which could be recognized as concepts and relations by the solver upon inspection of the problem):

- C_1 – matchbook
- C_2 – candle
- C_3 – box of thumbtacks OR box of nails
- C_4 – wall
- C_5 – table
- C_6 – thumbtacks OR nails
- R_1 – contains(matchbook, matches)
- R_2 – contains(Box_of_Thumbtacks, Thumbtacks) OR contains(Box_of_Nails, nails)

Each problem has a goal - which is about achieving a certain composed object, a certain set of relations, or performing some action. For example, the candle problem [36] has as a goal:

- C_x = candle_lit
- R_x = on(wall, candle)
- $\neg R_y$ = on(table, wax)

The object in each insight problem can be described in terms of its properties, and relations between its parts if the object is a composed object - as for the OROC system. A set of known problem and action templates can be defined for the KB of a CreaCogs agent. These templates consist of commonsense knowledge about actions which could be performed using the objects in the problem. The formalization of these problem templates can be done in terms of participating concepts or objects, relations, actions to do and solution states (consequences of action), as described in section 4. For example, the following templates are suitable for the candle problem:

PT_1 - how to take matches out of a matchbook: PT_1 = {c={matchbook}, r = {contains (matchbook, matches)}, h=take_out(matchbook, matches), sol = {c= matches}}

PT_2 - how to light a match: PT_2 = {c={match, lighting strip}, r={brushes(match, striking strip)}, h={swipe(matches, striking strip)}, sol={c=match on fire}}

PT_3 - how to light a candle: PT_3 = {c={candle, fire}, r={touches(candle_tip, fire)}, h={light(candle, fire}, sol = {c=candle_lit}}

PT_4 - how to attach poster with thumbtack to wall: PT_4 = {c={poster, pin, wall}, r={touches(poster,wall)}, h={push(thumbtack,(poster,wall))}, sol = {r=attached (poster,wall)}}

PT_5 - using a container to catch drips: PT_5 = {c={leaky radiator, water, container}, h={put(on floor(container), under(leaky radiator, container))}, sol = {r=catch drips (container,water)}}

PT_6 - shelf with vase on wall PT_6 = {c={shelf, nails, wall, vase}, h={attach (on nails(shelf, wall)), put(vase,shelf)}, sol = {r=on(wall,shelf), on(shelf,vase), on(wall,vase)}}

CreaCogs will then use the problem objects and the goals to search in its KB for the most suitable templates to reach the desired state. Parts of the goal can be reached with various affordance chains. For example, PT_1-PT_3 can be chained to reach the first goal - C_x=candle_lit. PT_4 can be used to attempt to attach the *candle* directly to the *wall*, if a search from problem requirements finds that template, by replacing the *candle* object in the *poster* slot. However, a property search would show a candle is too thick for the use of this template.

PT_5 could be used by replacing the *box* object in the *container* slot (as it was the case with participant fb6, and dripping water with dripping wax. If the object *box* was not salient before because of it being part of the C_3 (the box of thumbtacks composed object assembly), this can be salient upon a new search of objects triggered after finding PT_5 with the third requirement of the problem. This solves the $\neg R_y$ = on(table, wax) goal.

PT_6 could be triggered as a response to the relationship goal R_x = on(wall, candle), though it is an indirect way of attaching something to a wall. The object $shelf$ could be created out of *matchstick* parts, which could be found as suitable based on their material (wood) property. Their size would of course prove unsuitable for creating a shelf. However, the application of template PT_6 would allow the agent to understand the entire goal R_x = on(wall, candle) in a different light, thus restructure the problem under a new set of templates, and attempt to make a platform for the candle rather than attach it to the wall directly. Such a restructuring allows the larger use of the object *box*, and can produce its saliency in the problem space, even if this requires a new adaptation of the general template of using a platform, as *box* would provide a mixed platform-container affordance. If the *box* was already used to stop drips, a reuse might become cognitively harder as it requires re-parsing already applied templates to their containing elements, and backtracking from already achieved problem goals - operations which are most likely cognitively expensive. An understanding that the *box* in this case would provide both container and platform affordances, thus answer both the second and third problem requirements, would make the use of PT_5 unnecessary, supporting an evaluation for restructuring.

7.6.2 Modeling the Two Strings problem

The initial state of the Two Strings problem contains the following objects and relations, part of them offered in the problem statement and part in the problem picture:

- C_1, C_2 – String1, String2
- C_3 – Person
- C_4 – Chair
- C_5 - Pliers
- C_6 - Jar of nails
- C_7 - Sheets of paper
- C_8 - Nails
- R_1, R_2 - hanging(String1,ceiling), hanging(String2,ceiling)
- R_3, R_4, R_5 - onFloor(Chair), onFloor(Sheets of paper), onFloor(Jar of nails), onFloor(nails)
- R_6 - holds(Person,String)

The goal of the problem is H_x=tie(String1, String2), and the constraint that in the present object configuration, if R_x=holds(Person,String1), then $\neg R_y$=reach(Person,String2).

Upon closer inspection of the problem, C_3 can be inferred to contain other objects, which may only become salient when a search for objects to elongate strings with is performed: dressed(Person(Pants, Shoes, T-shirt). Also, the opposite of the constraint will be inferred, thus if R_y =holds(Person,String2), then $\neg R_x$= reach(Person,String2). The agent might inspect the components of C_6 - Jar of nails.

At the beginning of solving such a problem, various objects can be taken as a focus. A focus on the *Chair* object would trigger its affordance to be climbed upon, which is generally associated with *reach higher* templates, the activation of which might also be primed by a previous problem like Dusting the clock.

The goal action H_x=tie(String1, String2) can trigger different templates. The more general template of tying things together (out of which one is a string), might look like the following:

$PT_1 = \{c = \{o_1, String\}, r = \{overlap(o_1, String2)\}, h = \{tie(o_1, String)\}, sol = \{r = tied(o_1, String)\}\}$

In order to ensure the overlap or closeness of the two objects, two paths might be taken. Templates of elongating the String might be triggered, if the lack of affordance perceived in order to satisfy the tying things together template is that the objects are not long enough. Templates of bringing things closer together might also be triggered, as a prerequisite applying the tying affordance.

$Goal(tie(S1, S2)) \implies close(String1, String2) \implies PT - bringing\ closer$

$Goal(tie(S1, S2)) \implies tooShort(String1, String2) \implies PT - elongate(String1)$

Templates like the following might thus be triggered:

- PT_2 - bring objects closer: $PT_2 = \{c = \{obj_x, obj_y)\}$, r=\{far($obj_x, obj_y$)\}, h = \{move($obj_x, point_x$), move($obj_y, point_x$)\}, $sol_2 = \{r = close(obj_x, obj_y)\}\}$
- PT_3 - elongate string: PT_3 = \{c=\{String, obj_z\},r=\{close(String, obj_z)\}, h=\{attach (String, obj_z)\}, sol_3=\{c=longer String\}\}

The application of a template of elongation would yield an object search on what objects could be used to elongate the String. In this case, various objects might be used in alternative ways: the clothes of the person; the sheets of paper on the floor, folded as to resemble a string in width and fixed together; pulling one of the strings itself from its fixed place (though this could also be triggered by a bringing objects together template); the pliers, jar and even chair. When using the pliers or jar, the insight that the object thus obtained would move like a pendulum can emerge from the agent's commonsense knowledge.

Another template which could be used might be reflective of the constraint of the problem - which is a lack of ability to reach the other object. Other than elongating the string so it can be reached, this, together with the affordance of the pliers object to be held in one's hand and to grab onto objects with, might yield the special case of elongating one's hand and thus using the pliers in order to reach further. A possible development of the template in that direction which we haven't yet seen in human participants would be, for example, to attach the open pliers to the chair and attempt to reach further when grabbing the other string.

