# Knowledge Capturing via Conceptual Reframing: A Goal-oriented Framework for Knowledge Invention

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## ABSTRACT

In this work we describe a novel approach to goal-oriented knowledge capturing that, differently from the standard knowledge acquisition pipelines, employs a dynamic conceptual reframing mechanism relying on a non monotonic reasoning procedure. This approach has been implemented in a knowledge based system able to find the solution to not directly satisfiable goals by recombining, in an innovative way, at least two concepts of a given knowledge base (KB). The output of such combinatorial mechanism results, *de facto*, in an extension of the initial KB able to satisfy the original goal. The proposed approach has been tested in the task of goal-driven concept invention and has been compared with human responses.

## CCS CONCEPTS

**• Artificial Intelligence**; **• Knowledge Representation Formalisms and Methods** ; **• Problem Solving, Control Methods, and Search**;

## KEYWORDS

knowledge generation; cognitive agents; description logics; non-monotonic reasoning; knowledge representation; goal-reasoning

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## 1 INTRODUCTION

Natural and artificial systems able to exhibit intelligent behavior are goal-driven systems. In Artificial Intelligence (AI), a straightforward assumption followed in the design of such systems is that, if a given goal cannot be reached, a replanning strategy is required in order to change the original goal and/or reconfigure the set of actions originally selected to perform that goal [1]. Usually such goal reconfiguration is based on the availability of novel, additional, knowledge that can be then used to select novel sub-goals or novel operations to carry on. The classical moves to acquire novel knowledge usually follow one of the following paths: i) the novel knowledge can be externally injected in the declarative memory of an artificial system (e.g. by connecting its semantic module to external repository like DBPedia etc.) ii) the novel knowledge can be learned by the system itself by using a standard knowledge acquisition pipeline iii) the system can acquire such knowledge via a direct communication with other agents (being them either human or artificial). Differently from these classical approaches to knowledge acquisition and capturing, in this paper, we consider those situations where the solution to a given problem cannot come with such *extrinsic* classical means. On the other hand, in the considered scenarios, the key to the problem solution lies in an *intrinsic* agent capability of automatically reconfiguring its knowledge by recombining, in a dynamic and innovative way, the possessed knowledge in order to look with new eyes to the problem in hand and solve it.

In this paper we present a framework for the dynamic and automatic generation of novel knowledge obtained through a process of commonsense reasoning based on typicality-based concept combination. We exploit a recently introduced extension of a Description Logic of typicality able to combine prototypical descriptions of concepts in order to generate new prototypical concepts. Intuitively, in the context of our application of this logic, given a goal expressed as a set of properties, if the knowledge base does not contain a concept able to fulfill all these properties, then our system looks for at least two concepts to recombine in order to extend the original knowledge base and satisfy the goal.

The rest of the paper is organized as follows. In section 2 we describe the rationale of our proposal. In section 3 we describe the logical formalism driving the behavior of our system. The latter is described in section 4 and its whose efficacy is tested in section 5 in the task of concept invention based on the composition of domestic objects described in a KB. Finally, in section 6 we survey related approaches and conclude with a discussion on future works.


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## 2 COMMONSENSE CONCEPT INVENTION VIA DYNAMIC KNOWLEDGE COMBINATION

The generative capability of inventing novel concepts by combining the typical knowledge of pre-existing ones is an important phenomenon in human cognition. Such ability, in fact, concerns high-level capacities associated to creative thinking and problem solving. Still, it represents an open challenge in the field of artificial intelligence [4]. Dealing with this problem requires, from an AI and cognitive modelling perspective, the harmonization of two conflicting requirements that are hardly accommodated in symbolic systems: the need of a syntactic and semantic compositionality (typical of logical systems) and that one concerning the exhibition of typicality effects [7]. According to a well-known argument [24], in fact, prototypes (i.e. commonsense conceptual representations based on typical properties) are not compositional. The argument runs as follows: consider a concept like *pet fish*. It results from the composition of the concept *pet* and of the concept *fish*. However, the prototype of *pet fish* cannot result from the composition of the prototypes of a pet and a fish: e.g. a typical pet is furry and warm, a typical fish is grayish, but a typical pet fish is neither furry and warm nor grayish (typically, it is red). In this work we exploit a framework able to account for this type of human-like concept combination and propose to use it as a novel mechanism able to expand the spectrum of subgoaling procedures in cognitive artificial systems. In particular, we adopt a nonmonotonic extension of Description Logics (from now on DL) [1] able to reason on typicality and called $\mathbf{T}^{\text{CL}}$ (typicality-based compositional logic) introduced in [16, 18].

