Functional and Structural Models of Commonsense Reasoning in Cognitive Architectures

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AI and CogSci Approaches to Commonsense Reasoning (partial overview)

Cognitive Heuristics

Machine-oriented Heuristics

Fuzzy Logic
Zadeh, 1966

Frames
(Minsky, 1975)

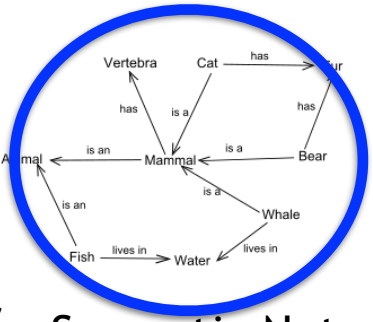
Scripts
(Shank & Abelson, 1977)

Circumscription
(Mc Carthy, 1980,86)

Conceptual Spaces
(Gärdenfors, 2000)

...

Newell Simon, GPS
(1962)

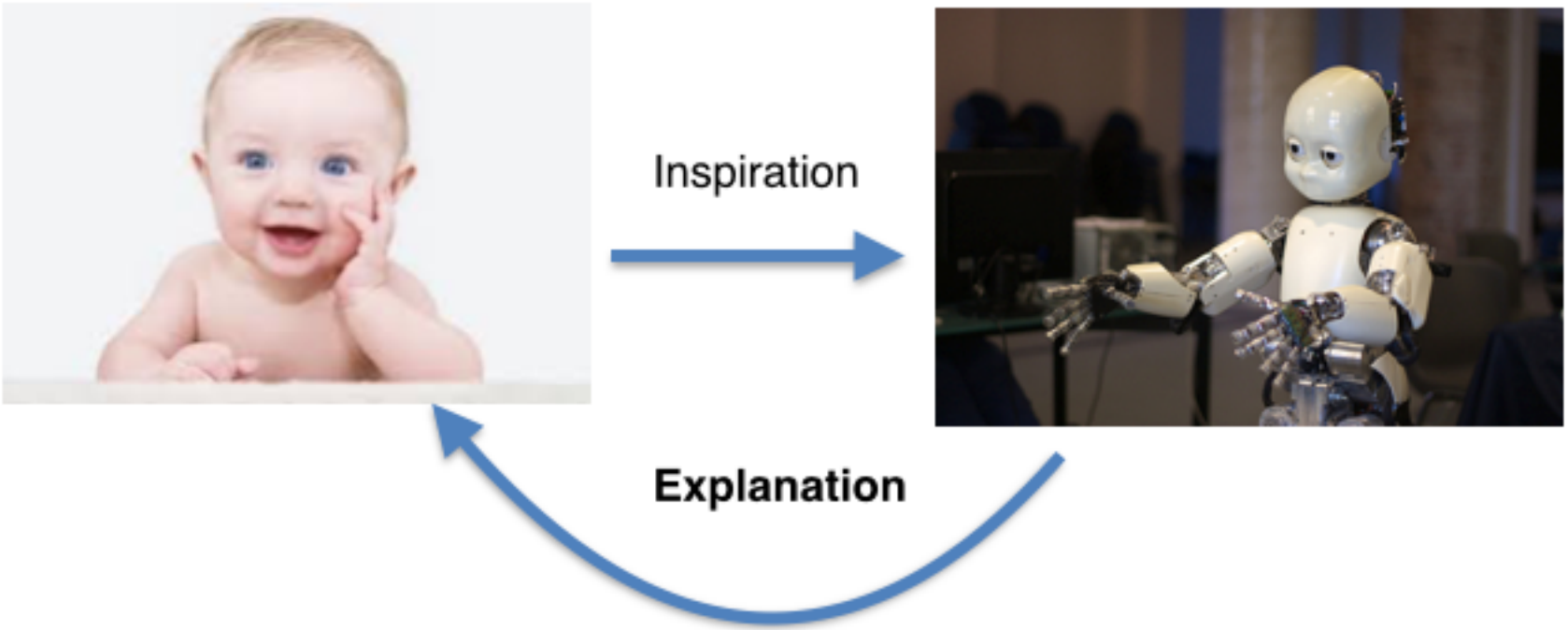


Semantic Networks
(Collins and Quillians, 1969)

Default Logic
Reiter (1980)

Qualitative Repres.
(Forbus, 1984)

Cognitive AI/Computational CogSci



Functionalist vs Structuralist Models

Same *input-out* spec. and s*urface resemblance* of the internal components and of their working mechanisms between artificial and natural system

Same *input-out* spec. + constrained *resemblance* of the internal components and of their working mechanisms between artificial and natural system

Evolutionistic Explanation

Teleological Explanation

Causal Explanation

Functionalist Models — Structuralist Models

continuum

Functional Explanation

IBE

Mechanistic Explanation

ROUTLEDGE

Cognitive Design for Artificial Minds

Antonio Lieto

Lieto, 2021, Cognitive Design for Artificial Minds, Routledge (Taylor & Francis, UK).

Commonsense reasoning

Concerns all the type of non deductive (or non monotonic) inference:

- induction
- abduction
- default reasoning
- …

Commonsense reasoning

Concerns all the type of non deductive (or non monotonic) inference:

- induction
- abduction
- default reasoning
- …

} **TYPICALITY**

Compositionality

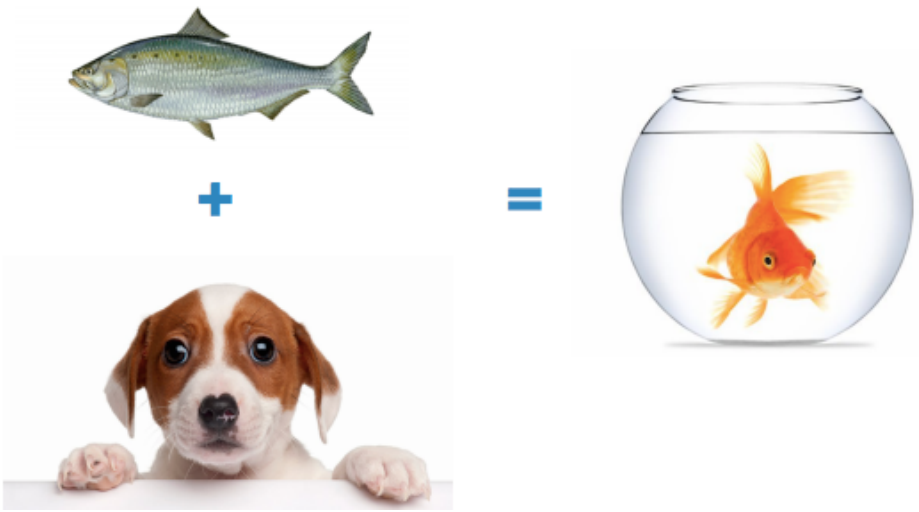
- **COMPOSITIONALITY** is an irrevocable trait of human cognition (Fodor and Pylyshyn, 88).

- A crucial generative requirement

Commonsense Compositionality

PET FISH Problem: **Prototypes are not compositional** (Osherson and Smith, 1981).

