Cognitive heuristics for commonsense reasoning in the next generation of AI systems

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a woman riding a horse on a dirt road

an airplane is parked on the tarmac at an airport

a group of people standing on top of a beach

Figure 6: Perceiving scenes without intuitive physics, intuitive psychology, compositionality, and causality. Image captions are generated by a deep neural network (Karpathy & Fei-Fei, 2015) using code from `github.com/karpathy/neuraltalk2`. Image credits: Gabriel Villena Fernández (left), TVBS Taiwan / Agence France-Presse (middle) and AP Photo / Dave Martin (right). Similar examples using images from Reuters news can be found at `twitter.com/interesting_jpg`.

Lake et al. 2017

SYSTEM PROMPT
(HUMAN-WRITTEN)

In a shocking finding, scientist discovered a herd of unicorns living in a remote, previously unexplored valley, in the Andes Mountains. Even more surprising to the researchers was the fact that the unicorns spoke perfect English.

MODEL COMPLETION
(MACHINE-WRITTEN, 10 TRIES)

The scientist named the population, after their distinctive horn, Ovid's Unicorn. These four-horned, silver-white unicorns were previously unknown to science.

Now, after almost two centuries, the mystery of what sparked this odd phenomenon is finally solved.

Dr. Jorge Pérez, an evolutionary biologist from the University of La Paz, and several companions, were exploring the Andes Mountains when they found a small valley, with no other animals or humans. Pérez noticed that the valley had what appeared to be a natural fountain, surrounded by two peaks of rock and silver snow.

Pérez and the others then ventured further into the valley. "By the time we reached the top of one peak, the water looked blue, with some crystals on top," said Pérez.

Pérez and his friends were astonished to see the unicorn herd. These creatures could be seen from the air without having to move too much to see them – they were so close they could touch their horns.

While examining these bizarre creatures the scientists discovered that the creatures also spoke some fairly regular English. Pérez stated, "We can see, for example, that they have a common 'language,' something like a dialect or dialectic."

Dr. Pérez believes that the unicorns may have originated in Argentina, where the animals were believed to be descendants of a lost race of people who lived there before the arrival of humans in those parts of South America.