## 3 THE $\mathbf{T}^{\text{CL}}$ LOGIC FOR COMMONSENSE CONCEPTUAL COMBINATION

This logic combines three main ingredients. The first one relies on the DL of typicality $\mathcal{ALC} + \mathbf{T_R}$ introduced in [9], which allows to describe the *protoype* of a concept. In this logic, "typical" properties can be directly specified by means of a "typicality" operator $\mathbf{T}$ enriching the underlying DL, and a TBox can contain inclusions of the form $\mathbf{T}(C) \sqsubseteq D$ to represent that "typical $C$s are also $D$s". As a difference with standard DLs, in the logic $\mathcal{ALC} + \mathbf{T_R}$ one can consistently express exceptions and reason about defeasible inheritance as well. For instance, a knowledge base can consistently express that "normally, athletes are fit", whereas "sumo wrestlers usually are not fit" by $\mathbf{T}(\mathit{Athlete}) \sqsubseteq \mathit{Fit}$ and $\mathbf{T}(\mathit{SumoWrestler}) \sqsubseteq \neg \mathit{Fit}$, given that $\mathit{SumoWreslter} \sqsubseteq \mathit{Athlete}$. The semantics of the $\mathbf{T}$ operator is characterized by the properties of *rational logic* [11], recognized as the core properties of nonmonotonic reasoning. $\mathcal{ALC} + \mathbf{T_R}$ is characterized by a minimal model semantics corresponding to an extension to DLs of a notion of *rational closure* as defined in [11] for propositional logic: the idea is to adopt a preference relation among $\mathcal{ALC} + \mathbf{T_R}$ models, where intuitively a model is preferred to another one if it contains less exceptional elements, as well as a notion of *minimal entailment* restricted to models that are minimal with respect to such preference relation. As a consequence, $\mathbf{T}$ inherits well-established properties like *specificity* and *irrelevance*: in the example, the logic $\mathcal{ALC} + \mathbf{T_R}$ allows us to infer $\mathbf{T}(\mathit{Athlete} \sqcap \mathit{Bald}) \sqsubseteq \mathit{Fit}$ (being bald is irrelevant with respect to being fit) and, if one knows that Hiroyuki is a typical sumo wrestler, to infer that he is not fit, giving preference to the most specific information.

As a second ingredient, we consider a distributed semantics similar to the one of probabilistic DLs known as DISPONTE [25], allowing to label inclusions $\mathbf{T}(C) \sqsubseteq D$ with a real number between 0.5 and 1, representing its degree of belief/probability, assuming that each axiom is independent from each others. Degrees of belief in typicality inclusions allow to define a probability distribution over *scenarios*: roughly speaking, a scenario is obtained by choosing, for each typicality inclusion, whether it is considered as true or false In a slight extension of the above example, we could have the need of representing that both the typicality inclusions about athletes and sumo wrestlers have a degree of belief of $80\%$, whereas we also believe that athletes are usually young with a higher degree of $95\%$, with the following KB: (1) $\mathit{SumoWrestler} \sqsubseteq \mathit{Athlete}$; (2) $0.8 \ :: \ \mathbf{T}(\mathit{Athlete}) \sqsubseteq \mathit{Fit}$; (3) $0.8 \ :: \ \mathbf{T}(\mathit{SumoWrestler}) \sqsubseteq \neg \mathit{Fit}$; (4) $0.95 \ :: \ \mathbf{T}(\mathit{Athlete}) \sqsubseteq \mathit{YoungPerson}$. We consider eight different scenarios, representing all possible combinations of typicality inclusion: as an example, $\{((2), 1), ((3), 0), ((4), 1)\}$ represents the scenario in which (2) and (4) hold, whereas (3) does not. We equip each scenario with a probability depending on those of the involved inclusions: the scenario of the example, has probability $0.8 \times 0.95$ (since 2 and 4 are involved) $\times (1 - 0.8)$ (since 3 is not involved) $= 0.152 = 15.2\%$. Such probabilities are then taken into account in order to choose the most adequate scenario describing the prototype of the combined concept.