Fish = {Greyish, Lives-in Water, not Warm.. }

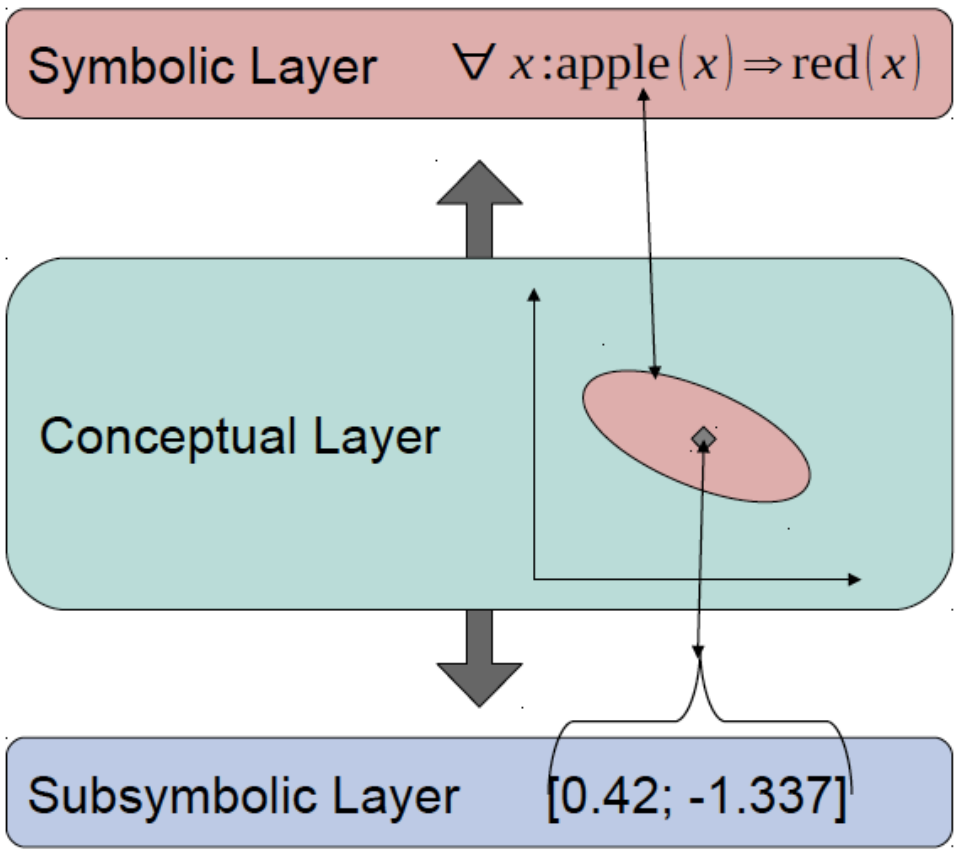


PET Fish =
{**Lives-in Water, not Warm, Red..** }

PET = {hasFur, Warm, not Lives-in Water… }

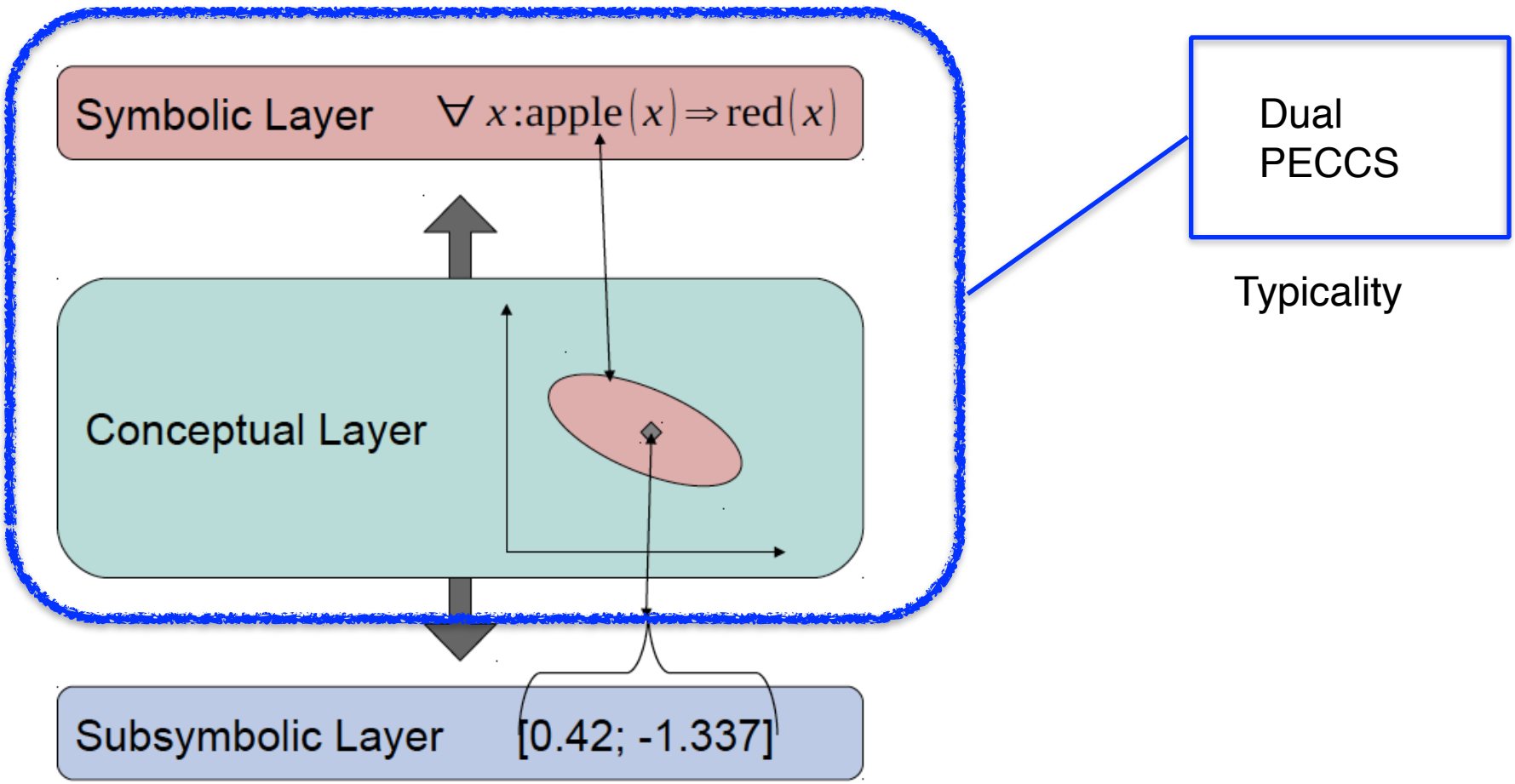
The resulting PET FISH concept is not merely composed by the additive inclusion of the typical features of the two composing concepts (i.e. PET and FISH).

Levels of Representations

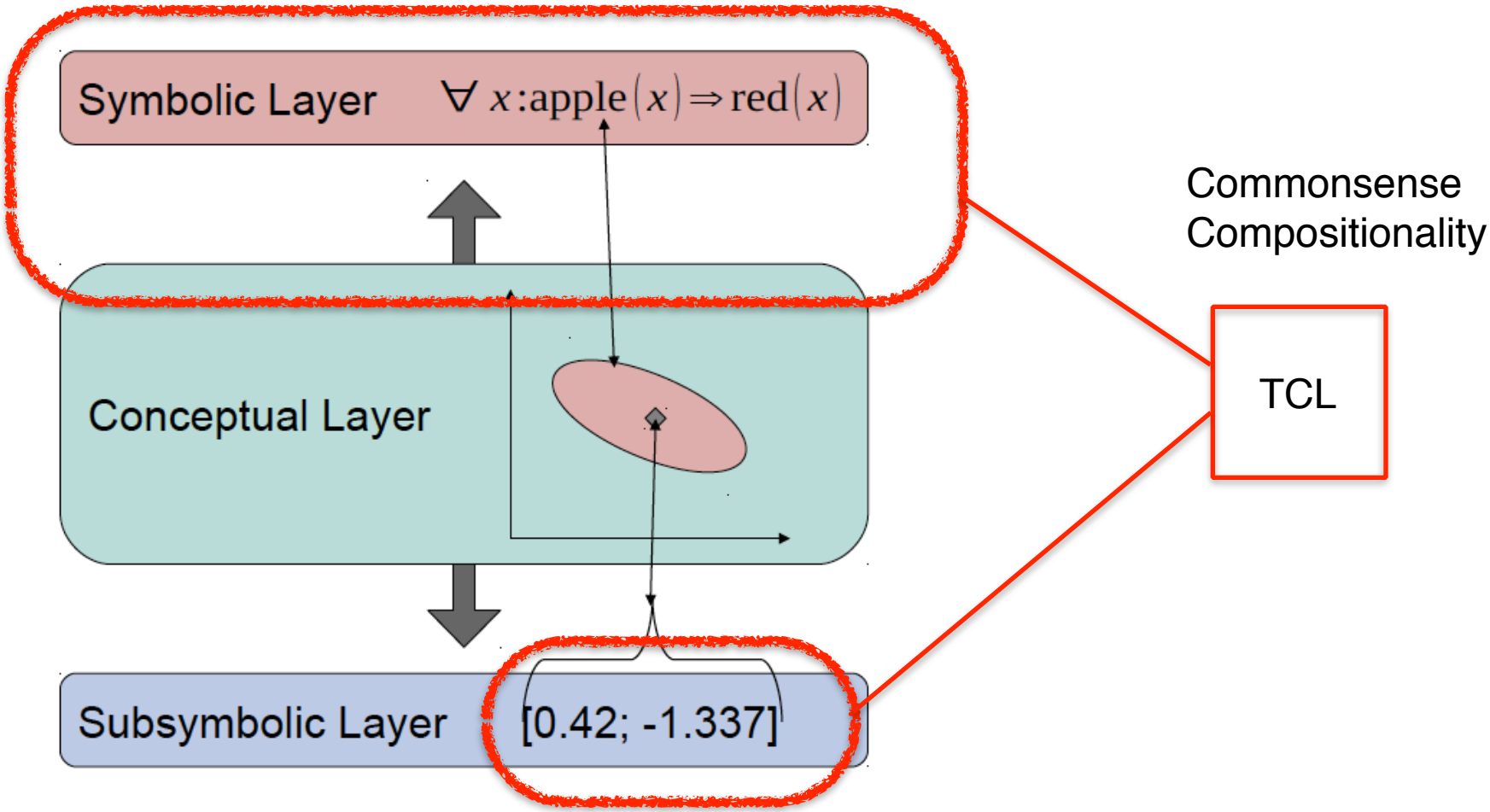


Lieto, Chella, Frixione, 2017. Conceptual Spaces for Cognitive Architectures: A Lingua Franca for Different Levels of Representations, Biologically Inspired Cognitive Architectures.