Bringing things together can in itself be done in various ways: (i) moving both obj_x, obj_y at once, which is made impossible by the constraint of not reaching the second string when holding the other; (ii) moving one object at a time, but only if the object remains fixed, which would trigger other *fix object to point$_x$* templates - which are visible in the human participants' attempts to fix one of the strings to the ceiling or to one of the walls; (iii) through personal motion; (iv) through the motion of a second agent that accomplishes that task (sometimes human participants ask if they have someone else to help), or the motion of the object itself - a reframing which generally triggers a productive template, if a way to make the object move by itself in a suitable way is found.

7.7 Discussion and future work

The think aloud protocol set up in this section with practical object insight problems has shown that: (i) new practical object insight or creative problems with one or multiple solutions can be created following a strategy; (ii) a set of codes corresponding to the CreaCogs framework can be derived to suitably analyze such data and (iii) the CreaCogs framework shows promise in modeling the processes used by human participants when solving such problems.

An initial question was whether the human participants will consider the created problems to be problems which require insight and/or creativity. In terms of them requiring insight, only an fMRI scan could issue a strong answer on this matter. However, the various codes which we used for marking restructuring and insight showed that participants manifested both in the context of the newly created problems. The Jack and Jill Weighting problem comes perhaps closest to classical insight problems, in terms of requiring one specific type of restructuring to solve. The Dusting the clock and Blown Away teddy problems were built to allow for multiple solutions, and thus prompt the participants to deploy a variety of composition and restructuring processes in a rich problem environment which allowed it. In order to have turned these latter two problems to a form closer to classical insight problems, we would probably need to remove many objects and allow for one possible reliable solution. In terms of future work, these problems could be given with one solution only, and in various conditions which would trigger more or less functional fixedness and different ways of (unproductively) structuring the problem. A strong control over such variables would allow the further study of structuring and restructuring costs. These costs might be different for different individuals, however this could be accounted for by deploying other creativity tests previously. For example, the Alternative Uses Test, and measurements in Fluency and Flexibility might correlate with the number of restructurings over solving period per participant. In terms of future work, a larger battery of such problems could also be created, and used for gathering normative data, and for the knowledge acquisition of systems aiming to solve such problems or to work with creative uses of object affordances.

The set of codes described in 7.2 shows that there are differences and overlaps between classical and creative problem solving. Classical problem solving is generally seen as the search for a path in a problem space, using operators or functions which move the solver from one state to another. Creative problem solving shares evaluation (looking at the goal to check if one is approaching the solution, or has reached it), backtracking and the exploration of one already framed problem space with classical problem solving. However, the problem space can be restructured in creative problem solving, thus yielding a possible different (interpreted)“initial state” depending on what objects are considered salient in the environment, and what object templates, affordances and problem templates are activated in the KB of the solver. The problem goals can also be restructured in creative problem solving, as they are sometimes ambiguous and therefore can be interpreted in a variety of ways by the solver. During such creative solving, objects which did not exist in the given environment can be brought forward from the KB of the solver, and then created in the problem space. This changes the problem space, and the possible states to be reached from it. The operators in classical problem solving correspond loosely in practical object insight problems to: a) object moves; b) projection of object affordance on other objects and c) composition of new objects and templates using object property and affordance chaining.

For future work, a computational prototype of the CreaCogs framework will be implemented to solve the set of practical object insight problems described in this chapter. This requires the formalization of a set of problem templates, which could be acquired directly or indirectly from human data. A direct strategy would be to ask human participants to provide such templates regarding a set of objects. An indirect one would be, for example, to analyze, extract and formalize part of the templates used by participants in this think aloud protocol, and use the rest of the sessions as comparative data points to the prototype's solving process.

Such a system could further be used to automatize the creation of practical object insight problems. This could be done, as shown in section 7.1.2, by reversing the process of creative problem solving, as follows: (i) using object and problem templates to generate problems and solutions; (ii) creating the possibility for the solution to be found by placing objects with similar affordances as to fit the object and problem templates in the problem environment and (iii) adding different other objects to the problem scene which would provide an interference effect by triggering different templates.

7.8 Conclusion

Three new practical object problems were designed, and a think aloud protocol of a collection of 5 classical insight problems + 3 newly created problems were given to human participants. A set of codes reflecting the CreaCogs framework was deployed to analyze the think aloud protocols. Two case studies of highly performant human participants solving these problems were presented. The codes and their correspondence to processes which already exist or can be implemented in CreaCogs was explained. A summary of process flow was analysed. Two such problems where worked manually to show how they would be solved under CreaCogs. The framework shows promise in an ability to model the solving of practical insight problems. As future work, this analysis will be used to implement a computational model for solving such problems. For this purpose, a set of PTs need to be formalized and added to the KB. The data obtained from human participants can further be used for such cognitive knowledge acquisition.

Chapter 8

Discussion, Conclusions and Future work

An overview of the contributions of this thesis will be presented in Section 8.1. The experimental contributions will then be discussed in the perspective of the larger framework in Section 8.2. A general approach to modeling systems from a cognitive comparability approach will be proposed in Section 8.3. The conclusions are then presented in Section 8.4 and the future work perspective in Section 8.5.

8.1 Overview of contributions

The main contributions of this thesis have been the following:

1) A theoretical framework of the creative problem-solving process has been proposed in Chapter 3. This is cognitively-inspired and aims to enable AI agents with a wide scale of creative problem-solving capabilities. The framework proposes that certain types of knowledge organization might help enable creative processes.

2) A formalization of the representations and processes of this theoretical framework has been presented in Chapter 4, together with examples of how these processes can describe creative problem solving in various domains.

3) Experiments have been conducted on prototype implementations of these processes in different problem domains. These prototype implementation contributions are as follows:

(a) A Remote Associates Test computational solver was implemented (comRAT - Chapter 5), which offers correct and plausible results to the RAT creativity test, and has been compared to human data;
(b) A proof of concept expansion of the Remote Associates Test to the visual domain, and of the computational solver comRAT-C to comRAT-V has been performed in Section 5.9;

(c) A creative object replacement and object constructor in an everyday object domain has been implemented (OROC - Chapter 6) and evaluated with human judges and categories from a think aloud experiment

4) Empirical data has been gathered and analyzed on the human creative solving of various tasks, and on the comparability between human data and data from the prototype systems. This has taken different forms:

(a) Comparability data between the performance of the comRAT-C system and normative human data when solving compound RAT queries;
(b) An initial prototype of a visual variant of the human Remote Associates Test was set up and related data on human performance was collected;
(c) Comparability data has been obtained between the object replacement system and human answers to the Alternative Uses test. Likability and Usefulness metrics of human appraisals of performance on AUT where investigated together with the traditional Novelty metrics. Data on property use in new answers to the Alternative Uses test has been analyzed;
(d) A process for developing practical insight and creative object problems has been explained, a think aloud study has been conducted and think aloud protocols have been encoded in a model shown to correspond to processes in the CreaCogs framework in Chapter 7.

8.2 Experimental work and the CreaCogs framework

The CreaCogs framework aims to provide theoretical support of knowledge organization for the enabling of creative processes across a variety of tasks. The experimental work performed has shown that the CreaCogs principles of knowledge organization can enable creative processes, with results comparable to those of human participants to a variety of creativity tasks.

The prototype comRAT-C system has shown that associative convergent processes can be used by a computational solver to successfully match human performance in the compound Remote Associates Test. The use of frequency of expressions in a probability of finding the answer algorithm has correlated with human performance in such problems, thus providing further validation that the principles used here reflect some of the cognitive reality of solving such tasks by human participants. This correlation can further point the way towards developing comRAT-C as a model for solving the RAT, and exploring various hypotheses in order to further understand cognitive solving. Furthermore, comRAT shows promise to become a generative system, which can be used for further cognitive investigation of the RAT task with controlled variables.

The construction of a visual RAT test for humans enables further comparison of cross-domain process in solving the RAT. This is the only creativity test that we know of which can be administered in two different forms, corresponding to two different modalities.

Such cross-domain investigation will enable further differentiation between modality specific proficiency and creative process proficiency when solving the RAT. The implementation of comRAT-V has shown that the same computational principles can be applied to both variants of the RAT test. More data is needed to make a strong argument about a correlation between comRAT-V's probability of solving queries and human cognitive difficulty in solving the same queries; however, the analysis with current data shows that this correlation will be achieved with the visual test as well as the compound verbal one.