As a third element of the proposed formalization we employ a method inspired by cognitive semantics [10] for the identification of a dominance effect between the concepts to be combined: for every combination, we distinguish a HEAD, representing the stronger element of the combination, and a MODIFIER. The basic idea is: given a KB and two concepts $C_H$ (HEAD) and $C_M$ (MODIFIER) occurring in it, we consider only *some* scenarios in order to define a revised knowledge base, enriched by typical properties of the combined concept $C \sqsubseteq C_H \sqcap C_M$.

Given a KB $\mathcal{K} = \langle \mathcal{R}, \mathcal{T}, \mathcal{A} \rangle$ and given two concepts $C_H$ and $C_M$ occurring in $\mathcal{K}$, the logic $\mathbf{T}^{\text{CL}}$ allows defining a prototype of the compound concept $C$ as the combination of the HEAD $C_H$ and the MODIFIER $C_M$, where the typical properties of the form $\mathbf{T}(C) \sqsubseteq D$ (or, equivalently, $\mathbf{T}(C_H \sqcap C_M) \sqsubseteq D$) to ascribe to the concept $C$ are obtained by considering blocks of scenarios with the same probability, in decreasing order starting from the highest one. We first discard all the inconsistent scenarios, then:

- we discard those scenarios considered as *trivial*, consistently inheriting all the properties from the HEAD from the starting concepts to be combined. This choice is motivated by the challenges provided by task of commonsense conceptual combination itself: in order to generate plausible and creative compounds it is necessary to maintain a level of surprise in the combination. Thus both scenarios inheriting all the properties of the two concepts and all the properties of the HEAD are discarded since prevent this surprise;

[1] As it is well known, Description Logics are a class of decidedable fragments of first order logics that are at the base of Ontology Web Language (OWL and OWL 2) used for the realization of computational ontologies. Nowadays DLs are the most important and widespread symbolic knowledge-representation formalisms. We remind to [3] for an introduction.

- among the remaining ones, we discard those inheriting properties from the MODIFIER in conflict with properties that could be consistently inherited from the HEAD;
- if the set of scenarios of the current block is empty, i.e. all the scenarios have been discarded either because trivial or because preferring the MODIFIER, we repeat the procedure by considering the block of scenarios, having the immediately lower probability.

Remaining scenarios are those selected by the logic $\mathbf{T}^{\mathsf{CL}}$. The ultimate output of our mechanism is a knowledge base in the logic $\mathbf{T}^{\mathsf{CL}}$ whose set of typicality properties is enriched by those of the compound concept $C$. Given a scenario $w$ satisfying the above properties, we define the properties of $C$ as the set of inclusions $p \ :: \ \mathbf{T}(C) \sqsubseteq D$, for all $\mathbf{T}(C) \sqsubseteq D$ that are entailed from $w$ in the logic $\mathbf{T}^{\mathsf{CL}}$. The probability $p$ is such that:

- if $\mathbf{T}(C_H) \sqsubseteq D$ is entailed from $w$, that is to say $D$ is a property inherited either from the HEAD (or from both the HEAD and the MODIFIER), then $p$ corresponds to the degree of belief of such inclusion of the HEAD in the initial knowledge base, i.e. $p \ : \ \mathbf{T}(C_H) \sqsubseteq D \in \mathcal{T}$;
- otherwise, i.e. $\mathbf{T}(C_M) \sqsubseteq D$ is entailed from $w$, then $p$ corresponds to the degree of belief of such inclusion of a MODIFIER in the initial knowledge base, i.e. $p \ : \ \mathbf{T}(C_M) \sqsubseteq D \in \mathcal{T}$.

