# A Dynamic Knowledge Generation System for Cognitive Agents

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***Abstract*—In this work we describe a knowledge based system employed for the dynamic, goal-directed and creative generation of novel knowledge in cognitive agents. This system exploits a recently introduced extension of a Description Logic of typicality ($\mathbf{T}^{\mathsf{CL}}$) able to combine prototypical (i.e. commonsense) descriptions of concepts. In particular: given a goal expressed as a set of properties, in case an intelligent agent cannot find a concept in its knowledge base able to fulfill these properties, our system exploits the Description Logic $\mathbf{T}^{\mathsf{CL}}$ in order to find at least two concepts whose creative combination allows to satisfy the goal. The knowledge base of the agent is then extended via a mechanism of commonsense concept combination where the resulting combined concept represents the solution for the initial goal. The proposed approach has been tested in the task of object composition and compared with the responses provided by the OROC system.**

## I. Introduction

Goal-directed problem solving is a crucial everyday activity for both natural and artificial systems. A straightforward assumption in goal-directed systems is that, in the cases where 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 [Aha, 2018]. 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. In this paper, we consider those situations where the solution to a given problem cannot come with the classical means usually adopted for obtaining new knowledge (and leading to a goal-redefinition). In particular, we consider scenarios where the availability of novel knowledge cannot be obtained in an *extrinsic* way (e.g. via communication with another agent or, via a novel learning process or by an external injection of novel knowledge in the declarative memory of an artificial system). On the other hand, in such scenarios, the key to the problem solution lies in an *intrinsic* agent capability of automatically generating novel 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 II we describe the rationale of our proposal. In section III we describe the system adopting the proposed logic, whose efficacy is tested in section IV in the task of object composition. Finally, in section V we survey related approaches and conclude with a discussion on future works.

## II. Commonsense Concept Invention via Dynamic Knowledge Combination

The capability of inventing novel concepts by combining the typical knowledge of pre-existing ones is an important generative phenomenon highlighting some crucial aspects of the knowledge processing capabilities 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 [Boden, 1998]. 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 [Frixione and Lieto, 2011]): the need of a syntactic and semantic compositionality (typical of logical systems) and that one concerning the exhibition of typicality effects. According to a well-known argument [Osherson and Smith, 1981], in fact, prototypes (i.e. commonsense conceptual representations based on typical properties) are not compositional. The classical characterization of such argument is the following one: 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 $\mathbf{T}^{\mathsf{CL}}$ (typicality-based compositional logic) introduced in [Lieto and Pozzato, 2019b], [Lieto and Pozzato, 2018].

This logic combines three main ingredients. The first one relies on the DL of typicality $\mathcal{ALC} + \mathbf{T_R}$ introduced in [Giordano et al., 2015], 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 $Ds$". 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* [Lehmann and Magidor, 1992], 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 [Lehmann and Magidor, 1992] 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 [Riguzzi et al., 2015], 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 [Hampton, 1987] 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 $\mathbf{T}^{\mathsf{CL}}$ 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;
- 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 $\mathbf{T}(C) \sqsubseteq D$

[1] Description Logics are a class of decidable fragments of first order logics that are at the base of Ontology Web Language (OWL) used for the realization of computational ontologies. Nowadays DLs are the most important and widespread symbolic knowledge-representation systems. We remind to [Baader et al., 2003] for a complete introduction.

that are entailed from $w$ in the logic $\mathbf{T}^{\textsf{CL}}$. 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 [Lieto and Pozzato, 2019b] we have shown that reasoning in $\mathbf{T}^{\textsf{CL}}$ remains in the same complexity class of standard $\mathcal{ALC}$ Description Logics.

*Theorem 2.1:* Reasoning in $\mathbf{T}^{\textsf{CL}}$ is EXPTIME-complete.

## III. A Goal-directed System for Dynamic Knowledge Generation and Invention

In this section we describe a goal-directed system relying on the above illustrated $\mathbf{T}^{\textsf{CL}}$ logic [2]. In particular, the 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 $\mathbf{T}^{\textsf{CL}}$, 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 $\{\mathit{Object}, \mathit{Cutting}, \mathit{Graspable}\}$ 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 $\mathbf{T}^{\textsf{CL}}$, 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 $\mathbf{T}^{\textsf{CL}}$.