The prototype OROC system implements use of property similarity between concepts, to enable object replacement and object composition, which further allows creative transfer of affordance between different objects, as posited by the CreaCogs framework. OROC shows that such processes can yield creative answers similar to those made by humans, and which can be evaluated with similar metrics as human answers using the Alternative Uses Test. Such answers have been appreciated as on Novelty, Usefulness and Likability by human judges. A comparative analysis to human processes of solving the Alternative Uses Test from a think aloud protocol has shown that property use and disassembly are some of the main strategies which enable humans to solve such problems. Both of them can be accounted for by OROC. Further analysis of the answers given by our participants to the same objects as OROC to the Alternative Uses test have indicated that shape and material are the most used such properties when making a creative inference about the ability to use an object with a new affordance.

The think aloud experiment performed on human participants with insight and creative object problems has shown that their solving processes find correspondence in the CreaCogs processes of object replacement, composition, and restructuring using objects and templates.

The creation of a few new practical creative problems has helped us propose a set of strategies for building such problems. These strategies can in the future can be used for building a larger set of problems, on which normative data could be obtained, and which could be studied in varied conditions (with various interfering objects, with one or multiple paths of solving, with the solution split over a smaller or larger set of objects, made more or less salient, etc.). Furthermore, the existence of such strategies enables the further computational implementation of a system that can generate such problems.

The creation of a set of codes for analyzing these think aloud protocols has shown that human participants indeed apply many of the processes posited by CreaCogs when solving such problems, for example: (i) they focus on various sets of objects and object affordances when solving such problems; (ii) such affordances are linked into a constructive whole; (iii) they use property-based search to select replacements for missing objects; (iv) they search for objects with a problem template in mind; (v) problem templates are searched for and adapted in order to find something templates corresponding to problem requirements and problem objects; (vi) problem elements can be restructured under various templates brought from the KB, which sometimes adds the creation of new objects to the initial problem elements, etc. The same processes for object replacement and object composition can be used for implementing a CreaCogs prototype computational solver of practical insight problems, together with other processes posited by CreaCogs related to problem template search and re-representation of the given problem objects under various templates.

The principles proposed by CreaCogs thus show (i) validity for a unified implementation which will enable artificial cognitive systems to perform a wide variety of creative solving tasks and (ii) promise in terms of developing tools which can further be used for the cognitive modeling and exploration of such tasks in the wider goal of understanding human creative cognition.

8.3 Towards generalizing a comparability approach in creative computational cognition

A general approach for the building and assessment of further systems which yield comparable results to humans in creativity tests and tasks can be extrapolated from our previously described work. Such an approach would involve the following steps:

1. Choosing a human creativity test the results of which are to be replicated via an artificial cognitive system, or choosing a creative problem-solving skill that is more general and enables some adjacent empirical validation[1].
2. Obtaining human normative data or using such data from the literature, where available.
3. Finding a source of knowledge for cognitive knowledge acquisition (like the n-grams from a balanced language corpus used for the KB of comRAT-C), or establishing forms of knowledge acquisition and organization which are cognitively inspired. Such forms of cognitive knowledge acquisition and organization which might yield further validating cognitive results. For example, the OROC solver demonstrates other cognitive effects, like shape bias [72, 88], comRAT-C correlates to human difficulty, etc.
4. Implementing a system which uses cognitive processes, like association, use of similarity and structure, re-representation, etc.
5. Evaluating the results of the artificial cognitive system using either or both of the following: a) human normative data and b) evaluation techniques used for assessing the human creativity task.
6. Deploying data analysis measures to observe new possible relations of scientific interest.
7. Aiming to model such tasks in multiple sensory domains, if possible, as to gather unified data of the creative process.
8. Aiming to enable the artificial cognitive system with generative abilities for that particular test or task (if possible), as to allow for new empirical testing of human participants with controlled variables. This will lead to both further refinements

[1] In the example of our previously described work, the general creative problem-solving skill was creative object replacement, and the specific human test used for validation of part of the processes implemented was the Alternative Uses test.

in the hypotheses about cognitive creative processes, and the enabling of better systems.

8.4 Conclusions

A theoretical framework called CreaCogs was proposed for creative problem solving. The processes types of knowledge organization in this framework have been formalized. A computational solver for the compound Remote Associates Test was implemented using CreaCogs (comRAT-C). The agreement of response between comRAT-C and the human data was 97.92% in the cases in which the 3 query items plus answer were present in its KB, and 30.36% in the cases in which only 2 query items plus answer were present in its KB. comRAT-C showed an ability to give other plausible answers than the ones considered correct. A moderate inverse correlation has been observed between time taken to solve a query by humans and the probability of finding a specific answer by comRAT-C. A moderate correlation has been observed between the percentage of participants solving the test and the probability of finding a specific answer in the comRAT-C KB. Both correlations proved highly significant. A method for empirically investigating preference of answer in the case of multiple possible answers and its relation to frequency were proposed.

A visual variant of the Remote Associates Test has been constructed and explored empirically with human participants. Visual associates given by human participants were used as cognitive knowledge for the KB of comRAT-V, a prototype system meant to solve visual RAT queries. The vRAT queries constructed showed different degrees of difficulty. Human participants have solved successfully 63% of the given queries, and reported to have first perceived the answer visually in 56.6% of the cases. The comRAT-V prototype solved 72.73% of the given queries. Analysis on the limited amount of data showed a correlation between comRAT-V's ability to solve queries with given visual associates and the difficulty of the queries as appraised by human participants which might prove of future investigative interest. The process of creating vRAT queries which has been established as part of this work can be generalized and applied to construct a larger set of visual queries, on which normative data can be obtained. The cognitive acquisition of more visual associates could also enable the production of a set of such queries, using the generative properties of comRAT-V.

An Object Replacement and Object Composition (OROC) system was also implemented using CreaCogs. The system was shown to solve the Alternative Uses Test - a creativity divergent thought test used for humans. An evaluation of the results of OROC was carried out using the same methods used to assess human performance in the Alternative Uses test. Part of this evaluation was done using human judges which assessed the Novelty, Likability and Usefulness of OROC's alternative use answers. This assessment has shown a reasonable amount of inter-agreement, and Likability and Usefulness were shown to positively correlate with each other. OROC's processes were also evaluated taking into account analyses performed on human data obtained from think aloud protocols. Human answers were analyzed to determine most important properties when making creative affordance inference.

Five classical practical insight problems and three newly created practical problems where given to human participants to solve in a think aloud protocol. A set of codes was developed to analyze the think aloud protocols of the participants. Two case studies of the best performing male and female participants have been described. The developed set of codes shows many of the CreaCogs processes can be found in the human solving of such problems. The various possibilities of process flow during such solving have been explored, and two problems have been described in the context of CreaCogs, in preparation for a prototype solver of such problems. The strategies described for building new insight and creative practical problems can be used in a further computational implementation to generate such problems.

This thesis has shown that a unified framework for modeling diverse creative tasks and processes is possible. The proposed theoretical framework - CreaCogs - and its processes have been shown to reflect interesting creative properties and the implementation of various creative tasks has further confirmed the validity and usefulness of the proposed framework. Furthermore, the application of these principles has shown that computational cognitive systems which give answers similar to those given by humans in creative tests can be built and evaluated in the same way as human answers.

8.5 Future work

The breadth of this thesis opens a wide avenue for further work. Main directions of further work are presented in the following list, part of which are elaborated below:

- evaluating and informing more parts of the model with quantitative and qualitative human data;
- improving the OROC model by adding a subsymbolic layer, learning directly from sensory data stimuli and producing metric distances;
- developing a practical insight problem solving system;
- using the generativity part of these systems to refine cognitive hypotheses;
- developing and implementing more of the constructive creative processes posited by CreaCogs (like concept creation, PT creation, etc.)
- further work in the direction of classifying creative problem-solving types depending on the processes they employ;
- philosophy of information work on the impact of structured cognition on informativity measures (for a position paper on this see [120]);
- applying the principles deployed here to make creative assistive systems.