The knowledge base obtained as the result of combining concepts $C_H$ and $C_M$ into the compound concept $C$ is called *C-revised* knowledge base, and it is defined as follows:

$$\mathcal{K}_C = \langle \mathcal{R}, \mathcal{T} \cup \{p \ : \ \mathbf{T}(C) \sqsubseteq D\}, \mathcal{A} \rangle,$$

for all $D$ such that either $\mathbf{T}(C_H) \sqsubseteq D$ is entailed in $w$ or $\mathbf{T}(C_M) \sqsubseteq D$ is entailed in $w$, and $p$ is defined as above.

In [16] we have shown that reasoning in $\mathbf{T}^{\mathsf{CL}}$ remains in the same complexity class of standard $\mathcal{ALC}$ Description Logics.

THEOREM 3.1. *Reasoning in $\mathbf{T}^{\mathsf{CL}}$ is* ExpTime-*complete.*

# 4 A GOAL-DIRECTED SYSTEM FOR DYNAMIC KNOWLEDGE GENERATION AND INVENTION

In this section we describe the goal-directed system relying on the above illustrated $\mathbf{T}^{\mathsf{CL}}$ logic [2]. Our system (available at http://di.unito.it/GOCCIOLA) is able to dynamically generate novel knowledge in the cases in which the original goal cannot be directly solved by a given agent only by resorting to its available knowledge. The process of automatic knowledge generation, as mentioned, is obtained by adopting the process of commonsense concept combination of $\mathbf{T}^{\mathsf{CL}}$, namely: by combining concepts in the knowledge base which are relevant for the task to solve.

The overall pipeline of the system can be described as follows: the system receives in input a certain goal to achieve. The goal is expressed in terms of tuples representing the desired final state. For example: a goal can be expressed as $\{Object, Cutting, Graspable\}$ to identify the scope of retrieving, from the inventory of the available knowledge in the agent declarative memory, an element that is a graspable object able to cut some surfaces. Once processed the input, the system verifies, via a searching process in the hybrid, probabilistic, knowledge base assumed in $\mathbf{T}^{\mathsf{CL}}$, whether there is some element that can directly satisfy the desired conditions. If so, the element(s) (if any) satisfying the request are returned and ranked in descending order of probability. If not, the system tries to perform a task of semantic-driven goal-reformulation by looking for WordNet synonyms and hyperonyms[3] of the terms specified in input (in order to find at least a minimal set of candidate concepts sharing, if considered jointly, all the required goal desiderata). Once this process is also executed, and the minimal set of candidate concepts that (jointly) can be combined to satisfy the goal is reached, the system adopt the typicality-based reasoning procedure of concept combination developed in $\mathbf{T}^{\mathsf{CL}}$.

More formally:

DEFINITION 4.1. *Given a knowledge base $\mathcal{K}$ in the logic $\mathbf{T}^{\mathsf{CL}}$, let $\mathcal{G}$ be a set of concepts $\{D_1, D_2, \dots, D_n\}$ called* goal. *We say that a concept $C$ is a* solution *to the goal $\mathcal{G}$ if either:*

- *for all $D_i \in \mathcal{G}$, either $\mathcal{K} \models C \sqsubseteq D_i$ or $\mathcal{K}' \models \mathbf{T}(C) \sqsubseteq D_i$ in the logic $\mathbf{T}^{\mathsf{CL}}$*