Levels of Representations



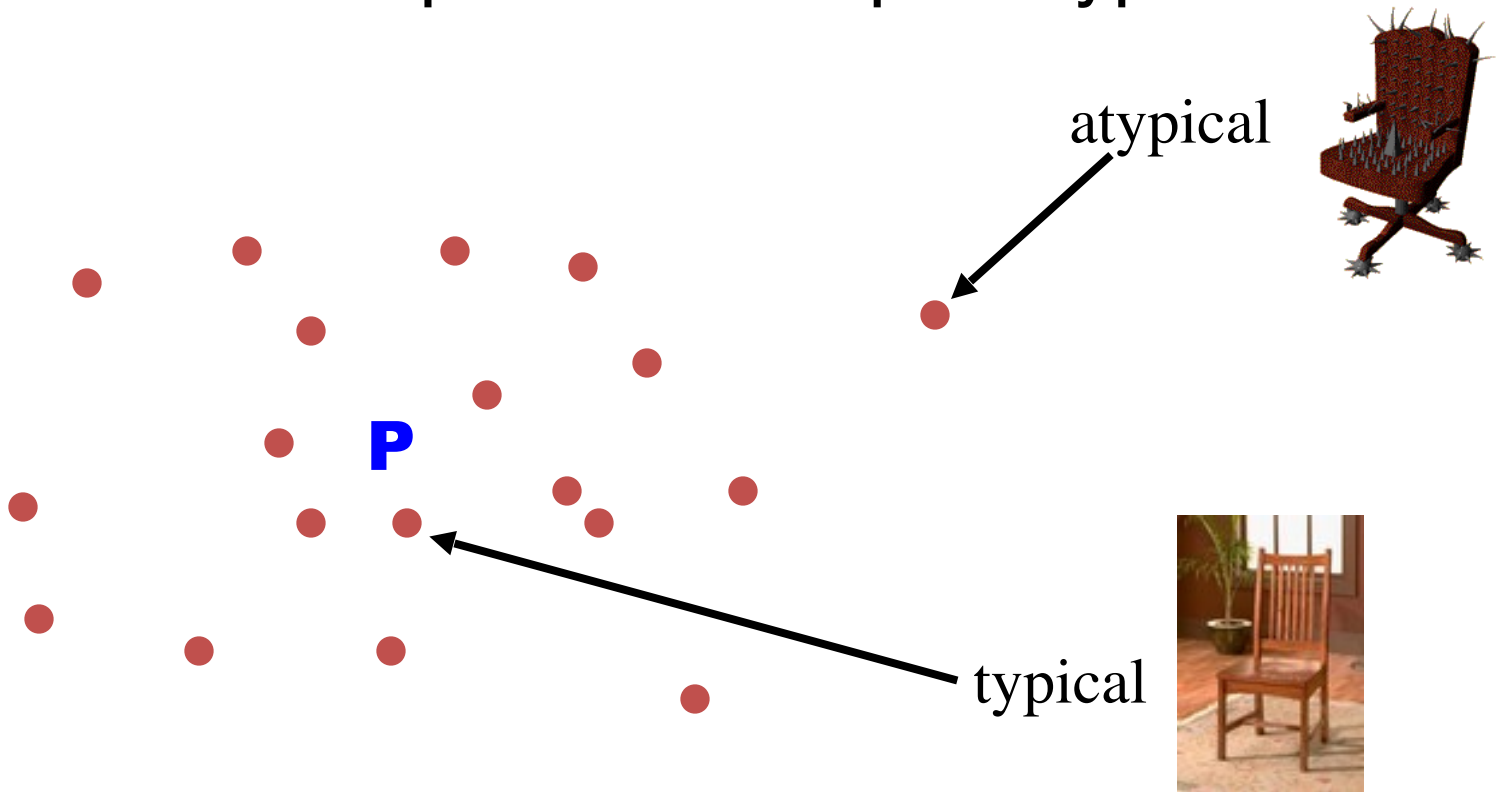
Levels of Representations



Typicality

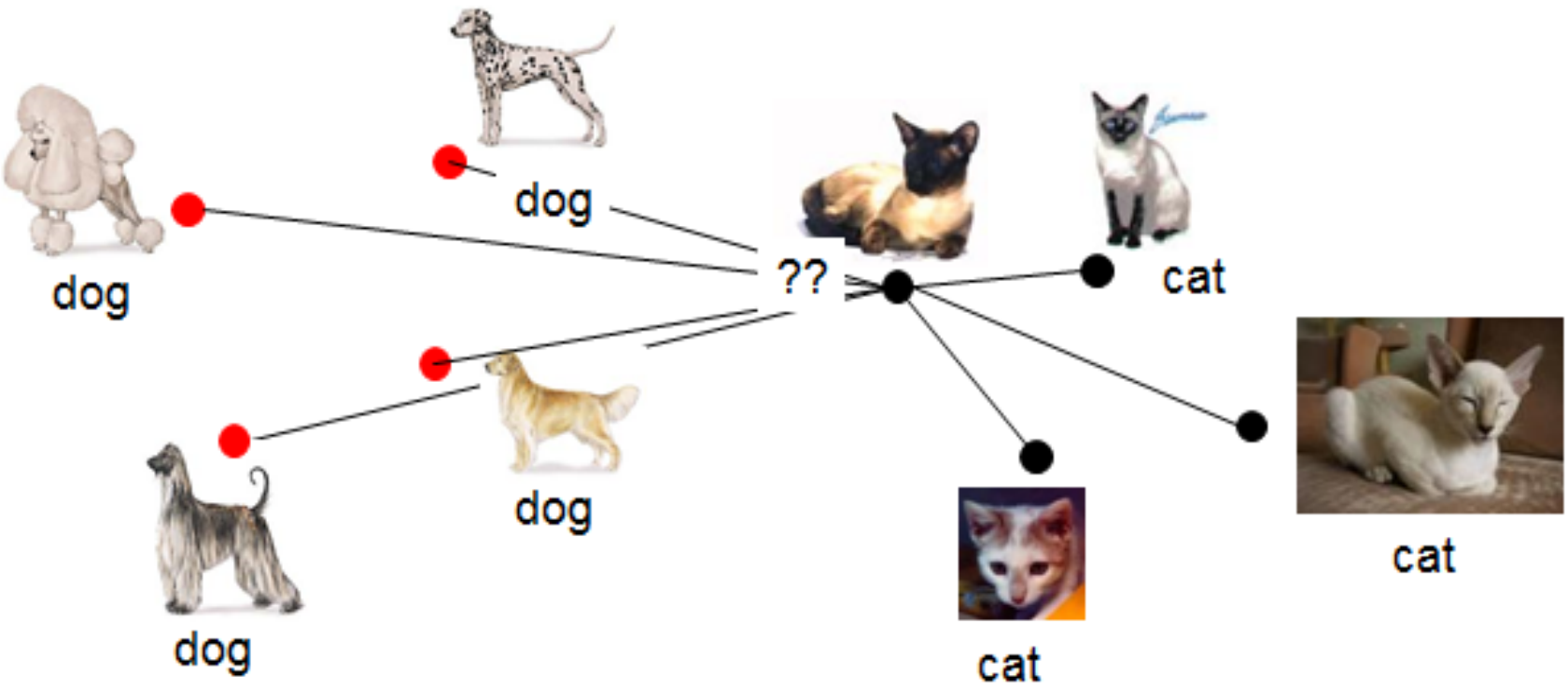
Prototypes and Prototypical Reasoning

- Categories based on prototypes (Rosh,1975)
- New items are compared to the prototype



Exemplars and Exemplar-based Reasoning

- Categories as composed by a list of exemplars. New percepts are compared to known exemplars (**not to Prototypes**).



Conflicting Theories?

- **Exemplars theory** overcomes the **Prototypes** (it can explain so called **OLD ITEM EFFECT**).

- Still in some situations **prototypes** are preferred in categorization tasks.

Prototypes, Exemplars and other conceptual **representations (for the same concept)** can co-exists and be activated in different contexts (Malt 1989).

