GOCCIOLA: Generating New Knowledge by Combining Concepts in Description Logics of Typicality

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Outline

- Dynamic goal-directed knowledge generation systems (Motivation)

- Our approach: Dynamic Knowledge Generation via common sense concept combination (intro to the underlying logic $\mathbf{T}^{\mathbf{CL}}$ **(Typicality Based Compositional Logic).**

- The system **GOCCIOLA** (**G**enerating kn**O**wledge by **C**oncept **C**ombination **I**n descripti**O**n **L**ogics of typic**A**lity)

- Demo & Preliminary Results in Concept Composition task

Goal-Directed Systems

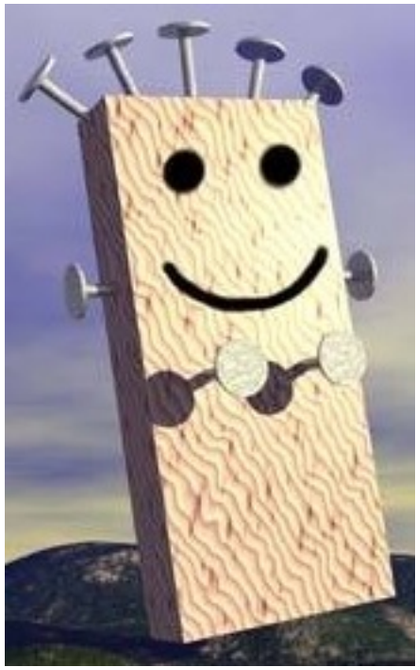
Goal-directed problem solving is a crucial activity for natural and artificial intelligent systems (Aha 2018).

Classical strategies for achieving a goal (if the coal cannot be directly reached) concern **knowledge expansion/ augmentation activities**:

- e.g. via the communication with another agents
- via a learning process
- via an external injection of novel knowledge in the declarative memory of an artificial system

Goal-Directed Systems

We consider scenarios where 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 available **knowledg**e in order to look with new eyes to the problem in hand and solve it.



“Quelo"

La risposta è dentro di te…

Knowledge Generation via Combinatorics

- **Creating novel concepts** by combining the typical knowledge of the pre-existing ones represents a crucial creative ability of human cognition

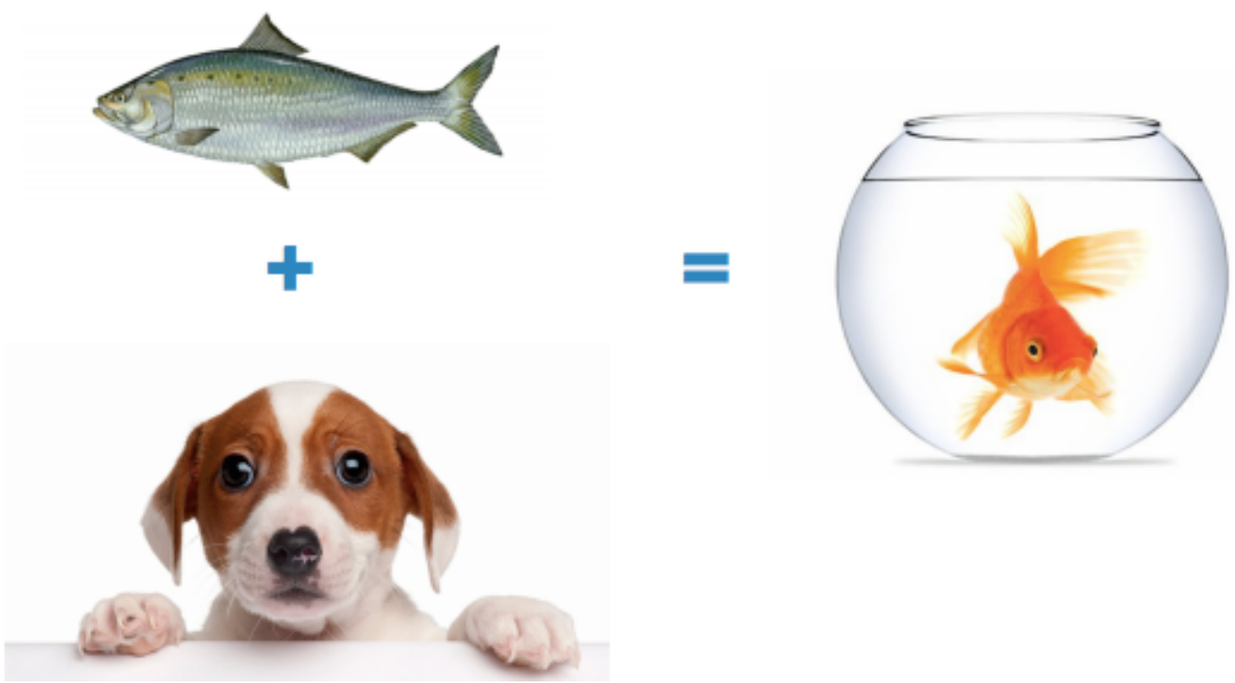
- It is essential for high-level capacities associated to **creative thinking**, **problem solving** …