*or*

- *$C$ corresponds to the combination of, at least, two concepts $C_1$ and $C_2$ occurring in $\mathcal{K}$, i.e. $C \equiv C_1 \sqcap C_2$, and the $C$-revised knowledge base $\mathcal{K}_C$ provided by the logic $\mathbf{T}^{\mathsf{CL}}$ is such that, for all $D_i \in \mathcal{G}$, either $\mathcal{K}_C \models C \sqsubseteq D_i$ or $\mathcal{K}_C \models \mathbf{T}(C) \sqsubseteq D_i$.*

In case the goal cannot be achieved in a direct way (i.e. there is no element in the KB satysfying the goal desiderata) the system computes a list of concepts of the initial knowledge base satisfying at least a property of the goal (using Wordnet if the initial goal formulation does not satisfy such condition). As an example, suppose to have:

$$\mathcal{G} = \{Object, Graspable, Cutting\},$$

and suppose that the following inclusions belong to the knowledge base:

$Spoon \sqsubseteq Graspable$
$0.85 \ :: \ \mathbf{T}(Spoon) \sqsubseteq \neg Cutting$
$0.9 \ :: \ \mathbf{T}(Vase) \sqsubseteq Graspable$
$Vase \sqsubseteq Object$

Both *Vase* and *Spoon* are included in the list of candidate concepts to be combined (along with other concepts satysfying, for example other properties of the goal such as, for example, being able to cut some surface). As a second step, for each item in the list of candidate concepts to be combined, the system computes a rank of the concept as the sum of the probabilities of the properties also belonging to the goal, assuming a score of 1 in case of a rigid property. In the example, *Vase* is ranked as $0.9 + 1 = 1.9$, since both *Graspable* and *Object* are properties belonging to the goal: for the former we take the probability 0.9 of the typicality inclusion $\mathbf{T}(Vase) \sqsubseteq Graspable$, for the latter we provide a score of 1 since the property $Vase \sqsubseteq Object$ is rigid. Concerning the concept *Spoon*, the system computes a rank of 1: indeed, the only inclusion matching the goal is the rigid one $Spoon \sqsubseteq Graspable$. Finally, the system checks whether the concept obtained by combining the candidate concepts with the highest ranks,

[2]In other works we have already shown how such logic can be used to model complex cognitive phenomena [18] (including methaphors generation) and to build intelligent applications in the field of computational creativity [17].

[3]WordNet is a widely known lexical database [21].

(e.g. $C_1$ and $C_2$ in case of only 2 concepts), is able to satisfy the initial goal. The system computes a double attempt, by considering first $C_1$ as the HEAD and $C_2$ as the MODIFIER and, in case of failure, $C_2$ as the HEAD and $C_1$ as the MODIFIER.

In order to combine the two candidate concepts $C_1$ and $C_2$, our system exploits COCOS [19], a tool generating scenarios and choosing the selected one(s) according to the logic $\mathbf{T}^{\mathsf{CL}}$. COCOS makes use of the library `owlready2` [4] that allows one to rely on the services of efficient DL reasoners, e.g. the HermiT reasoner.

## 5 EXPERIMENTATION

In this section, we describe the experimental setup and the obtained results of our system in task of concept invention via conceptual composition. The case study has been carried out on a KB of domestic objects from which to build, when possible, compound tools. The ability of creating such tools is a very important and creative one, found only in primates (specifically, humans and great apes) and, more recently, in ravens [26]. It still represents an open challenge in the field of AI and cognitive modelling, however, due to the lack of a realistic benchmark for evaluating the performance on this complex task for both humans and artificial systems is still lacking. In this paper we re-consider proof-of-concept evaluation presented in [14] by providing a comparison with the responses provided by human judges for the concept composition task.