DUAL PECCS: **DUAL**- **P**rototype and **E**xemplars **C**onceptual **C**ategorization **S**ystem

Lieto, Radicioni, Rho (**IJCAI** 2015, **JETAI** 2017)

2 Cognitive Assumptions

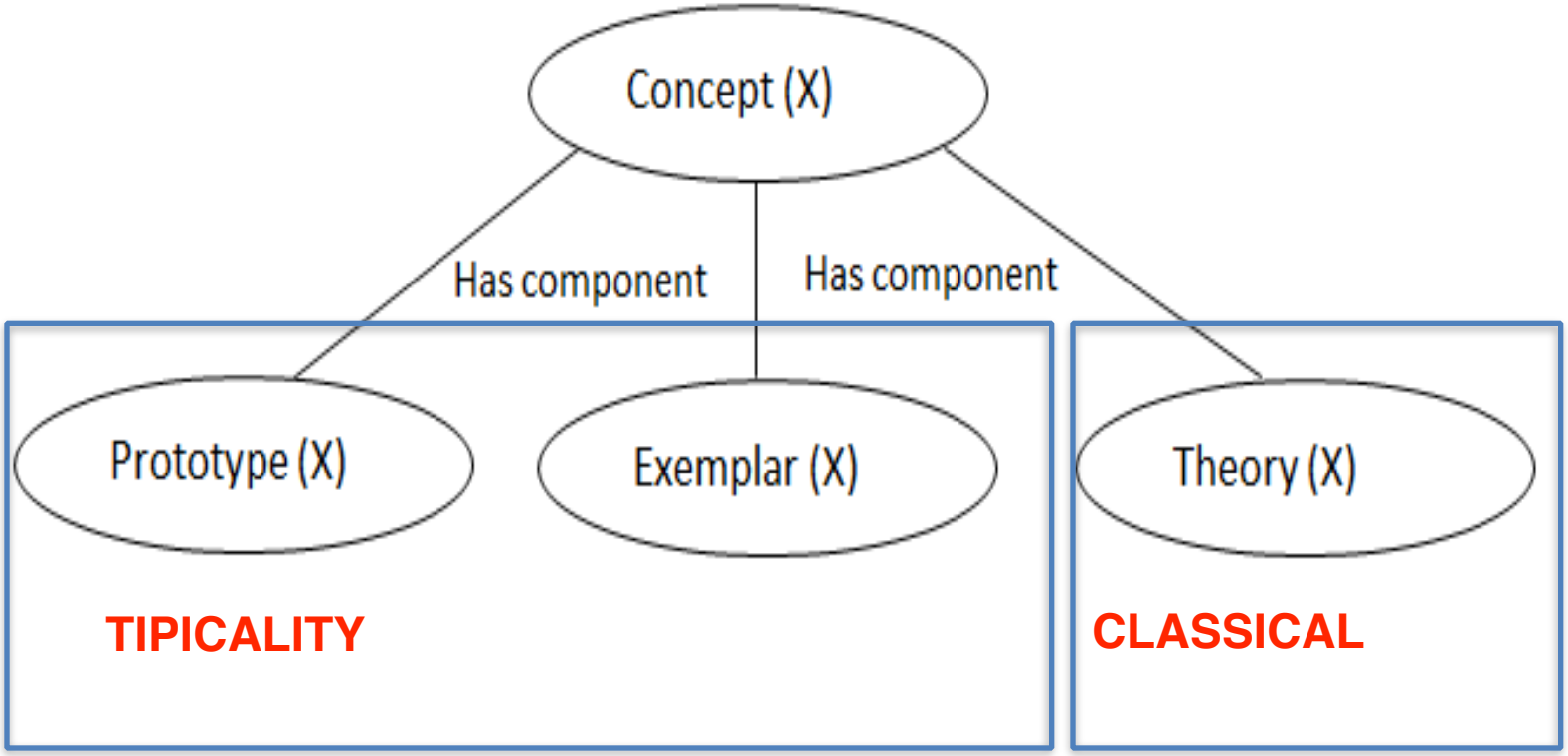
1) Multiple representations for the same concept

2) On such diverse, but connected, representation are executed different types of reasoning (**System 1/ System 2**) to integrate.

Type 1 Processes	Type 2 Processes
Automatic	Controllable
Parallel, Fast	Sequential, Slow
Pragmatic/contextualized …	Logical/Abstract …

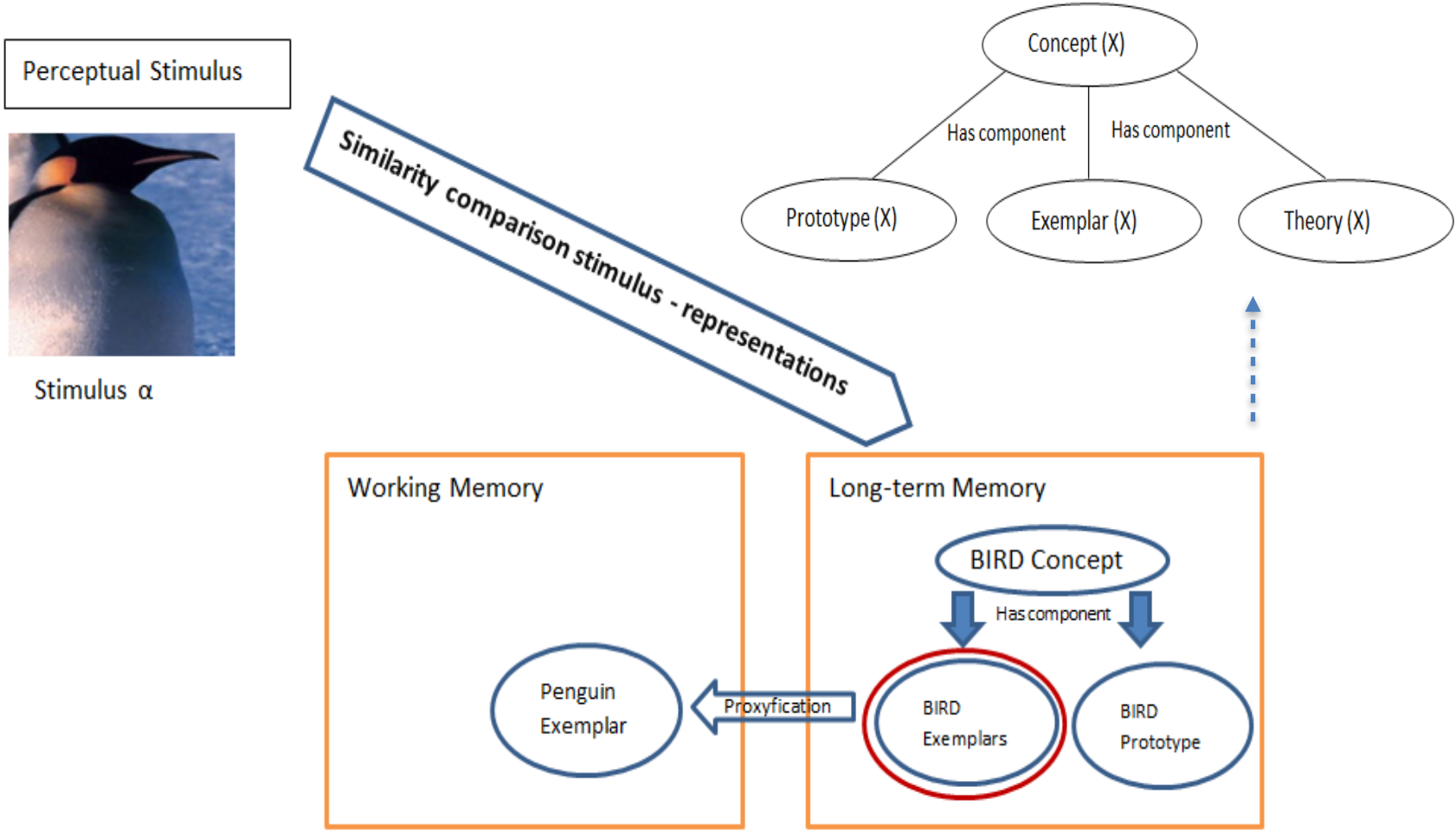
Heterogeneous Proxytypes Hypothesis

The diverse **types of connected representations** can coexist and point to the same conceptual entity. Each representation can be activated as a **proxy** (for the entire concept) from the long term memory to the working memory of a cognitive agent.