The comRAT-V system shows promise in terms of extrapolating the same principles to a multimodal series of the Remote Associates Tests. However, only 20 queries have been designed so far, in comparison to the 144 queries for the linguistic compound RAT provided by the literature [11], together with normative data. A larger set of visual queries needs to be constructed. More visual associates need to be gathered either by (i) asking human participants to provide them or by (ii) establishing a way to automatically extract visual associates from images of groups of objects or scenes. More such data will enable stronger conclusions to be drawn regarding the correlation between human participants solving the RAT-V and the processes employed by comRAT-V.

The difference between functional and compound Remote Associates can further be explored by implementing a comRAT-F system which takes as knowledge base a set of functional associates. Part of this could be done using an ontology, and different relations could be obtained by other means. The relations between functional and compound items in terms of the visual variant of the RAT test can also be further explored. The relationship between visual, semantic and linguistic items can further be explored through a paradigm which employs a mixed version of the test, which we will call RAT-CV. Participants to such a version can previously be tested for both language and visual skills with established tests. Then their performance in RAT-CV together with data in their performance in language and visual tests can be analyzed in order to discern between creative ability of bringing forth associates, and specific fluency in a particular modality.

A strategy could be developed to enable comRAT to solve, on its part, visual and language mixed queries. This could be done by either (i) improving the visual associates database or (ii) using the semantic web and/or data mining strategies. The relation between processes using visual and language queries could then be studied further computationally.

Further comparison of performance and response times across compound and functional versions of the RAT will allow for a better understanding of the processes deployed in such a test.

The generativity properties of comRAT-C can be explored in order to create well controlled Remote Associates tests to further investigate various cognitive hypotheses, including but not-restricted to: (i) human preference of response in the case of queries with multiple answers; (ii) influence of query and answer terms order on query difficulty; (iii) influence of frequency of items over human appraisals of queries as more or less creative or surprising; (iv) influence of semantic domain on difficulty.

Adding different knowledge bases to comRAT-C in collaboration with linguists might help generate Remote Associates Tests in languages in which such tests are non-existent.

A subsymbolic implementation of the proof of concept OROC system will add to its cognitive validity, would permit further development of the system and the further investigation of the impact of property similarity on creative processes. The subsymbolic layer could be developed as to learn from given sensory data, case in which the similarity functions over feature spaces could be implemented at a subsymbolic level too. The refinement of such similarity functions in comparison to human performance might enable further models which aim at explaining why certain objects are triggered as answers in the Alternative Uses test more than others.

Designing an Alternative Uses test of a larger scale, meant to gather normative data for human performance with a set of everyday objects will have an important impact on: (i) further understanding of the importance similarity of property has on creative processes; (ii) finding out how often composition and decomposition strategies are used; (iii) performing knowledge acquisition for the development of an everyday object domain creative problem-solving system, which could aim to solve ampler problems involving the creative use of objects.

Designing a multiple condition Alternative Uses test might help determine the importance of shape and other feature similarity for humans, and the influence this can have on the creative object uses they come up with. This will allow integrating more fine-grained knowledge about shape and size into OROC, and modeling more refined hypotheses about the influence of property similarity and composition-decomposition strategies in object replacement and object composition.

Further increasing and refining the knowledge base of OROC with more objects and more fine-grained properties will probably allow it to perform the Wallach-Kogan test successfully, thus establishing a new comparison point with normative empirical data.

An object composition creative test can be designed in order to establish normative points of reference in human performance in this task, and further evaluation and development of OROC's object composition module. Computational investigation of shape-based composition, use of object templates,"fitting" of new objects to older templates and investigation into what shapes seem more suitable than others for composition might bring further advances for AI and robotics.

A computational proof of concept system needs to be constructed for solving ampler creative problems and practical insight problems. With the knowledge gathered in chapter 7, this is now possible. However, a mechanism of performing knowledge acquisition of problem templates from human participants needs to be designed.

Our theory of how insight problems can be created can and should also be tested. A possible way of doing this, if a computational system able to solve such problems and with enough knowledge has been built, would be to automatically generate such problems using the hypotheses presented in 7.1.2 and empirically evaluate such problems with human participants. fMRI or EEG techniques could be used in order to check in which cases such problems come closer to the category of insight problems.

Various processes of the posited theoretical framework have been implemented separately. The various parts of the framework need to be integrated in a larger system, adding all these processes together, and investigating their unified properties, benefits and power in solving the tasks detailed above.

Considering the amount of further work which is now possible in order to refine this cognitive framework for creative problem solving and the state of the art in understanding the creative process via both computational and empirical means, we consider the current work has fully reached its purpose.

Appendix A

comRAT Human and System Answers

Table A.1: List of Compound Remote Associate Test Queries, Human and Solver Answers for comRAT v1

No.	Query	System	Human	Correct	Plausible
1	Cottage Swiss Cake	Cheese	Cheese	Yes	-
2	Cream Skate Water	Ice	Ice	Yes	-
3	Loser Throat Spot	Sore	Sore	Yes	-
4	Show Life Row	Single	Boat	No	Yes
5	Night Wrist Stop	Surgery	Watch	No	Partial
6	Duck Fold Dollar	Fat	Bill	No	Yes
7	Rocking Wheel High	Chair	Chair	Yes	-
8	Dew Comb Bee	Honey	Honey	Yes	-
9	Fountain Baking Pop	Soda	Soda	Yes	-
10	Preserve Ranger Tropical	Forest	Forest	Yes	-
11	Aid Rubber Wagon	Station	Band	No	Partial
12	Flake Mobile Cone	Homes	Snow	No	No
13	Cracker Fly Fighter	Freedom	Fire	No	No
14	Safety Cushion Point	Road	Pin	No	Partial
15	Cane Daddy Plum	Sugar	Sugar	Yes	-
16	Dream Break Light	Bad	Day	No	Partial
17	Fish Mine Rush	Gold	Gold	Yes	-
18	Political Surprise Line	Party	Party	Yes	-
19	Measure Worm Video	Tape	Tape	Yes	-
20	High District House	School	School	Yes	-
21	Sense Courtesy Place	Common	Common	Yes	-
22	Worm Shelf End	Short	Book	No	Yes
23	Piece Mind Dating	Brilliant	Game	No	Partial
24	Flower Friend Scout	Girl	Girl	Yes	-
25	River Note Account	Book	Bank	No	Partial

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Table A.1 *Continued from previous page*

No.	Query	System	Human	Correct	Plausible
26	Print Berry Bird	Blue	Blue	Yes	-
27	Pie Luck Belly	Pot	Pot	Yes	-
28	Date Alley Fold	Blind	Blind	Yes	-
29	Opera Hand Dish	Soap	Soap	Yes	-
30	Cadet Capsule Ship	Space	Space	Yes	-
31	Fur Rack Tail	Coat	Coat	Yes	-
32	Stick Maker Point	Decision	Match	No	Partial
33	Hound Pressure Shot	Put	Blood	No	Partial
34	Fox Man Peep	Show	Hole	No	Partial
35	Sleeping Bean Trash	Bag	Bag	Yes	-
36	Dust Cereal Fish	Bowl	Bowl	Yes	-
37	Light Birthday Stick	Coming	Candle	No	No
38	Food Forward Break	Movement	Fast	No	Yes
39	Shine Beam Struck	Support	Moon	No	No
40	Peach Arm Tar	Muscles	Pit	No	No
41	Water Mine Shaker	Salt	Salt	Yes	-
42	Palm Shoe House	Tree	Tree	Yes	-
43	Basket Eight Snow	Ball	Ball	Yes	-
44	Wheel Hand Shopping	Going	Cart	No	Partial
45	Right Cat Carbon	House	Copy	No	Partial
46	Home Sea Bed	Water	Sick	No	Yes
47	Nuclear Feud Album	Family	Family	Yes	-
48	Sandwich House Golf	Playing	Club	No	Partial
49	Cross Rain Tie	Blue	Bow	No	Partial
50	Sage Paint Hair	Green	Brush	No	Yes
51	French Car Shoe	Company	Horn	No	Yes
52	Boot Summer Ground	Glass	Camp	No	No
53	Chamber Mask Natural	Death	Gas	No	Yes
54	Mill Tooth Dust	Fine	Saw	No	No
55	Main Sweeper Light	Street	Street	Yes	-
56	Pike Coat Signal	Green	Turn	Yes	No
57	Office Mail Hat	Box	Box	Yes	-
58	Fly Clip Wall	Art	Paper	No	No
59	Age Mile Sand	Stone	Stone	Yes	-
60	Catcher Food Hot	Dog	Dog	Yes	-
61	Wagon Break Radio	Station	Station	Yes	-
62	Tank Hill Secret	Top	Top	Yes	-
63	Health Taker Less	Risk	Care	No	Yes
64	Lift Card Mask	System	Face	No	No
65	Dress Dial Flower	Blue	Sun	No	Yes
66	Force Line Mail	Service	Air	No	Yes
67	Guy Rain Down	Just	Fall	No	No
68	Eight Skate Stick	Shift	Figure	No	No
69	Down Question Check	Able	Mark	No	No
70	Animal Back Rat	House	Pack	No	Yes