### 5.1 Setup

Knowledge about goals, objects and entities can be represented in our system in symbolic terms. As an example, let us consider the above mentioned goal: *object, cutting, graspable*. The initial knowledge base is formalized in the language of the logic $\mathbf{T}^{\mathsf{CL}}$ and it is stored in a suitable file. Rigid properties, holding for all individuals of a given class, are stored as pairs object-property, whereas typical properties are formalized as triples object-property-probability. We have considered an extension with probabilities of a portion of the ontology `Open Cyc` [12] [5] referring to physical objects and tools of ordinary use in a domestic environment (e.g. a glass, a vase etc.). The considered branch of the Cyc ontology (formalized in standard Description Logic and, as a consequence, not able to represent and reason on typicality-based information) has been manually extended in the language of the logic $\mathbf{T}^{\mathsf{CL}}$. Therefore the symbolic representation of the ontological objects additionally includes the following typical and functional characteristics: color, size, function, physical affordance, shape, material. Please note that it was not mandatory to fill every property of the schema for the description of objects.

As an example, the concept *Vase* is represented as follows (on the right the corresponding knowledge base in $\mathbf{T}^{\mathsf{CL}}$):

| | |
|---|---|
| vase, object | $Vase \sqsubseteq Object$ |
| vase, high convexity | $Vase \sqsubseteq HighConvexity$ |
| vase, ceramic, 0.8 | $0.8 :: \mathbf{T}(Vase) \sqsubseteq Ceramic$ |
| vase, to put plants, 0.9 | $0.9 :: \mathbf{T}(Vase) \sqsubseteq ToPutPlants$ |
| vase, to contain objects, 0.9 | $0.9 :: \mathbf{T}(Vase) \sqsubseteq ToContainObjects$ |
| vase, graspable, 0.9 | $0.9 :: \mathbf{T}(Vase) \sqsubseteq Graspable$ |

[4] https://pythonhosted.org/Owlready2/

[5] https://github.com/asanchez75/opencyc/blob/master/opencyc-latest.owl.gz.

### 5.2 Results of Knowledge Generation via Concept Composition

We tested the proposed framework in the task of object composition. In particular, for this task we used the same setup adopted in [14] by using a limited sample of the Cyc ontology about domestic objects.

In particular, we asked our system to combine objects in order to obtain the following goals:

$$\mathcal{G}_1 = \{Object, Cutting, Graspable\},$$

$$\mathcal{G}_2 = \{Object, Graspable, LaunchingObjectsAtDistance\},$$

$$\mathcal{G}_3 = \{Object, Support, LiftingFromTheGround\},$$

As mentioned, we have considered an extension of the knowledge base `Open Cyc` where we manually introduced, in the language of $\mathbf{T}^{\mathsf{CL}}$, typicality-based properties/inclusions that were not originally available in the ontology due to the fact that standard ontological semantics does not support representing and reasoning on typicality and exceptions [8]. An example of the introduced inclusions/properties (for the concepts Shelf, Stone, Stump, RubberBand) is reported below:

$Shelf \sqsubseteq Object$
$0.8 :: \mathbf{T}(Shelf) \sqsubseteq Wood$
$0.9 :: \mathbf{T}(Shelf) \sqsubseteq Rectangular$
$0.8 :: \mathbf{T}(Shelf) \sqsubseteq Containment$
$0.8 :: \mathbf{T}(Shelf) \sqsubseteq Support$

$0.8 :: \mathbf{T}(Stump) \sqsubseteq Wood$
$0.7 :: \mathbf{T}(Stump) \sqsubseteq Medium$
$0.8 :: \mathbf{T}(Stump) \sqsubseteq Linear$
$0.7 :: \mathbf{T}(Stump) \sqsubseteq LiftingFromGround$
$0.7 :: \mathbf{T}(Stump) \sqsubseteq Support$