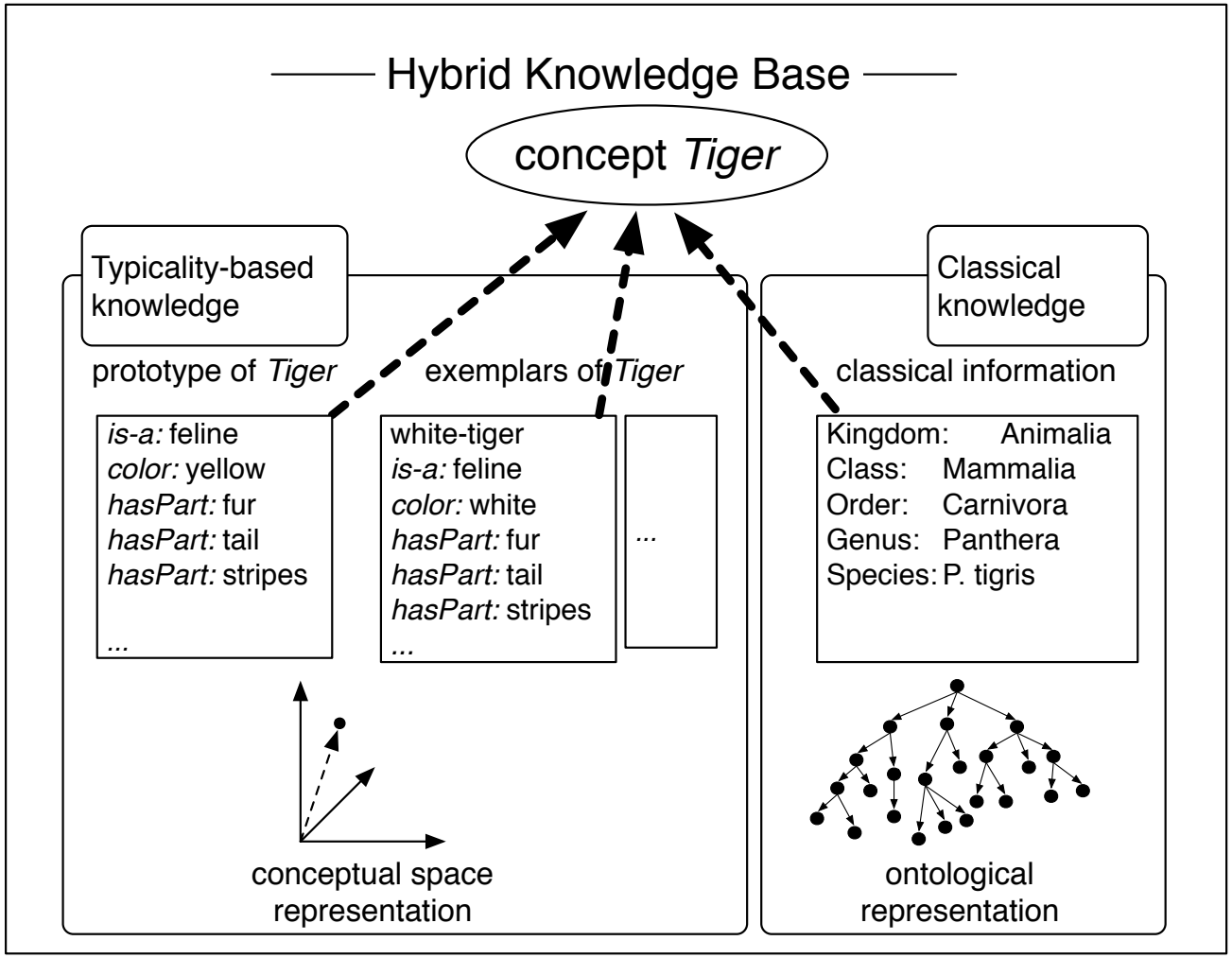


(Lieto, A. ***A Computational Framework for Concept Representation in Cognitive Systems and Architectures: Concepts as Heterogeneous Proxytypes***, Proc. of BICA 2014)

Ex. Heterogeneous Proxytypes at work

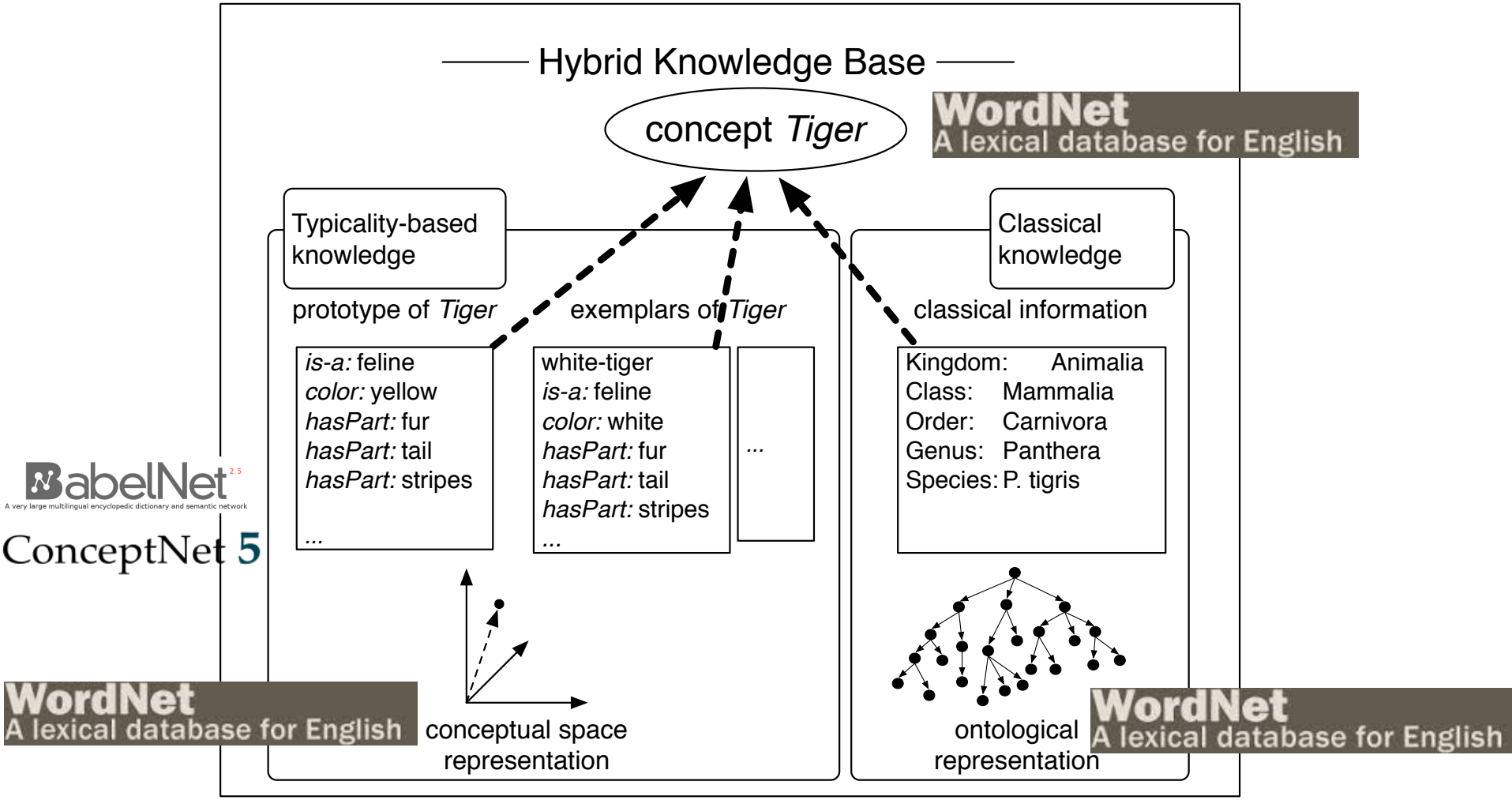


Co-referring representational Structures via Wordnet



Lieto, A., Radicioni, D. P., & Rho, V. (2017). **Dual PECCS: a cognitive system for conceptual representation and categorization**. Journal of Experimental & Theoretical Artificial Intelligence, 29(2), 433-452.

Co-referring representational Structures via Wordnet



Lieto, A., Mensa, E,, Radicioni, D., 2016. **A resource-driven approach for anchoring linguistic resources conceptual spaces**. In Conference of the Italian Association for Artificial Intelligence (pp. 435-449). Springer, Cham.

S1/S2 Categorization Algorithms

Data: Linguistic d
Result: A class assignment, as computed by $\mathcal{S}1$ and $\mathcal{S}2$

1 $trialCounter \leftarrow 0$;
2 $closed^{\mathcal{S}1} = \{\emptyset\}$
3 **while** $trialCounter < maxTrials$ **do**
    `// conceptual spaces output`
4 $\mathsf{c} \leftarrow \mathcal{S}1(d, closed^{\mathcal{S}1})$;
5 **if** $trialCounter == 0$ **then** $\mathsf{c}^* \leftarrow \mathsf{c}$;
    `// ontology based consistency chec`
6 $\mathsf{cc} \leftarrow \mathcal{S}2(d, conceptPointedBy(\mathsf{c}))$;
7 **if** cc $equals(conceptPointedBy(\mathsf{c}))$ **then**
8 **return** $\langle \mathsf{c}^*, \mathsf{cc} \rangle$;
9 **else**
10 $closed^{\mathcal{S}1}$ $add(conceptPointedBy(\mathsf{c}))$
11 **end**
12 $++trialCounter$;
13 **end**
14 $\mathsf{cc} \leftarrow \mathcal{S}2(\langle d, \mathsf{Thing} \rangle)$;
15 **return** $\langle \mathsf{c}^*, \mathsf{cc} \rangle$;