Continued on next page

Table A.1 *Continued from previous page*

No.	Query	System	Human	Correct	Plausible
71	Officer Cash Larceny	Petty	Petty	Yes	-
72	Pine Crab Sauce	Apple	Apple	Yes	-
73	House Thumb Pepper	Green	Green	Yes	-
74	Carpet Alert Ink	Red	Red	Yes	-
75	Master Toss Finger	Station	Ring	No	No
76	Hammer Gear Hunter	Box	Head	No	No
77	Knife Light Pal	Hot	Pen	No	No
78	Foul Ground Mate	Water	Play	No	No
79	Change Circuit Cake	Design	Short	No	Yes
80	Way Board Sleep	Deep	Walk	No	No
81	Blank List Mate	Check	Check	Yes	-
82	Tail Water Flood	Control	Gate	No	Yes
83	Marshal Child Piano	Grand	Grand	Yes	-
84	Cover Arm Wear	Political	Under	No	Partial
85	Rain Test Stomach	Acid	Acid	Yes	-
86	Time Blown Nelson	Glass	Full	No	No
87	Pile Market Room	Small	Stock	No	Yes
88	Mouse Bear Sand	Deep	Trap	No	No
89	Cat Number Phone	House	Call	No	Yes
90	Keg Puff Room	Powder	Powder	Yes	-
91	Trip House Goal	Field	Field	Yes	-
92	Fork Dark Man	Green	Pitch	No	Yes
93	Fence Card Master	Post	Post	Yes	-
94	Test Runner Map	Road	Road	Yes	-
95	Dive Light Rocket	Engine	Sky	No	Partial
96	Man Glue Star	power	Super	No	Yes
97	Tooth Potato Heart	Sweet	Sweet	Yes	-
98	Illness Bus Computer	Terminal	Terminal	Yes	-
99	Type Ghost Screen	Silent	Writer	No	Yes
100	Mail Board Lung	Service	Black	No	Partial
101	Teeth Arrest Start	False	False	Yes	-
102	Iron Shovel Engine	Old	Steam	No	Yes
103	Wet Law Business	Suit	Suit	Yes	-
104	Rope Truck Line	Tight	Tow	No	No
105	Off Military First	Duty	Base	No	Yes
106	Spoon Cloth Card	Table	Table	Yes	-
107	Cut Cream War	Cold	Cold	Yes	-
108	Note Chain Master	Key	Key	Yes	-
109	Shock Shave Taste	Treatment	After	No	Partial
110	Wise Work Tower	Clock	Clock	Yes	-
111	Grass King Meat	Dead	Crab	No	Yes
112	Baby Spring Cap	Blus	Shower	No	Partial
113	Break Bean Cake	Coffee	Coffee	Yes	-
114	Cry Front Ship	War	Battle	No	Yes
115	Hold Print Stool	Silver	Foot	No	No

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Table A.1 *Continued from previous page*

No.	Query	System	Human	Correct	Plausible
116	Roll Bean Fish	Sauce	Jelly	No	Partial
117	Horse Human Drag	Sense	Race	No	No
118	Oil Bar Tuna	Salad	Salad	Yes	-
119	Bottom Curve Hop	Level	Bell	No	No
120	Tomato Bomb Picker	Cherry	Cherry	Yes	-
121	Pea Shell Chest	Nuts	Nut	Yes	-
122	Line Fruit Drunk	Star	Punch	No	No
123	Bump Egg Step	Small	Goose	No	Yes
124	Fight Control Machine	Political	Gun	No	Yes
125	Home Arm Room	Free	Rest	No	Yes
126	Child Scan Wash	Body	Brain	No	Yes
127	Nose Stone Bear	Cold	Brown	No	Partial
128	End Line Lock	Dead	Dead	Yes	-
129	Control Place Rate	Actual	Birth	No	Yes
130	Lounge Hour Napkin	Cocktail	Cocktail	Yes	-
131	Artist Hatch Route	Escape	Escape	Yes	-
132	Pet Bottom Garden	Rock	Rock	Yes	-
133	Mate Shoes Total	Work	Running	No	Yes
134	Self Attorney Spending	Defense	Defense	Yes	-
135	Board Blade Back	Wall	Switch	No	Partial
136	Land Hand House	Just	Farm	No	Yes
137	Hungry Order Belt	Money	Money	Yes	-
138	Forward Flush Razor	Straight	Straight	Yes	-
139	Shadow Chart Drop	Eye	Eye	Yes	-
140	Way Ground Weather	Stations	Fair	No	Yes
141	Cast Side Jump	Different	Broad	No	Yes
142	Back Step Screen	Door	Door	Yes	-
143	Reading Service Stick	Man	Lip	No	Yes
144	Over Plant Horse	Dear	Power	No	No

TABLE A.2: Results of the comRAT v2 solver, where w_a, w_b, w_c are the 3 items proposed to solve the query and w'_1 is the answer obtained with its corresponding frequencies.