More formally:

*Definition 3.1:* Given a knowledge base $\mathcal{K}$ in the logic $\mathbf{T}^{\textsf{CL}}$, let $\mathcal{G}$ be a set of concepts $\{D_1, D_2, \ldots, D_n\}$ 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 $\mathbf{T}^{\textsf{CL}}$

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 $\mathbf{T}^{\textsf{CL}}$ 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:

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

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

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

Both $\mathit{Vase}$ and $\mathit{Spoon}$ 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, $\mathit{Vase}$ is ranked as $0.9 + 1 = 1.9$, since both $\mathit{Graspable}$ and $\mathit{Object}$ are properties belonging to the goal: for the former we take the probability 0.9 of the typicality inclusion $\mathbf{T}(\mathit{Vase}) \sqsubseteq \mathit{Graspable}$, for the latter we provide a score of 1 since the property $\mathit{Vase} \sqsubseteq \mathit{Object}$ is rigid. Concerning the concept $\mathit{Spoon}$, the system computes a rank of 1: indeed, the only inclusion matching the goal is the rigid one $\mathit{Spoon} \sqsubseteq \mathit{Graspable}$. Finally, the system checks whether the concept obtained by combining the candidate concepts with the highest ranks, (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.

[2] In other works we have already shown how such logic can be used to model complex cognitive phenomena [Lieto and Pozzato, 2019b] (including methaphors generation) and to build intelligent applications in the field of computational creativity [Lieto and Pozzato, 2019a].

[3] WordNet is a widely known lexical database [Miller, 1995].

In order to combine the two candidate concepts $C_1$ and $C_2$, our system exploits COCOS [Lieto et al., 2018b], 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.

## IV. Experimentation

In this section, we describe the experimental setup and the obtained results of our system in task of object composition of compound tools. Such ability represents a very important creative capability found only in primates (specifically, humans and great apes) and, more recently, in ravens [von Bayern et al., 2018]. It still represents an open challenge in the field of AI and cognitive modelling. As we will see later in detail, in fact, a major problem consists in the lack of realistic benchmarks for evaluating the performance on this task for both humans and artificial systems (this problem is also explicitly reported in [Olteţeanu and Falomir, 2016] that represent, to the best of our knowledge, the first attempt of modelling such faculty in an artificial system). Despite the lack of such a benchmark, for our purposes we decided to test our system on the proof-of-concept evaluation presented in [Olteţeanu and Falomir, 2016]. In addition, we also provided a comparison with responses provided by human judges for the concept composition task.

### A. 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` [Lenat, 1995] [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:

vase, object
vase, high convexity
vase, ceramic, 0.8
vase, to put plants, 0.9
vase, to contain objects, 0.9
vase, graspable, 0.9

corresponding to the following knowledge base in $\mathbf{T}^{\mathsf{CL}}$:

$Vase \sqsubseteq Object$
$Vase \sqsubseteq HighConvexity$
$0.8 \ :: \ \mathbf{T}(Vase) \sqsubseteq Ceramic$
$0.9 \ :: \ \mathbf{T}(Vase) \sqsubseteq ToPutPlants$
$0.9 \ :: \ \mathbf{T}(Vase) \sqsubseteq ToContainObjects$
$0.9 \ :: \ \mathbf{T}(Vase) \sqsubseteq Graspable$

### B. 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 [Olteţeanu and Falomir, 2016] by using a limited sample of the Cyc ontology about domestic objects.