- This generative phenomenon represents an **open problem** in current research in AI and automated reasoning: lack of heuristic frameworks able to automatically deal with this faculty.

- Why? the phenomenon of combining **prototypical** concepts is difficult to model: <u>Compositionality vs Typicality Effects</u>

Guppy Effect (aka Pet Fish Problem)

Prototypes are not compositional (Osherson and Smith, 1981; Fodor 1981).



The resulting PET FISH concept is not merely composed by the additive inclusion of the typical features of the two composing concepts (i.e. PET and FISH).

Our Proposal

We propose a non monotonic Description Logic of typicality ($\mathbf{T}^{\mathbf{CL}}$), that remains EXP-TIME Complete as *ALC*, for <u>typicality-based concept combination</u> based on 3 ingredients

- Description Logics with Typicality
- Probabilities and Distributed Semantics
- Heuristics from Cognitive Semantics

(Lieto & Pozzato, ISMIS 2018, to appear JETAI).

DL with Typicality (ALC+T)

Non-monotonic extensions of Description Logics for reasoning about prototypical properties and inheritance with exceptions.

Basic idea: to extend DLs with a typicality operator T (Giordano et al. 2015)

- A KB comprises assertions $T(C) \sqsubseteq D$

- $T(Student) \sqsubseteq FacebookUsers$ means “normally, students use Facebook” T is nonmonotonic

- $C \sqsubseteq D$ does not imply $T(C) \sqsubseteq T(D)$ (semantics of T based on Lehmann-Magidor axioms of rational logic R)

Distributed Semantics

We extended the **ALC+T** Logic with **typicality inclusions equipped by real numbers** representing probabilities/degrees of belief.

We adopted the **DISPONTE semantics** (Riguzzi et al 2015) restricted to typicality inclusions:

extension of ALC by inclusions **p :: T (C)** $\sqsubseteq$ **D**

epistemic interpretation: “we believe p that typical Cs are Ds”

The result of this integration allowed us to reason on typical probabilistic scenarios

($\mathbf{T}^{\mathbf{CL}}$) at work: PET FISH

Pet Fish

- $Fish \sqsubseteq \forall livesIn.Water$
- $0.9 \;::\; \mathbf{T}(Pet) \sqsubseteq \forall livesIn.(\neg Water)$
- $0.8 \;::\; \mathbf{T}(Pet) \sqsubseteq Affectionate$
- $0.7 \;::\; \mathbf{T}(Fish) \sqsubseteq \neg Affectionate$
- $0.8 \;::\; \mathbf{T}(Pet) \sqsubseteq Warm$
- $0.6 \;::\; \mathbf{T}(Fish) \sqsubseteq Greyish$
- $0.9 \;::\; \mathbf{T}(Fish) \sqsubseteq Scaly$
- $0.8 \;::\; \mathbf{T}(Fish) \sqsubseteq \neg Warm$

($\mathbf{T}^{\mathbf{CL}}$) at work: PET FISH

Pet Fish - Different scenarios

- $Fish \sqsubseteq \forall livesIn.Water$
- $0.9 \;::\; \mathbf{T}(Pet) \sqsubseteq \forall livesIn.(\neg Water)$
- $0.8 \;::\; \mathbf{T}(Pet) \sqsubseteq Affectionate$
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($\mathbf{T}^{\mathbf{CL}}$) at work: PET FISH

- $\mathit{Fish} \sqsubseteq \forall \mathit{livesIn}.\mathit{Water}$
- $0.9 \;::\; \mathbf{T}(\mathit{Pet}) \sqsubseteq \forall \mathit{livesIn}.(\neg \mathit{Water})$
- $0.8 \;::\; \mathbf{T}(\mathit{Pet}) \sqsubseteq \mathit{Affectionate}$
- $0.7 \;::\; \mathbf{T}(\mathit{Fish}) \sqsubseteq \neg \mathit{Affectionate}$
- $0.8 \;::\; \mathbf{T}(\mathit{Pet}) \sqsubseteq \mathit{Warm}$
- $0.6 \;::\; \mathbf{T}(\mathit{Fish}) \sqsubseteq \mathit{Greyish}$
- $0.9 \;::\; \mathbf{T}(\mathit{Fish}) \sqsubseteq \mathit{Scaly}$
- $0.8 \;::\; \mathbf{T}(\mathit{Fish}) \sqsubseteq \neg \mathit{Warm}$
- Probability: $(1 - 0.9) \times (1 - 0.8) \times 0.7 \times \cdots \times 0.8 = 0.1\%$

Cognitive Heuristics

Heuristics from **cognitive semantics** for the identification of plausible mechanisms for blocking-inheritance.