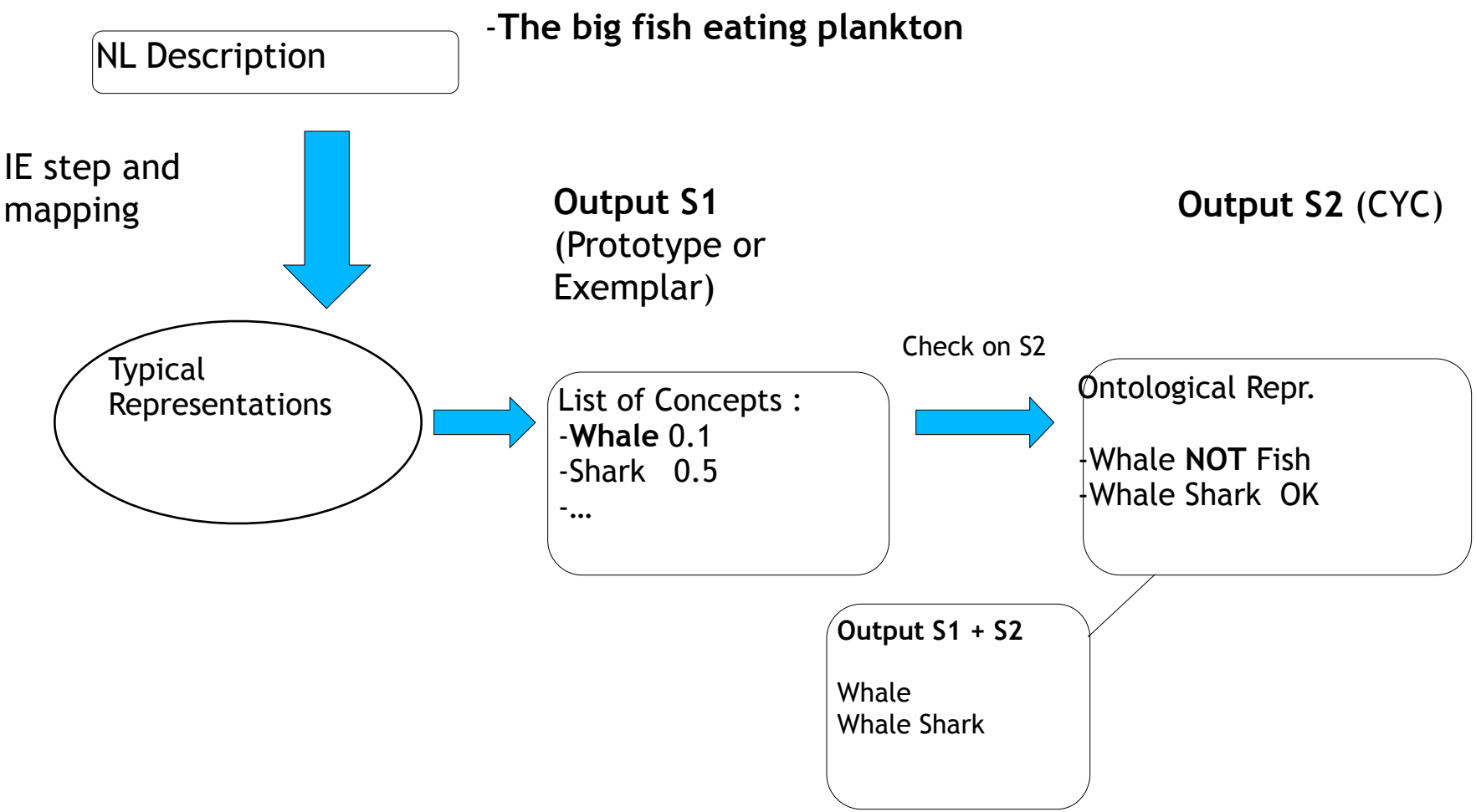
Algorithm 1: The $\mathcal{S}1$-$\mathcal{S}2$ categorization process.

Data: Linguistic description: d; list of inconsistent concepts: $closed^{\mathcal{S}1}$.
Result: A typicality based representation of a category.

1 $\mathcal{S}1_{\text{EX}} \leftarrow categorizeExemplars(d)$;
2 **if** $firstOf(\mathcal{S}1_{\text{EX}}, closed^{\mathcal{S}1}).distance(d) < similarityThreshold$ **then**
3 **return** $firstOf(\mathcal{S}1_{\text{EX}}, closed^{\mathcal{S}1})$;
4 **else**
5 $\mathcal{S}1_{\text{PR}} \leftarrow categorizePrototypes(d)$;
    `// in case of equal distance prefer exemplars`
6 $typicalityCategorization \leftarrow sortResults(\mathcal{S}1_{\text{EX}}, \mathcal{S}1_{\text{PR}})$;
7 **return** $firstOf(typicalityCategorization, closed^{\mathcal{S}1})$;
8 **end**

Algorithm 2: $\mathcal{S}1$ categorization with prototypes and exem plars implementing the instruction in Algorithm 1: line 4.

Overview


NL Description
-The big fish eating plankton
IE step and mapping
Typical Representations
Output S1 (Prototype or Exemplar)
List of Concepts :
-Whale 0.1
-Shark 0.5
-...
Check on S2
Output S2 (CYC)
Ontological Repr.
-Whale NOT Fish
-Whale Shark OK
Output S1 + S2
Whale
Whale Shark

DEMO https://www.youtube.com/watch?v=1KtnAWyxj-8

QuickTime Player File Edit View Window Help 100% Mon 19:26 radicio

ijcai15stimuli.txt — s1s2_deploy_test

actr_integration.properties | ie.properties | s1.properties | s1s2.properties | s2.properties | user.properties

```
32 A bird that has large yellow eyes and hunts small animals at night; owl;
33 A big animal that lives in the desert and has two humps; camel; PROTOTYP
34 A big animal with four legs, used to ride or to pull heavy things; horse
35 A big black wild feline; panther; PROTOTYPE
36 A big fish with very sharp teeth; shark; PROTOTYPE
37 A big strong wild animal with thick fur; bear; PROTOTYPE
38 A big, black and white sea bird that swims and cannot fly; penguin; PROT
39 A sea creature with ten legs and a circular body covered by a shell; cra
40 A tall African animal with a very long neck and long, thin legs; giraffe
41 An Australian animal like a small bear with grey fur which lives in tree
42 The big bird with hooked beak that eats carrions; vulture; PROTOTYPE
43 The big carnivore with yellow fur and black stripes; tiger; PROTOTYPE
44 The big herbivore with antlers; deer; PROTOTYPE
45 The carnivore with brown fur and short tail and tufted ears; lynx; PROTO
46 The carnivore with mane and big jaws; lion; PROTOTYPE
47 The insect with sting and black and yellow striped body that produces ho
48 The little black amphibian with yellow spots; salamander; PROTOTYPE
49 The mammal bred for milk and for slaughter; cow; PROTOTYPE
```

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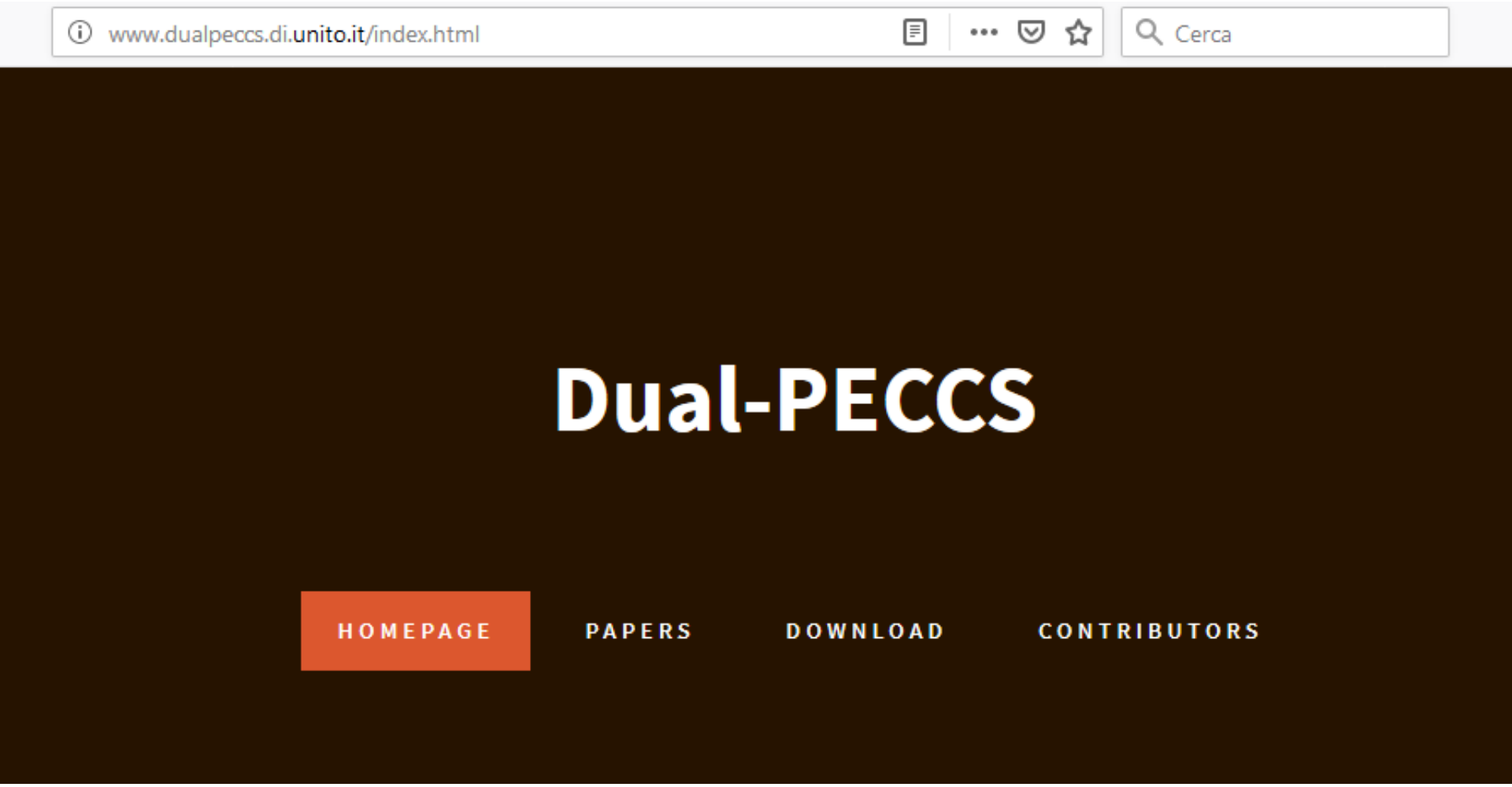
Current C

Antonio Lieto
15:41

- config
- examples
- files
- lib
- ChunkEncoder.ja
- Extended_Java_
- README_ACTR_
- README_S1S2_
- S1S2Controller.j

http://dualpeccs.di.unito.it



Evaluation

Gold standard of 112 common sense linguistic descriptions provided by a team of linguists, philosophers and neuroscientists interested in the neural basis of lexical processing (FMRI) and tested on **45 humans.**

For each description recorded the **human answers** for the categorization task.