w_a	w_b	w_c	w'_1	$\sum_{i=1}^{m}(w_a,w_i)$	$\sum_{i=1}^{n}(w_b,w_i)$	$\sum_{i=1}^{k}(w_c,w_i)$	$fr(w_a,w'_1)$	$fr(w_b w'_1)$	$fr(w_c w'_1)$	$P(w'_1 \mid w_a)$	$P(w'_1 \mid w_b)$	$P(w'_1 \mid w_c)$	$P(w'_1)$	$P(w_a \mid w'_1)$	$P(w_b \mid w'_1)$	$P(w_c \mid w'_1)$
cottage	swiss	cake	cheese	1089	1109	4105	342	233	50	0.314	0.2101	0.0122	0.1788	0.59	0.39	0.02
cream	skate	water	ice	14534	134	74199	6777	39	803	0.4663	0.291	0.0108	0.2561	0.61	0.38	0.01
loser	throat	spot	sore	218	1237	9251	52	351	112	0.2385	0.2838	0.0121	0.1781	0.45	0.53	0.02
rocking	wheel	high	chair	1008	4459	143097	653	876	184	0.6478	0.1965	0.0013	0.2819	0.77	0.23	0.0
fountain	baking	pop	soda	664	9129	4410	107	1329	127	0.1611	0.1456	0.0288	0.1118	0.48	0.43	0.09
preserve	ranger	tropical	Forest	174	547	3520	28	55	193	0.1609	0.1005	0.0548	0.1054	0.51	0.32	0.17
cane	daddy	plum	sugar	1038	155	1088	514	60	40	0.4952	0.3871	0.0368	0.3063	0.54	0.42	0.04
fish	mine	rush	gold	18898	2299	5431	45	566	632	0.0024	0.2462	0.1164	0.1216	0.01	0.67	0.32
political	surprise	line	party	133666	2852	50904	1551	85	446	0.0116	0.0298	0.0088	0.0167	0.23	0.59	0.17
high	district	house	school	143097	14468	79427	47596	3192	149	0.3326	0.2206	0.0019	0.185	0.6	0.4	0.0
sense	courtesy	place	common	19399	387	38640	3701	72	271	0.1908	0.186	0.007	0.1279	0.5	0.48	0.02
flower	friend	scout	girl	3517	16399	844	82	700	160	0.0233	0.0427	0.1896	0.0852	0.09	0.17	0.74
print	berry	bird	blue	4491	2197	4724	84	173	52	0.0187	0.0787	0.011	0.0362	0.17	0.73	0.1
pie	luck	belly	pot	3622	6662	1415	126	69	47	0.0348	0.0104	0.0332	0.0261	0.44	0.13	0.42
opera	hand	dish	soap	7994	46110	4359	962	29	143	0.1203	6.0E-4	0.0328	0.0513	0.78	0.0	0.21
cadet	capsule	ship	space	24	124	55325	24	73	110	1.0	0.5887	0.002	0.5302	0.63	0.37	0.0
sleeping	bean	trash	bag	4432	2706	1356	1054	76	159	0.2378	0.0281	0.1173	0.1277	0.62	0.07	0.31
dust	cereal	fish	bowl	3297	669	18898	65	74	55	0.0197	0.1106	0.0029	0.0444	0.15	0.83	0.02
nuclear	feud	album	family	34776	218	3883	437	125	69	0.0126	0.5734	0.0178	0.2012	0.02	0.95	0.03
chamber	mask	natural	gas	2931	1558	36751	248	232	4233	0.0846	0.1489	0.1152	0.1162	0.24	0.43	0.33
main	sweeper	light	street	33428	69	34498	849	39	110	0.0254	0.5652	0.0032	0.1979	0.04	0.95	0.01
age	mile	sand	Stone	71469	710	3077	448	124	170	0.0063	0.1746	0.0552	0.0787	0.03	0.74	0.23
catcher	food	hot	dog	141	44971	27313	28	366	930	0.1986	0.0081	0.034	0.0803	0.82	0.03	0.14
wagon	break	radio	station	1883	38241	24380	1101	144	1937	0.5847	0.0038	0.0795	0.2226	0.88	0.01	0.12
officer	cash	larceny	Petty	19472	7231	99	360	57	25	0.0185	0.0079	0.2525	0.093	0.07	0.03	0.91
pine	crab	sauce	apple	4923	1255	10418	439	78	35	0.0892	0.0622	0.0034	0.0516	0.58	0.4	0.02
house	thumb	pepper	green	79427	681	11046	3206	69	305	0.0404	0.1013	0.0276	0.0564	0.24	0.6	0.16
carpet	alert	ink	red	1707	874	1256	799	48	451	0.4681	0.0549	0.3591	0.294	0.53	0.06	0.41
marshal	child	piano	grand	360	35218	2277	75	26	311	0.2083	7.0E-4	0.1366	0.1152	0.6	0.0	0.4
rain	test	stomach	acid	7436	30341	1664	870	88	112	0.117	0.0029	0.0673	0.0624	0.62	0.02	0.36
keg	puff	room	powder	81	363	91097	81	37	111	1.0	0.1019	0.0012	0.3677	0.91	0.09	0.0
trip	house	goal	field	8420	79427	10348	682	87	1416	0.081	0.0011	0.1368	0.073	0.37	0.01	0.63
fence	card	master	post	2770	19369	4762	117	100	45	0.0422	0.0052	0.0094	0.019	0.74	0.09	0.17
test	runner	map	road	30341	658	3132	46	72	916	0.0015	0.1094	0.2925	0.1345	0.0	0.27	0.72
tooth	potato	heart	sweet	1077	3865	28454	199	867	446	0.1848	0.2243	0.0157	0.1416	0.43	0.53	0.04
illness	bus	computer	terminal	4269	7851	27385	197	85	176	0.0461	0.0108	0.0064	0.0211	0.73	0.17	0.1
wet	law	business	suit	4717	64118	65799	115	1686	338	0.0244	0.0263	0.0051	0.0186	0.44	0.47	0.09
spoon	cloth	card	table	16137	4018	19369	3422	172	325	0.2121	0.0428	0.0168	0.0905	0.78	0.16	0.06
note	chain	master	key	10749	5882	4762	597	162	30	0.0555	0.0275	0.0063	0.0298	0.62	0.31	0.07
wise	work	tower	clock	4239	102110	3110	66	65	129	0.0156	6.0E-4	0.0415	0.0192	0.27	0.01	0.72
break	bean	cake	coffee	38241	2706	4105	119	27	99	0.0031	0.01	0.0241	0.0124	0.08	0.27	0.65
oil	bar	tuna	salad	48522	20967	1075	68	170	122	0.0014	0.0081	0.1135	0.041	0.01	0.07	0.92
tomato	bomb	picker	cherry	3472	7526	210	68	25	24	0.0196	0.0033	0.1143	0.0457	0.14	0.02	0.83
end	line	lock	dead	28869	50904	1463	662	645	25	0.0229	0.0127	0.0171	0.0176	0.44	0.24	0.32
control	place	rate	birth	44203	38640	32204	2145	96	294	0.0485	0.0025	0.0091	0.02	0.81	0.04	0.15
artist	hatch	route	escape	6309	1137	2051	39	94	249	0.0062	0.0827	0.1214	0.0701	0.03	0.39	0.58
pet	bottom	garden	rock	4163	11488	8467	35	307	157	0.0084	0.0267	0.0185	0.0179	0.16	0.5	0.35
self	attorney	spending	defense	2471	19183	12439	144	2095	780	0.0583	0.1092	0.0627	0.0767	0.25	0.47	0.27
back	step	screen	door	59215	11411	11972	2906	27	1126	0.0491	0.0024	0.0941	0.0485	0.34	0.02	0.65

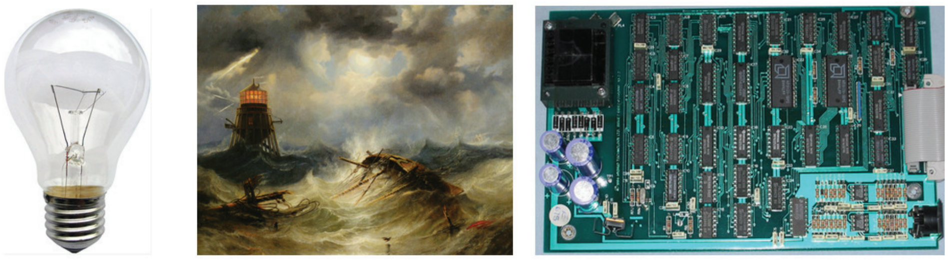
Table A.3: Using comRAT for query generation - Some examples of using the Answer item to navigate to the possible query items