HEAD-MODIFIER heuristics (Hampton, 2011):

- HEAD: stronger element of the combination
- MODIFIER weaker element

where $C \sqsubseteq CH \sqcap CM$

The compound concept C as the combination of the HEAD (CH) and the MODIFIER (CM)

($\mathbf{T}^{\mathbf{CL}}$) at work

INITIAL KNOWLEDGE BASE

RIGID PROPERTIES

$Fish \sqsubseteq \forall livesIn.Water$

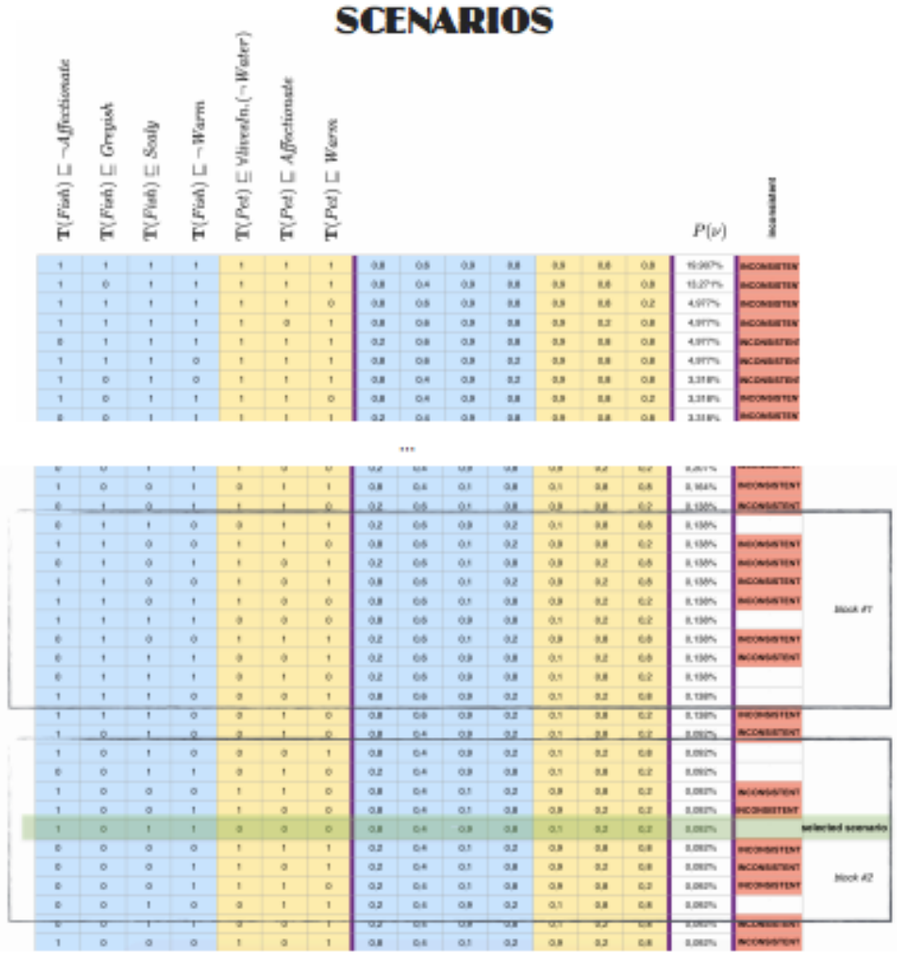
PROTOTYPE OF HEAD

$0.7 :: \mathbf{T}(Fish) \sqsubseteq \neg Affectionate$
$0.8 :: \mathbf{T}(Fish) \sqsubseteq \neg Warm$
$0.6 :: \mathbf{T}(Fish) \sqsubseteq Greyish$
$0.9 :: \mathbf{T}(Fish) \sqsubseteq Scaly$