Stimulus	Expected Concept	Expected Proxy-Representation	Type of Proxy-Representation
…	…	…	…
The primate with red nose	*Monkey*	*Mandrill*	*EX*
The feline with black fur that hunts mice	*Cat*	*Black cat*	*EX*
The big feline with yellow fur	*Tiger*	*Prototypical Tiger*	*PR*

Accuracy Metrics

- Two evaluation metrics have been devised:
  - Concept Categorization Accuracy: estimating how often the correct concept has been retrieved;
  - Proxyfication Accuracy: how often the correct concept has been retrieved AND the expected representation has been retrieved, as well.

test	CC-ACC	P-ACC
with no IE	89.3% (100/112)	79.0% (79/100)
with IE	77.7% (87/112)	71.3% (62/87)

Commonsense Compositionality

$\mathbf{T^{CL}}$

A non monotonic Description Logic of typicality ($\mathbf{T^{CL}}$), for <u>typicality-based concept combination</u> based on 3 ingredients

- Description Logics with Typicality (ALC + T)
- Probabilities and Distributed Semantics (Disponte)
- Heuristics from Cognitive Semantics (HEAD-MODIFER)

Lieto & Pozzato, "**A Description Logic Framework for Commonsense Conceptual Combination Integrating Typicality, Probabilities and Cognitive Heuristics**", in Journal of Experimental & Theoretical Artificial Intelligence, 32 (5), 769-804, 2020. https://arxiv.org/pdf/1811.02366.pdf

Typicality + 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

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 - Pipeline

1. **KB with real data**

INITIAL KNOWLEDGE BASE

RIGID PROPERTIES

$Fish \sqsubseteq \forall livesIn.Water$

PROTOTYPE OF HEAD

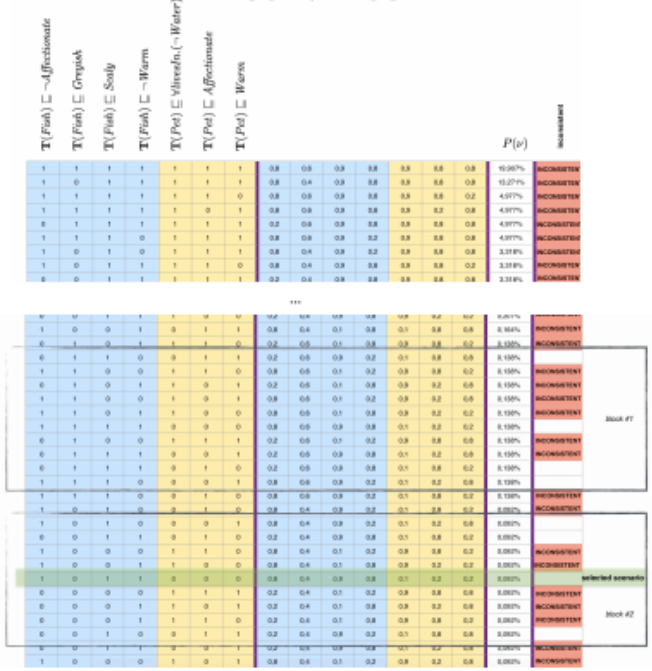
$0.7 :: \mathbf{T}(Fish) \sqsubseteq \neg Affectionate$
$0.8 :: \mathbf{T}(Fish) \sqsubseteq \neg Warm$
$0.6 :: \mathbf{T}(Fish) \sqsubseteq Greyish$
$0.9 :: \mathbf{T}(Fish) \sqsubseteq Scaly$

PROTOTYPE OF MODIFIER

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

2. **Probabilistic Scenarios**

SCENARIOS



3. **Selection of the most appropriate 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

$Fish \sqsubseteq \forall livesIn.Water$

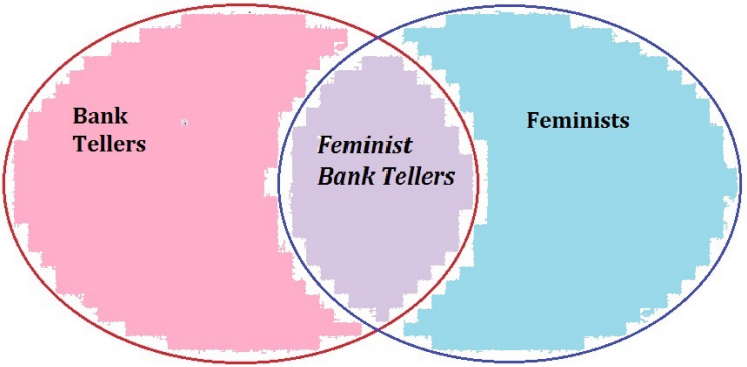
$0.7 :: \mathbf{T}(Fish) \sqsubseteq \neg Affectionate$
$0.8 :: \mathbf{T}(Fish) \sqsubseteq \neg Warm$ $0.9 :: \mathbf{T}(Fish) \sqsubseteq Scaly$
$0.6 :: \mathbf{T}(Fish) \sqsubseteq Greyish$

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

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

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

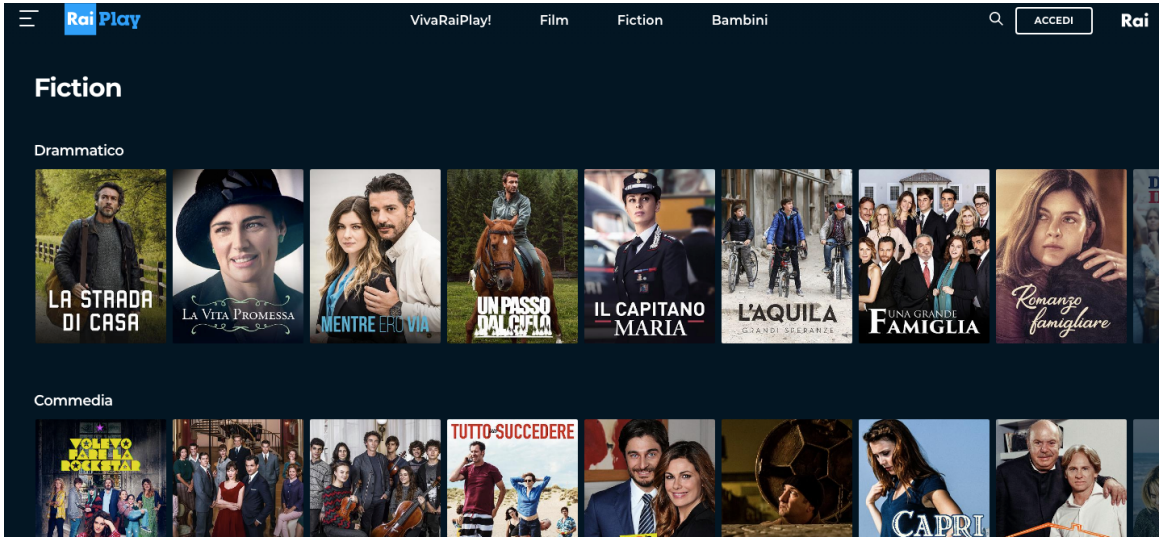
Applications



Cognitive modelling

Linda problem; Lieto & Pozzato, **JETAI 20)**

- **Computational Creativity**
- Characters Generation



- Novel Genre Generation
- Recommender Systems

(Chiodino et al, **ECAI 2020**)

with
Centro Ricerche RAI

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 = {Property1, Property2, Property3…}.