Answer	**Candidate query items** $w_1, w_2 ... w_n$
Health	care, insurance, problems, services, benefits, professionals, officials, issues, effects, risks, plan, department, system, status, home, food, problem, club, coverage, risk, policy, departments, education, plans, reform, maintenance, programs, conditions, information, outcomes, promotion, experts, workers, agencies, centers, community, state, issue, needs, concerns, clinic, service, clinics, center, hazards, hazard, professional, consequences, program, clubs, costs, reasons, authorities, government, heart, crisis, treatment, practitioners, insurers, threat, bone, providers, questions, child, disparities, condition, research, quality, agency, systems, school, county, impacts, concern, behaviors, organizations, field, facilities, community;
care	health, child, day, reform, system, providers, costs, patient, home, plan, services, unit, bill, workers, center, professionals, centers, facilities, provider, coverage, industry, needs, programs, quality, program, settings, plans, skin, facility, delivery, insurance, physicians, debate, products, organizations, hospital, benefits, hospice, emergency, systems, physician, legislation, units, charity, worker, crisis, companies, issues, spending, policy, doctors, hair;
room	living, dining, temperature, hotel, locker, emergency, waiting, conference, dressing, back, family, operating, control, Table, guest, sitting, hospital, drawing, laundry, service, motel, weight, dorm, engine, floor, door, meeting, jury, chat, storage, war, wiggle, music, delivery, rest, window, reception, breakfast, rec, interrogation, hearing, press, briefing, breathing, screening, training, reading, wall, standing, couch, recovery, examination, break, game, powder, rates, board, throne, computer, exam, number, mail, air, basement, interview;
law	enforcement, school, firm, state, professor, firms, degree, schools, immigration, practice, case, tax, student, students, office, family, labor, canon, practice, rights, election, professors, clerk, partner, copyright, reform, clerks, tort, antitrust, review, offices, books, counsel, competition;
parking	lot, garage, space, area, spaces, spot, valet, tickets, ticket, street, place;
family	members, member, life, values, history, planning, room, business, friend, income, support, man, tree, name, structure, farm, relationships, reunion, doctor, tradition, unit, ties, time, problems, vacation, issues, size, affair, law, therapist, leave, car, photos, farms, background, physician, therapy, practice, dinner, system, court, environment, gatherings, dog, friends, responsibilities, crime, dynamics, systems, involvement, violence, connections, relations, groups, matters, reunification, stories, counseling, businesses, situation, fortune, photo, activities, incomes, medicine, reunions, photographs, drama, farmers, budget, doctors, obligations, vacations, pictures, portrait, home, estate, entertainment, caregivers, trip, group, needs;
ice	cream, water, cubes, vanilla, age, sea, hockey, sheet, cube, crystals, pack, chest, storm, rink, cap, sheets, water, caps, creams, chocolate, ages, bucket;
call	phone, wake-up, conference, telephone, roll, information, center, judgment, wakeup, house; etc.

(A) Training query 1

(B) Training query 2

(C) Q1



(D) Q2

(E) Q3

FIGURE A.1: vRAT training and test queries *(continues on next page)*

(F) Q4

(G) Q5

(H) Q6

(I) Q7

(J) Q8

FIGURE A.1: vRAT training and test queries *(continues on next page)*

(k) Q9

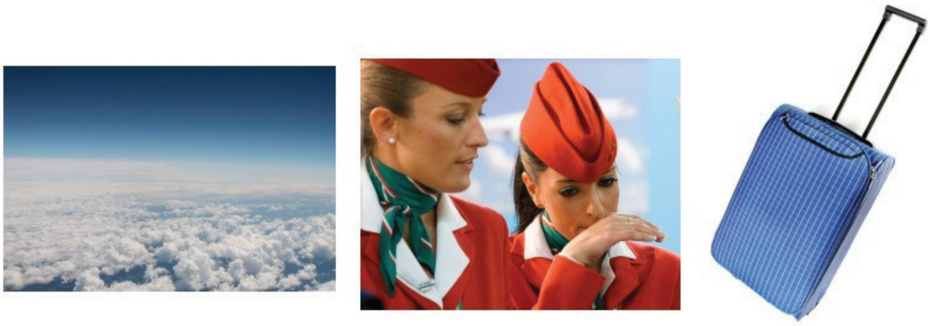
(l) Q10

(m) Q11

(n) Q12

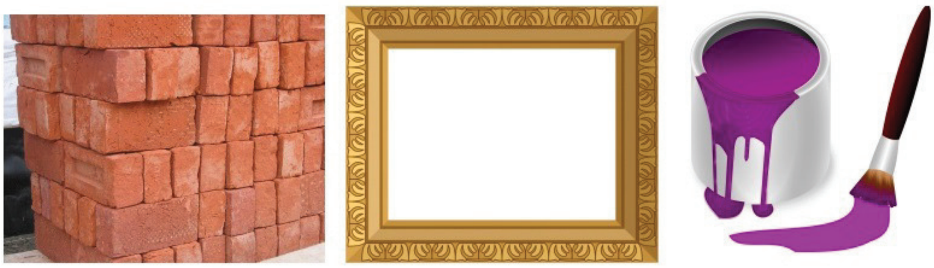
(o) Q13

Figure A.1: vRAT training and test queries *(continues on next page)*



(p) Q14

(q) Q15



(r) Q16

(s) Q17

(t) Q18

Figure A.1: vRAT training and test queries *(continues on next page)*

(u) Q19

(v) Q20

Figure A.1: vRAT training and test queries

Appendix B

OROC Results

Table B.1: More examples of Object Replacement made by *OROC* with a knowledge base that includes items from a household domain.

More object replacement results with *OROC*
Maybe Book can be used as decoration
Maybe Newspaper can be used as decoration
Maybe Newspaper can be used to wipe dishes with
Maybe Newspaper can be used to wipe kitchen surfaces with
Maybe Newspaper can be used to wipe your hands with
Maybe Newspaper can be used to dry off your body
Maybe Newspaper can be used to write on
Maybe Newspaper can be used to wipe shoes on
Maybe Newspaper can be used to hang in front of window in order to shade window with
Maybe Bucket can be used to drink from
Maybe Bucket can be used to put flowers in
Maybe Bucket can be used as food container
Maybe Bucket can be used to hold earth and plants
Maybe Bucket can be used to cook in
Maybe Vase can be used to drink from
Maybe Vase can be used to carry water
Maybe Vase can be used as food container
Maybe Vase can be used to hold earth and plants
Maybe Shelf can be used to surf on
Maybe Surfboard can be used as support
Maybe Bowl can be used to drink from
Maybe Bowl can be used to carry water
Maybe Bowl can be used to put flowers in
Maybe Bowl can be used to hold earth and plants
Maybe Bowl can be used to cook in
Maybe Nail can be used to separate objects
Maybe Nail can be used to pin object in place
Maybe Nail can be used to separate wood
Maybe Nail can be used as a weapon
Maybe Nail can be used to scratch with
Maybe Nail can be used to stop door from closing
Maybe Flowerpot can be used to drink from
Maybe Flowerpot can be used to carry water
Maybe Flowerpot can be used to put flowers in
Maybe Flowerpot can be used as food container
Maybe Flowerpot can be used to cook in
Maybe Flowerpot can be used to keep things in
Maybe Pot can be used to drink from
Maybe Pot can be used to carry water
Maybe Pot can be used to put flowers in
Maybe Pot can be used as food container
Maybe Pot can be used to hold earth and plants
Maybe Pan can be used to defend from rain
Maybe Pan can be used to put on top of a pot so that the warmth stays in
Maybe Rubber band can be used to hold hair with
Maybe Tree stumps can be used to support tabletop
...

Table B.2: Evaluation of 30 alternative use statements from *OROC* on Novelty, Likability, Usefulness (mean) by human judges.

No.	**Statement**	**Novelty**	**Likability**	**Usefulness**
1.	A cup may be used to carry water	1,68	4,53	5,53
2.	A Newspaper may be used to wipe kitchen surfaces with	3,03	2,85	3,65
3.	A toothbrush may be used to brush a coat with	4,44	2,91	3,03
4.	A cup may be used to store food in	2,65	3,88	4,47
5.	A newspaper may be used to hang in front of a window in order to shade window with	2,97	3,06	4,56
6.	Dental floss can be used to tie things with	4,65	3,38	4,50
7.	A carpet may be used as wall decoration	2,12	3,71	5,00
8.	A cup may be used to put flowers in	1,88	4,53	5,03
9.	A newspaper may be used to wipe dishes with	4,26	2,00	2,74
10.	A toothbrush may be used to brush shoes with	3,50	3,97	4,41
11.	Dental floss can be used to hang objects on the wall with	5,03	3,53	3,76
12.	A carpet may be used to wrap self with and warm up	4,44	2,88	3,50
13.	A newspaper may be used to wipe your hands with	3,29	2,56	3,50
14.	A toothbrush may be used to sweep the floor	4,44	2,12	1,88
15.	Dental floss may be used for sewing	5,41	3,97	4,29
16.	A carpet can be used to cover and protect the sofa	4,85	2,74	3,62
17.	A cup may be used to hold earth and plants	2,91	4,59	4,85
18.	A newspaper may be used to dry off your body	5,15	1,82	2,59
19.	A toothbrush may be used to clean the toilet with	4,21	2,53	3,03
20.	A cup may be used to keep objects in	2,21	4,79	5,18
21.	A carpet may be used as a bed cover	4,59	2,56	3,32
22.	Dental floss may be used to hang clothes on to dry	6,00	2,68	2,06
23.	A carpet can be used on the bed as a sheet	5,59	1,79	1,85
24.	A cup may be used to cook in	4,38	3,12	2,94
25.	A newspaper may be used to write on	1,65	3,91	4,32
26.	A toothbrush can be used to paint the wall with	4,85	2,74	2,53
27.	Dental floss can be used to tie shoes with	5,53	2,71	3,03
28.	A carpet can be used to sleep on	2,41	3,47	4,29
29.	A cup may be used to hold a candle	2,53	4,65	5,59
30.	A newspaper may be used to wipe shoes on	3,03	3,71	3,94