PROTOTYPE OF MODIFIER

$0.9 :: \mathbf{T}(Pet) \sqsubseteq \forall livesIn.Water$
$0.8 :: \mathbf{T}(Pet) \sqsubseteq Affectionate$
$0.8 :: \mathbf{T}(Pet) \sqsubseteq Warm$

SCENARIOS



PROTOTYPE OF COMBINED CONCEPT

$0.8 :: \mathbf{T}(Pet \sqcap Fish) \sqsubseteq \neg Warm$
$0.8 :: \mathbf{T}(Pet \sqcap Fish) \sqsubseteq \neg Affectionate$
$0.6 :: \mathbf{T}(Pet \sqcap Fish) \sqsubseteq Scaly$

REVISED KNOWLEDGE BASE

$Fish \sqsubseteq \forall livesIn.Water$

$0.7 :: \mathbf{T}(Fish) \sqsubseteq \neg Affectionate$
$0.8 :: \mathbf{T}(Fish) \sqsubseteq \neg Warm$ $0.9 :: \mathbf{T}(Fish) \sqsubseteq Scaly$
$0.6 :: \mathbf{T}(Fish) \sqsubseteq Greyish$

$0.9 :: \mathbf{T}(Pet) \sqsubseteq \forall livesIn.Water$
$0.8 :: \mathbf{T}(Pet) \sqsubseteq Affectionate$ $0.8 :: \mathbf{T}(Pet) \sqsubseteq Warm$

$0.8 :: \mathbf{T}(Pet \sqcap Fish) \sqsubseteq \neg Warm$
$0.8 :: \mathbf{T}(Pet \sqcap Fish) \sqsubseteq \neg Affectionate$
$0.6 :: \mathbf{T}(Pet \sqcap Fish) \sqsubseteq Scaly$
$0.9 :: \mathbf{T}(Pet \sqcap Fish) \sqsubseteq Red$

Additional Element: in Logic $\mathbf{T}^{\mathbf{CL}}$ we assume a hybrid KB (Rigid and Typical Roles)

Selection Criteria

The typical properties of the form T(C) $\sqsubseteq$ D to ascribe to the concept C are obtained in the set of scenarios, obtained by applying the DISPONTE semantics, that are:

- **consistent** with respect to KB;
- **not trivial**, e.g. those ascribing all properties of the HEAD are discarded;
- giving **preference to CH w.r.t. CM** with the highest probability

Goal oriented Knowledge Generation

Definition 1. Given a knowledge base **K** in the logic $\mathbf{T}^{\mathbf{CL}}$, let **G** be a set of concepts {D1, D2, . . . , Dn} called goal.

G = {AfterMealDrink, HotBeverage, Sweet, TasteOfMilk}.

We say that a concept C is a solution to the goal G if either:

– for all $D_i \in G$, either $K \models C \sqsubseteq D$ or $K0 \models T(C) \sqsubseteq D$ in the logic $\mathbf{T}^{\mathbf{CL}}$ or:

– C corresponds to the **combination of at least two concepts** C1 and C2 occurring in K, i.e.

$C \equiv C1 \sqcap C2$, and the C-revised knowledge base K_c provided by the logic $\mathbf{T}^{\mathbf{CL}}$ is such that, for all $D_i \in G$, either $K_c \models C \sqsubseteq D$ or $Kc \models T(C) \sqsubseteq D$ in $\mathbf{T}^{\mathbf{CL}}$

Concept composition

We tested our system on a task of **concept composition** for a KB of **objects**.