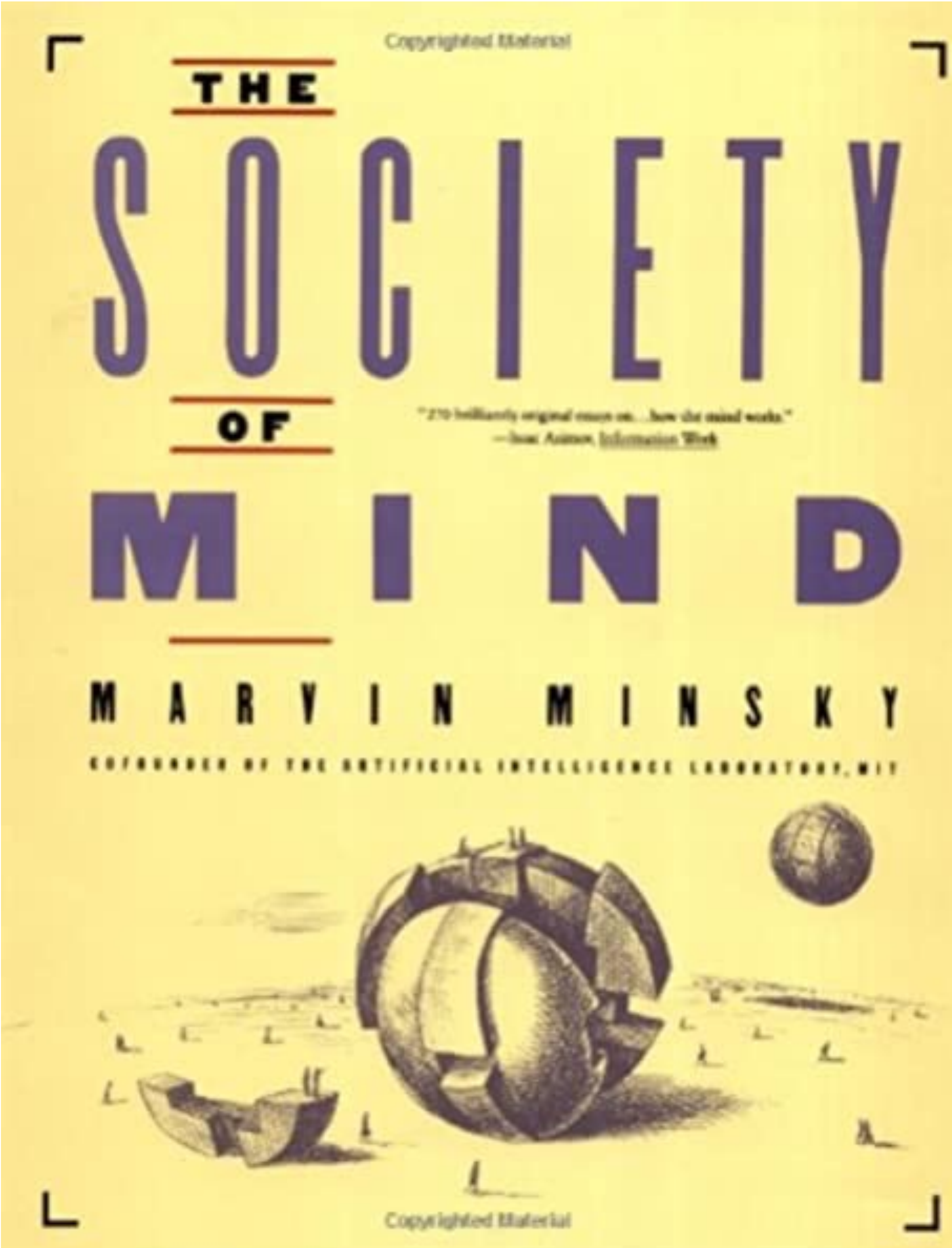
https://opena

GPT-3/Problems

- Text completion is a prediction test, not a test of compositionality
- Lack of commonsense reasoning

You are having a small dinner party. You want to serve dinner in the living room. The dining room table is wider than the doorway, so to get it into the living room, you will have to **remove the door. You have a table saw, so you cut the door in half and remove the top half.**

from https://cs.nyu.edu/~davise/papers/GPT3CompleteTests.html



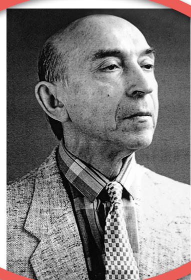
Commonsense knowledge as grounding element of layers of growing thinking capabilities

Commonsense knowledge and reasoning capabilities

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)

...

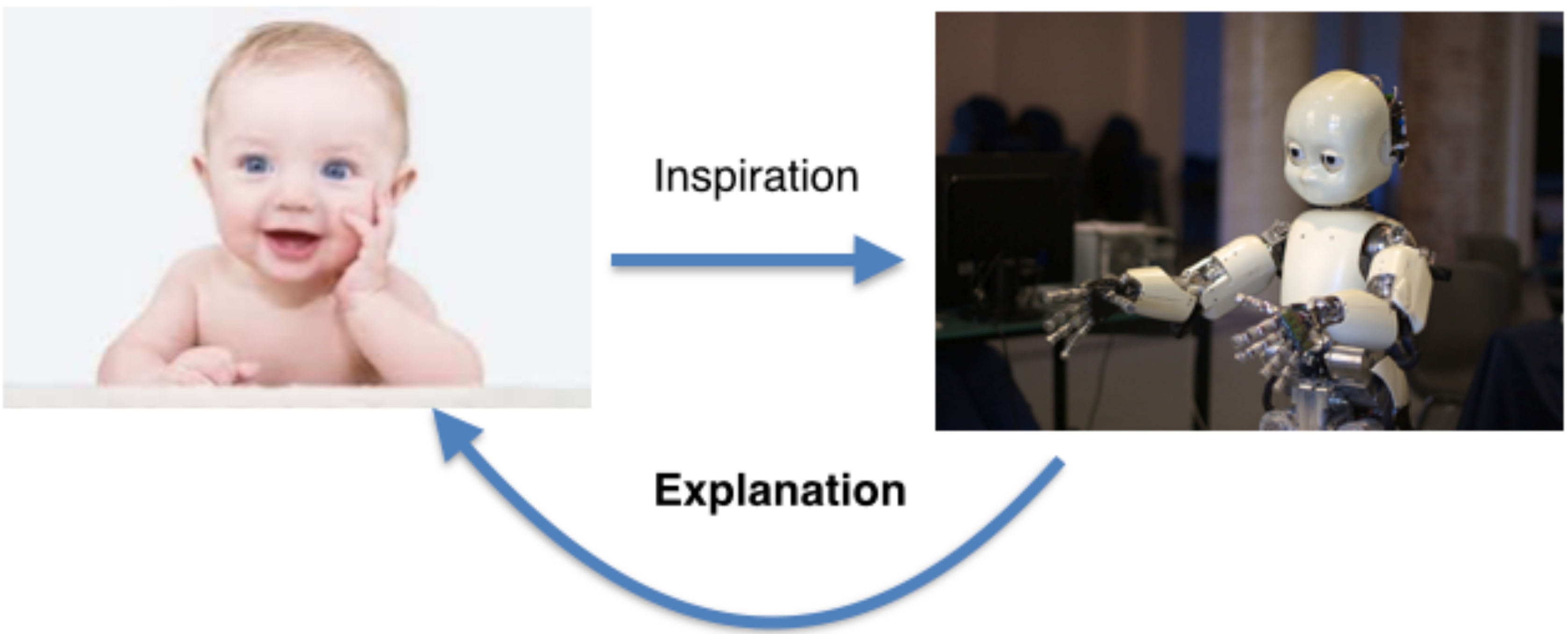
Newell Simon, GPS
(1962)