Table B.3: Other uses answers by human participants for 5 given objects

Object	Other Uses	Freq.
Cup	to put things in (dessert, pencils/pens/brushes, mix sauce, mix paint, coffee, etc.)	9
	for sound(speaker/headphone/musical instrumental,hear through a wall)	7
	to draw shapes(shapes)	3
	bird feeder	2
	build a tower with other cups(incl sand)	2
	hat	2
	make a mosaic with a broken cup	2
	to cook in	2
	to throw with	2
	to use as a decoration	2
	use as a painting(canvas/)	2
	as a bell	1
	as a shelf separator (for identical one on each corner)	1
	cap for a bottle	1
	clay pigeon (shooting)	1
	device for competitive sport	1
	hammer	1
	mortar to make allioli	1
	paperweight	1
	put publicity in it	1
	shovel (dig on earth)	1
	to eat from	1
	to measure quantities	1
	use it as a mace to smash a garlic using the basis of the cup	1
	use it as a spoon	1
	use it with a knife	1
Newspaper	to make shapes and origami figures(boat/hat)	10
	to wrap something	8
	clean(glass/brush/toilet)	5
	cover(tablecloth/bed/book)	5
	to cut images/text from and make a collage/word	3
	wall decoration	2
	adjust one of the legs of a table	1
	adjust the window or a pot that does not close hermetically	1
	an umbrella	1
	containers of grains	1
	filling shoes to store for a long period	1
	keep temperature of food	1
	levelling material for tables	1
	make baskets or containers hardening it with strips	1
	preventing bleeding (as a plaster)	1

Continued on next page

Table B.3 *Continued from previous page*

Object	Other Uses	Freq.
	protecting against cold weather	1
	protection when painting	1
	rolled around a weak chair-leg or any weak tube to make it stronger	1
	the newspaper can be applied to open a bottle of beer	1
	to burn	1
	to dry the floor	1
	to protect the table when cutting using a cutter	1
	to protect your hands when taking something from the oven or the cooker	1
	twisting it to make a stick to mix paintings	1
	wrapping a mommy for a fancy dress event	1
Toothbrush	clean(small objects, parts, things, copper, corners)	16
	brushing(car,hedgehog,eyebrows,hair,ceils)	4
	combing	3
	a toothbrush can be used to hang things	1
	as a nail of a sundial	1
	constructing funny animals	1
	for dying your hair	1
	making sand drawings	1
	rabbets or splines in the windows	1
	stabbing device	1
	sticking holes into things	1
	to exfoliate the skin making circles with the toothbrush	1
	to put grease on it and use it to collect the hair and make a bun	1
	to put soap and use it to remove something with water to make foam	1
	to put wax and polish shoes	1
	toy for children	1
	tubes	1
	weapon against raptors	1
Dental floss	fishing line	4
	necklace,earring,bracelet like jewelry	4
	crocheting something out of it	2
	as a belt	1
	as a police cordon	1
	caress/massage	1
	crafts	1
	cutting soft materials (e.g. butter)	1
	dental floss can be used as tripping hazard	1
	dental floss can be used for painting	1
	fire starter (esp. waxed floss)	1
	guitar string	1
	hold a bikini	1
	impregnated with glue can be a 3d printer wire	1

Continued on next page

Table B.3 *Continued from previous page*

Object	Other Uses	Freq.
	keyring	1
	macrame	1
	pack	1
	to use as a rope to escape from jail	1
	to cut soft things	1
	to kill a person	1
	to pull a tooth	1
	to stimulate skin	1
	to stop bleeding an injury	1
	to tickle	1
	to tie it to a tissue or handkerchief or scarf and make a bag	1
	to tie it to the handle of a door to close it at a distance	1
	to tie the curtain	1
	to tie the kitchen paper so that it is perfectly folded	1
Carpet	damping noise/vibrations	2
	keeping fire lit	2
	to wrap objects	2
	a carpet can be used as a curtain	1
	as an umbrella to protect from the sun	1
	build a tent for playing with children	1
	carpets can be used to slide a slide	1
	door	1
	easing access to water on stony beach	1
	hiding cleopatra	1
	hieroglyphic drawings.	1
	moving light furniture around with (or objects)	1
	packing stuff in	1
	posters or drawing sheets by rolling them together	1
	rolled can be a cushion or armrest	1
	separation of spaces	1
	small carpets are a good lying surface for pets	1
	sunbathing on the beach	1
	to add water to and plant seeds to germinate	1
	to cut it and stick it to your shoes to get new soles	1
	to fly	1
	to make spiral drawings by rolling the carpet and put it inside a bucket of painting	1
	to paint it and create a new carpet	1
	to protect a piece of furniture from the dust	1
	to protect against wind	1
	to protect architectural drawings	1
	to stick it to the wall of a bath to transform the bath in a seat	1
	wall	1

Appendix C

Publications of the Author Relevant to this PhD Thesis

1. Olteţeanu, Ana-Maria and Falomir, Zoe (2015) - *comRAT-C: A Computational Compound Remote Associate Test Solver based on Language Data and its Comparison to Human Performance.* In Pattern Recognition Letters, SI:"Cognitive Systems for Knowledge Discovery", ed. Lledó Museros, Núria Agell, and Oriol Pujol, vol. 67 (1): 81-90. doi:10.1016/j.patrec.2015.05.015

2. Olteţeanu, Ana-Maria and Falomir, Zoe (2016) - *Object Replacement and Object Composition in a Creative Cognitive System. Towards a Computational Solver of the Alternative Uses Test.* In "From Human to Artificial Cognition (and back): New Perspectives on Cognitively Inspired AI Systems", ed. Antonio Lieto and Daniele P. Radicioni, Cognitive Systems Research, vol. 39, pp. 15-32. doi:10.1016/j.cogsys.2015.12.011

3. Olteţeanu, Ana-Maria; Bibek, Gautam and Falomir, Zoe (2015) - *Towards a Visual Remote Associates Test and its Computational Solver.* In Proceedings of the International Workshop on Artificial Intelligence and Cognition – AIC 2015, CEUR-Ws Vol. 1510, ISSN:1613-0073.

4. Olteţeanu, Ana-Maria (2015) - *The role of cognitive processing, knowledge acquisition and evaluation in artificial cognitive systems that can answer human creativity tests. A general approach and two case studies.* In Cognitum workshop on Cognitive Knowledge Acquisition, IJCAI 2015.

5. Olteţeanu, Ana-Maria (2015) - *"Seeing as" and Re-representation: Their Relation to Insight, Creative Problem-Solving and Types of Creativity.* In Proceedings of the Workshop "Computational Creativity, Concept Invention, and General Intelligence", 2015.

6. Olteţeanu, Ana-Maria (2015) - *The Input, Coherence, Generativity (ICG) Factors. Towards a Model of Cognitive Informativity Measures for Productive Cognitive Systems.* In Proceedings of the Workshop "Computational Creativity, Concept Invention, and General Intelligence", 2015.

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