$Stone \sqsubseteq MineralAggregate$
$0.7 :: \mathbf{T}(Stone) \sqsubseteq Roundish$
$0.7 :: \mathbf{T}(Stone) \sqsubseteq Greyish$
$0.7 :: \mathbf{T}(Stone) \sqsubseteq BuildingArrowHeads$
$0.8 :: \mathbf{T}(Stone) \sqsubseteq ShapingObjects$
$0.7 :: \mathbf{T}(Stone) \sqsubseteq Cutting$
$0.6 :: \mathbf{T}(Stone) \sqsubseteq Support$
$0.8 :: \mathbf{T}(Stone) \sqsubseteq StrikeAtDistance$
$0.9 :: \mathbf{T}(Stone) \sqsubseteq Graspable$
$0.7 :: \mathbf{T}(Stone) \sqsubseteq Narrow$

$RubberBand \sqsubseteq Object$
$RubberBand \sqsubseteq Plastic$
$0.9 :: \mathbf{T}(RubberBand) \sqsubseteq Propeller$
$0.9 :: \mathbf{T}(RubberBand) \sqsubseteq LaunchingObjectsAtDistance$
$0.7 :: \mathbf{T}(RubberBand) \sqsubseteq Small$

Given a KB extended in $\mathbf{T}^{\mathsf{CL}}$ as reported above, we employed our system for solving the first 3 goals. For what concerns the first goal, i.e. where the purpose of our intelligent system consisted is looking for a graspable object able to cut, the system was not able to find a unique object satisfying all the properties and, therefore, proposed the combination $Stone \sqcap Branch$ as a solution, thus suggesting a combined concept having the characteristics resembling a rudimentary *KnifeWithAWoodHandle*

For what concerns the second goal, where the system was asked to look for a graspable object able to launch objects at distance, the systems asked COCOS to combine the concepts *Branch* and *RubberBand*, being those with the highest rank with respect to $\mathcal{G}_2$. The ($Stone \sqcap RubberBand$)-revised knowledge base, suggested by adopting *Stone* as the HEAD, is such that all the properties of both concepts are considered, with the exception of *Support*. Therefore the knowledge base of the agent is extended (among the others) by the following inclusions:

$$0.9 \ :: \ \mathbf{T}(Branch \sqcap RubberBand) \sqsubseteq Graspable$$
$$0.9 \ :: \ \mathbf{T}(Branch \sqcap RubberBand) \sqsubseteq LaunchingObjectsAtDistance$$

and the combination $Branch \sqcap RubberBand$ is a solution for the goal $\mathcal{G}_2$. The intentional description of the combined concept for $\mathcal{G}_2$ corresponds to the concept *Slingshot*.

For what concerns the third goal, the system provides a solution by combining *Shelf* and *Stump*. Notice that also $Stump \sqcap RubberBand$ would be a solution: however, our system gives preference to the concept *Shelf* because it has a higher rank with respect to the goal, being also, normally, a member of the concept *Support*. The intentional description of the combined concept for $\mathcal{G}_3$ corresponds to the concept *Table*.

In order to extend the evaluation presented in [14] we collected valid data from 30 human subjects (11 males, 19 females, mostly university students between 18 and 27 years old) that were asked to solve the same type of goal by considering the same subset of domestic object considered by our system for the combination. The human judges were instructed to attempt, for the 3 goals above, only combinations without considering alterations of the objects (e.g. breaking a glass in order to obtain small pieces of cutting objects was not an allowed solution). The results provided for the 3 goals are reported in Figure 1. In particular, the most rated results are compliant with the results reported by our system. Apart from the mere choice of the concept to select for the combination, we also asked to the human subject to indicate which kind of object they were thinking for justifying their combination (the datum is reported in the round parenthesis in the table, along with the percentage of the people that responded in favor of the most rated combination). Interestingly enough, human subjects were also able to provide multiple valid solutions for these constrained goal.

## 6 DISCUSSION AND CONCLUSIONS

The capability of generating in a dynamic way novel knowledge to solve problems is one of the functional criteria of intelligence for artificial systems individuated by Allen Newell [23]. In this paper, we have presented a system aimed at specifically addressing through a dynamical, goal-driven, enrichment of an agent knowledge base obtained via a procedure exploiting a process of commonsense conceptual combination based on the logic $\mathbf{T}^{\mathsf{CL}}$.