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

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

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

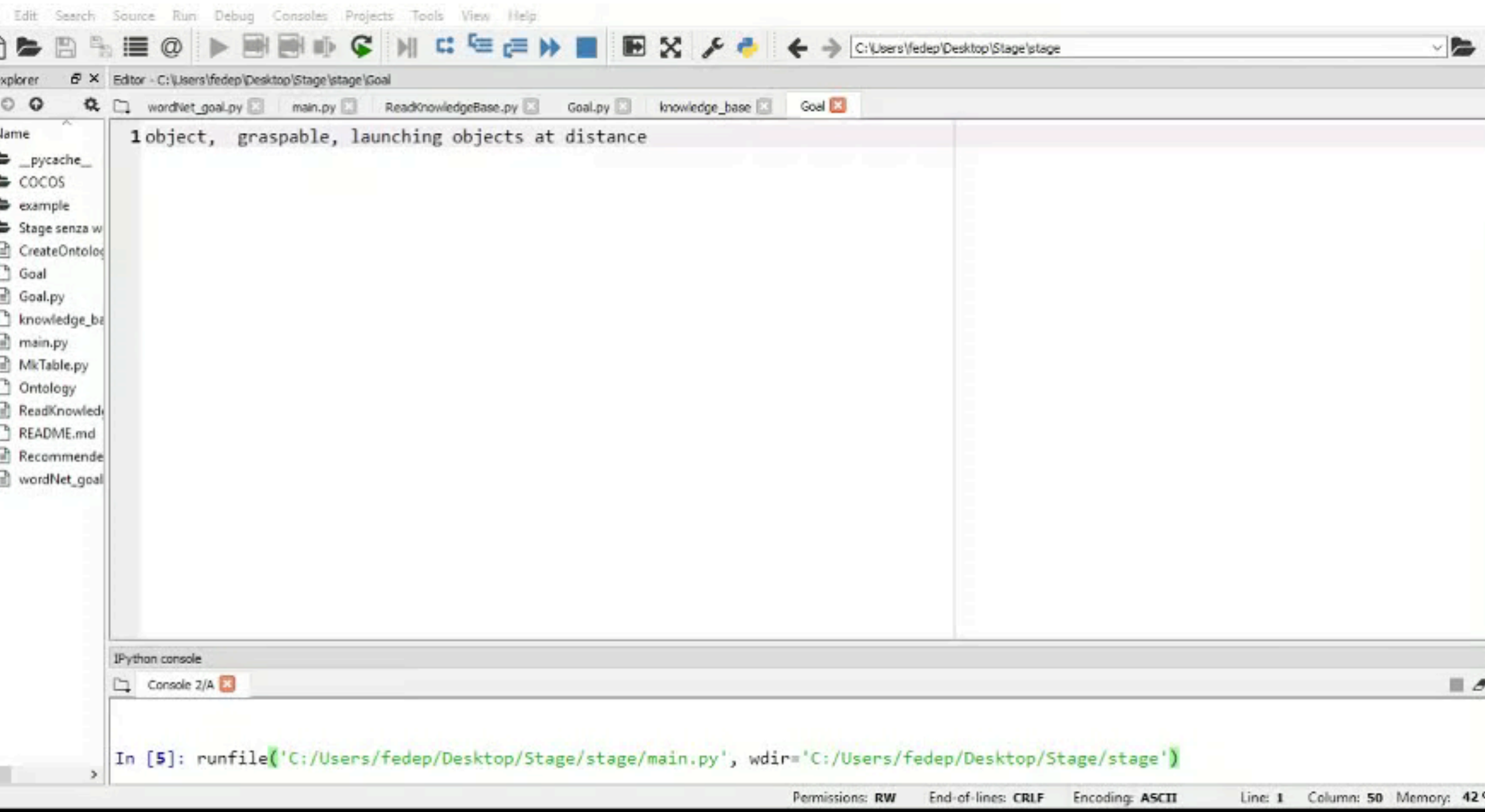
GOALS

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	$0.9 :: \mathbf{T}(Vase) \sqsubseteq Graspable$

KB $\mathbf{T}^{CL}$

GOCCIOLA

http://di.unito.it/gocciola



Preliminary Evaluation

	$\mathcal{G}_1$	$\mathcal{G}_2$	$\mathcal{G}_3$
System	$Stone \sqcap Branch$	$Branch \sqcap RubberBand$	$Shelf \sqcap Stump$
Human	$Stone \sqcap Branch$ $(KnifeWithHandle, 52\%)$	$Branch \sqcap RubberBand$ $(Slingshot, 42\%)$	$Shelf \sqcap Stump$ $(Table, 59\%)$
System	-	$Book \sqcap RubberBand$	$Stump \sqcap SurfBoard$
Human	$Stone \sqcap Towel$ $(13, 3\%)$	$Towel \sqcap RubberBand$ $(10, 8\%)$	$Vase \sqcap Shelf$ $(22, 5\%)$

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

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

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

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

- **GOCCIOLA** also exploits **WordNet** sysnsets in order to extend its search space in case of a failure

- In detail, if the goal contains properties not belonging to the initial knowledge base, GOCCIOLA looks for **hypernyms** or **hyponyms** in order to rewrite such properties

- It has been proposed that the system can extend the sub-goaling procedures of the **SOAR** cognitive architecture (Lieto, Pozzato, Perrone, Chiodino, submitted)

Future works

- The logic $\mathbf{T}^{\mathbf{CL}}$ underlying the system is also able to **combine more than two concepts** at a time, as well as to involve compound concepts (and not only atomic ones) in a concept combination. We aim at extending our approach in order to also exploit this feature.

- Moreover, in future works, we plan to consider the case in which the system is able to provide a partial solution, satisfying a **proper subset** of the initial goals.

Thanks !