As mentioned in [Olteţeanu and Falomir, 2016], there is no benchmark test available for this kind of task on both human participants and artificial systems. Therefore, we tested our system by comparing our results with the ones described by [Olteţeanu and Falomir, 2016] (table 5, p.23) for the OROC system (to the best of our knowledge, the only available in the literature) by considering the 5 goals they used as testbed. In particular, we asked our system to combine objects in order to obtain the following goals:

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

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

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

$$\mathcal{G}_4 = \{CandlewithSupport\},$$

$$\mathcal{G}_5 = \{Noteebook\}$$

In particular, we discarded the goals 4 and 5 since they are intended as a composition based on a simple meronimy. Goal 4, in fact, is achievable by just composing the two objects *Candle* and *Candle Support* available in the knowledge base. Also the goal of realizing a Notebook was achievable by composing two constituents part of the object available in the KB: *Blank pages* and *Cover*. Such goals can be easily reached by using a standard Description Logic reasoner, without resorting to the sophistication of $\mathbf{T}^{\mathsf{CL}}$ for the commonsense conceptual composition. For the goals 1, 2 and 3, on the contrary we adopted the framework proposed in this paper.

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 [Giordano et al., 2013]. An example of the introduced inclusions/properties (for the concepts Shelf, Stone, Stump, RubberBand) is reported below:

$Shelf \sqsubseteq Object$
$0.8 \ :: \ \mathbf{T}(Shelf) \sqsubseteq Wood$

[4] https://pythonhosted.org/Owlready2/
[5] https://github.com/asanchez75/opencyc/blob/master/opencyc-latest.owl.gz.

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

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

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

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

Given a KB extended in $\mathbf{T}^{\text{CL}}$ 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 $\mathit{Stone} \sqcap \mathit{Branch}$ as a solution, thus suggesting a combined concept having the characteristics resembling a rudimentary $\mathit{KnifeWithAWoodHandle}$

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 $\mathit{Branch}$ and $\mathit{RubberBand}$, being those with the highest rank with respect to $\mathcal{G}_2$. The $(\mathit{Stone} \sqcap \mathit{RubberBand})$-revised knowledge base, suggested by adopting $\mathit{Stone}$ as the HEAD, is such that all the properties of both concepts are considered, with the exception of $\mathit{Support}$. Therefore the knowledge base of the agent is extended (among the others) by the following inclusions:

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

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

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

Therefore our system provided the same results provided in the OROC system [Olteţeanu and Falomir, 2016].

## V. Discussion and Conclusions

In this paper, we have presented a system aimed at specifically addressing this problem by proposing an extension of classical subgoaling procedures 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 $\mathbf{T}^{\text{CL}}$.

The proposed approach has been tested in the task of object composition and compared with the available results of the system OROC [Olteţeanu and Falomir, 2016] that is, to the best of our knowledge, the first system proposing a proof-of-concept procedure for the evaluation of such tasks. In particular, we have shown how our framework is able to generate the same results provide by the OROC system by adopting different representational and reasoning assumptions. As a further element, it is also important to point put that the overall approach can be used to extend the knowledge processing capabilities (see [Lieto et al., 2018a] of cognitive architectures like SOAR (see [Lieto et al., 2019] on this aspect). Our proposal, in fact, is compliant with the idea of a having goal-directed contextual activation of concepts [Lieto, 2014] going from the long-term memory to the short term memory of a cognitive agent. Such extension has been already employed in knowledge-based systems like DUAL-PECCS [Lieto et al., 2017] integrated with different cognitive architectures.

### A. Related Works

Other attempts similar to the one proposed here concern 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 [Nagai and Taura, 2006]). It is worth noticing that both these approaches deal with the problem of *conceptual blending*, while our logic provides a nonmonotonic DL for dealing with conceptual combination. The difference between these two concept synthesis tasks can be roughly explained as follows (for details see [Nagai and Taura, 2006]): while in concept combination the compound concept is a subset of the composing concepts, in conceptual blending the obtained concept is *entirely novel*, it has no strong association with the two base concepts. In this setting, [Confalonieri et al., 2016] 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 [Eppe et al., 2018], 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 [Lieto and Pozzato, 2019b], 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 [Confalonieri et al., 2016] and [Eppe et al., 2018] would be able to model (in toto or in part) conceptual combination problems like the object composition task. 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).

### *B. Future Works*

In future research 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, in future works, we plan to consider cases in which the system is able to provide a partial solution, satisfying a proper subset of the initial goals. The system described in section III 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 [Alberti et al., 2017] 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 two directions: the first one concerns the release of a richer dataset to use for the task of task of Object Composition for testing both human and artificial creativity (and this will require a truly interdisciplinary effort). The second one goes 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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