The proposed approach has been tested and compared with a psychological evaluation involving human subjects in the task of object composition.

The obtained evidence of compliance with human-like mechanisms, in our opinion, potentially opens the doors to a suitable integration of our proposal with standard standard semantic web tools. In particular, the adoption of such a cognitively inspired framework can be useful in situations where a given query (i.e. the informational goal of an agent) does not find direct answers neither within a single ontology nor in network of linked knowledge graphs. In such cases, the exploitation of the cognitive mechanisms enabled by our approach can provide a way to overcome such informational impasses. Thus, the proposed system (that is already able to deal with ontological KBs and extend them in the language of $\mathbf{T}^{\mathsf{CL}}$) could work as a cognitive middleware called to provide plausible answers to unanswered queries via the process of knowledge generation described above. In the next section we review the related works and conclude with some pointers to future developments. As a further element, it is also important to point put that it has been showed that the overall approach can be used to extend the knowledge processing capabilities of cognitive architectures like SOAR (see [13] on the theoretical aspects of this aspect and [15] for a first concrete attempt) by following the same integrative procedure used for other systems [20].

### 6.1 Related Works

Other attempts of knowledge augmentation and invention similar to the one proposed here concerns the modelling of the conceptual blending phenomenon: a task where the obtained concept is *entirely novel* and has no strong association with the two base concepts (for details about the differences between conceptual combination and conceptual blending see [22]). In this setting, [5] proposed a mechanism for conceptual blending based on the DL $\mathcal{EL}^{++}$. They construct the generic space of two concepts by introducing an upward refinement operator that is used for finding common generalizations of $\mathcal{EL}^{++}$ concepts. However, differently from us, what they call prototypes are expressed in the standard monotonic formalism, which does not allow to reason about typicality and defeasible inheritance. More recently, a different approach is proposed in [6], where the authors see the problem of concept blending as a nonmonotonic search problem and proposed to use Answer Set Programming (ASP) to deal with this search problem. As we have shown in [18], the approach adopted in our system is flexible enough to be applied also to the case of conceptual blending. There is no evidence, however, that both the frameworks of [5] and [6] would be able to model (in toto or in part) conceptual combination problems like the object composition task (which is, on the other hand, very important since it involves all the major foundational issues about the problem of commonsense concept combination described in section 2). As such, $\mathbf{T}^{\mathsf{CL}}$ seems to provide a more general mechanism for modelling the combinatorial phenomenon of concept invention (that can be obtained both with combination and blending).

### 6.2 Future Works

We aim at extending our approach to more expressive symbolic formalisms and Description Logics such as, for example, those underlying the standard OWL language (i.e. the standard for ontological knowledge bases). Moreover, we plan to consider cases in which the system is able to provide a partial solution, satisfying a

| | $\mathcal{G}_1$ | $\mathcal{G}_2$ | $\mathcal{G}_3$ |
|---|---|---|---|
| **System** | $Stone \sqcap Stump$ | $Stone \sqcap RubberBand$ | $Shelf \sqcap Stump$ |
| **Human** | $Stone \sqcap Stump$ $(KnifeWithHandle, 52\%)$ | $Stone \sqcap RubberBand$ $(Slingshot, 42\%)$ | $Shelf \sqcap Stump$ $(Table, 59\%)$ |

**Figure 1: Comparison on Concept Composition in a Domestic Domain.**

proper subset of the initial goals. The system described in section 4 relies on COCOS, a tool for combining concepts in the logic $\mathbf{T}^{\mathsf{CL}}$. In future research, we aim at studying the application of optimization techniques in [2] in order to improve the efficiency of COCOS and, a consequence, of the proposed goal-driven knowledge generation system. Finally, we aim at extending the evaluation provided in this paper in the direction of testing our dynamic knowledge generation system on larger knowledge bases. This aspect would require to analyze in more detail heuristic aspects concerning the efficiency about the concept selection and combination.

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