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

– for all $D_i \in G$, either K |= C ⊑ D or K0 |= T(C) ⊑ 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 ≡ C1 ⊓ 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* |= C ⊑ D or Kc |= T(C) ⊑ D in $\mathbf{T}^{\mathbf{CL}}$

Concept composition

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

GOALS

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

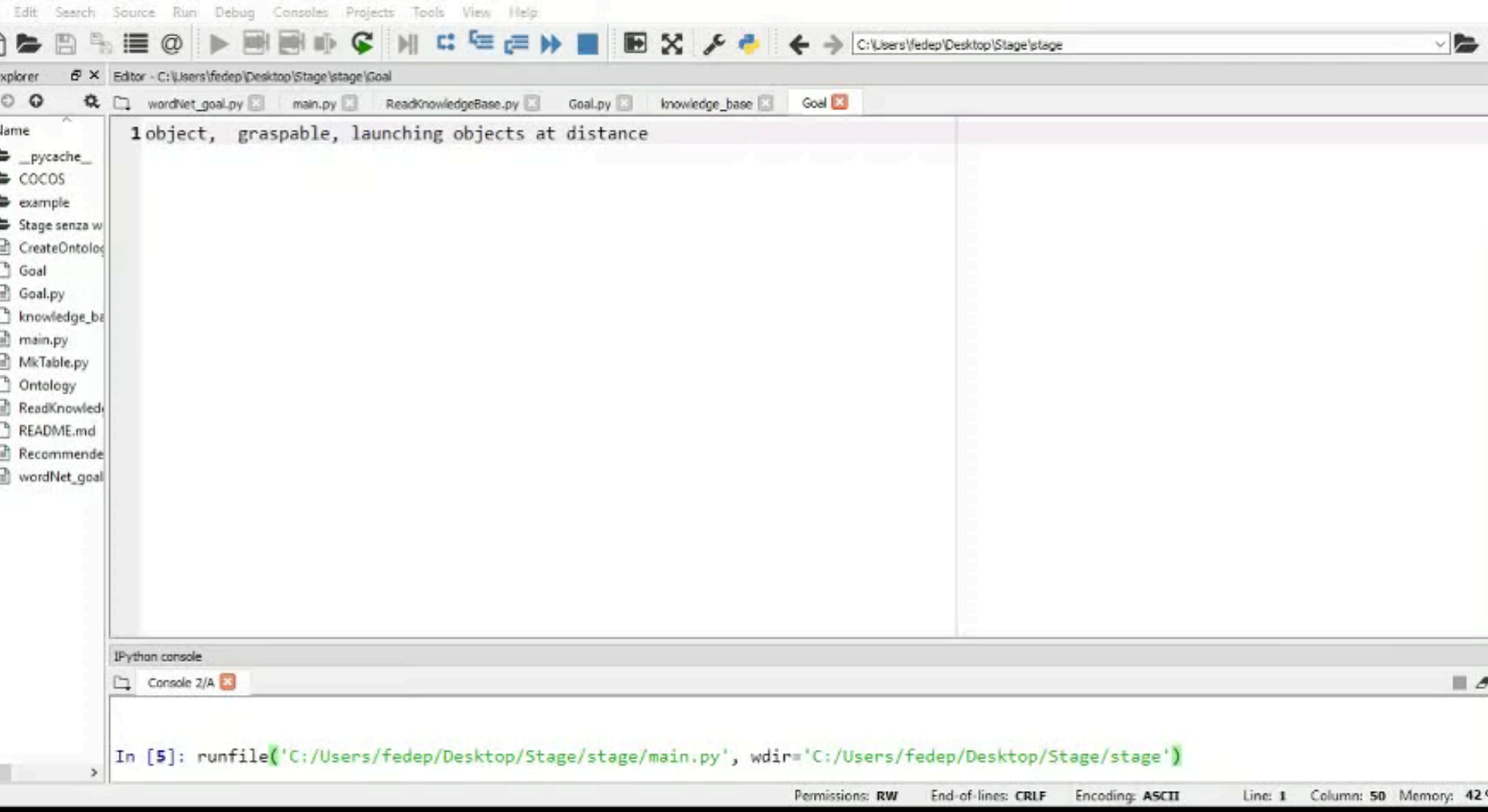
$$\mathcal{G}_2 = \{Object, Graspable, LaunchingObjectsAtDistance\},$$

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

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

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

G = {Object, Graspable, Launching objects at distance}



Evaluation (30 subjects)

	$\mathcal{G}_1$	$\mathcal{G}_2$	$\mathcal{G}_3$
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	$Stone \sqcap Towel$ $(13, 3\%)$	$Towel \sqcap RubberBand$ $(10, 8\%)$	$Vase \sqcap Shelf$ $(22, 5\%)$

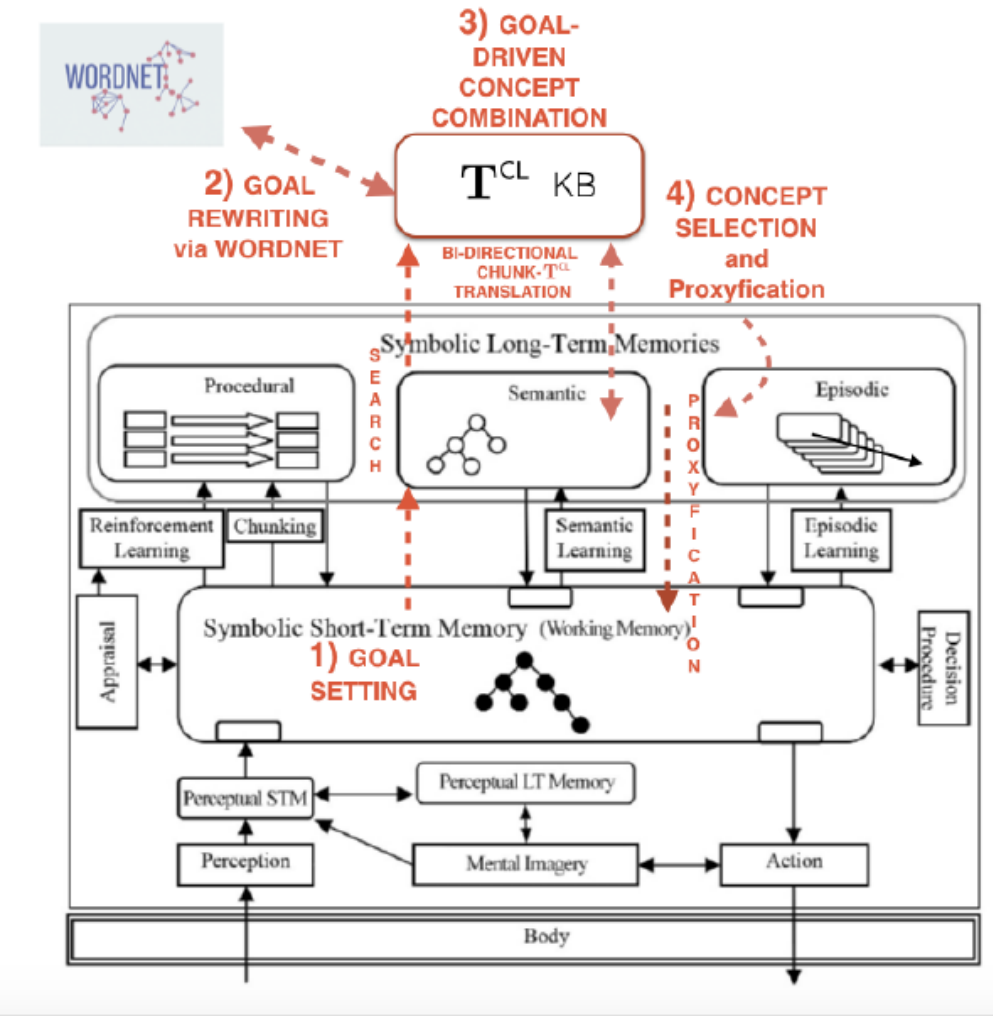
Figure 1: Comparison on Concept Composition in a Domestic Domain.

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

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

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

SOAR Integration



Lieto et al. 2019, Cognitive Systems Research, **Beyond Subgoaling, A dynamic knowledge generation framework for creative problem solving in cognitive architectures**.

Minimal Cognitive Grid

"a **non subjective**, **graded**, evaluation framework allowing both **quantitative** and **qualitative** analysis about the **cognitive adequacy** and the **human-like performances** of artificial systems in both **single** and **multi-tasking** settings." (Lieto, 2021)

Functional/Structural Ratio
Generality
Performance match (including errors and psychometric measures)

Functionalist Models — Structuralist Models

TCL

Dual
Peccs

Upshots

- I have shown **two different types of systems** addressing, at different levels of representation, some crucial **requirements** of commonsense reasoning

- Such systems rely on the assumption that artificial cognitive agents should address **different problems** at the **most convenient level** and provide a way to foster the integration of such levels (non ad-hoc)

- A possibile **integration** can be obtained by relying on external linguistic resources like **Wordnet** (possibile extension also to visual tasks/modules)

- **Functional** and **structural models** of cognition have a different explanatory power (aspect to take into account when attributing cognitive faculties to a simulation)

References

Lieto, A. (2021). Cognitive Design for Artificial Minds, Routledge.

Lieto, A., Perrone, F., Pozzato, G. L (2020). A Description Logic Framework for Commonsense Conceptual Combination Integrating Typicality, Probabilities and Cognitive Heuristics. ournal of Experimental & Theoretical Artificial Intelligence, 32 (5), 769-804.

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