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 *surface 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

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

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- …

TYPICALITY

Compositionality

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

- A crucial generative requirement

Commonsense Compositionality

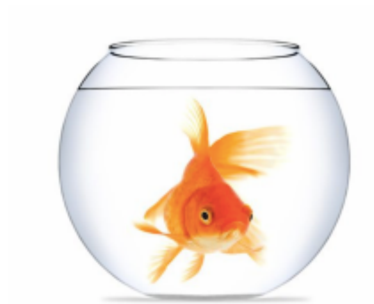
PET FISH Problem: **Prototypes are not compositional** (Osherson and Smith, 1981).

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

+

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

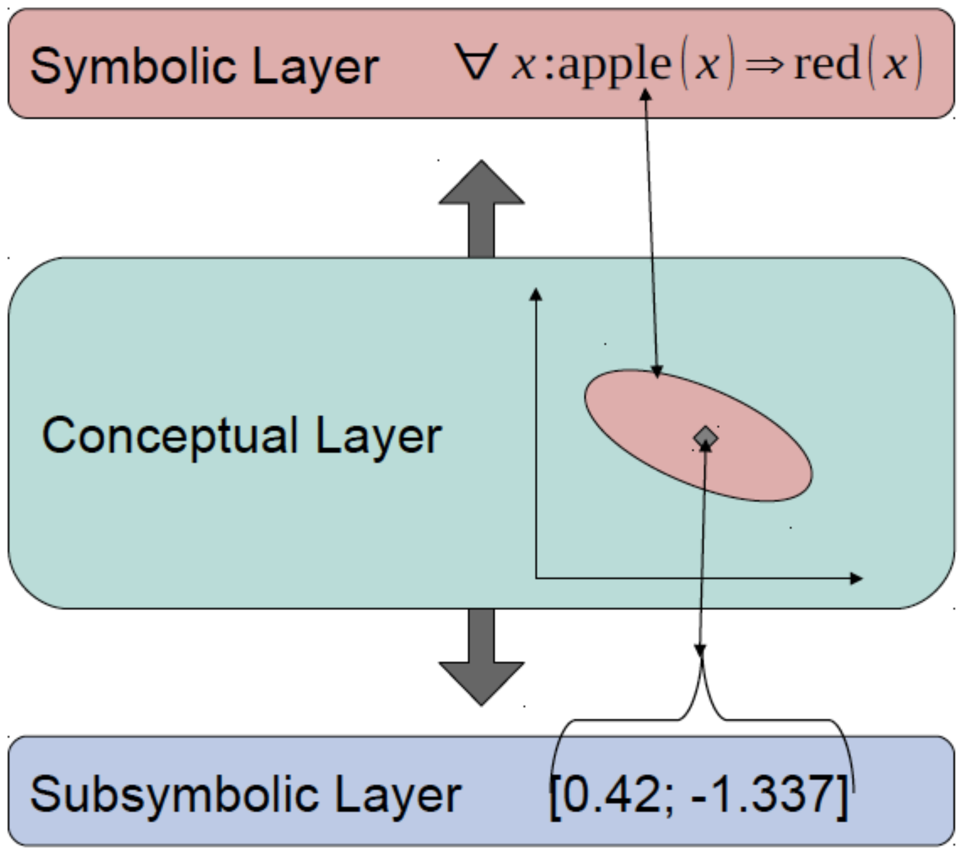
=



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

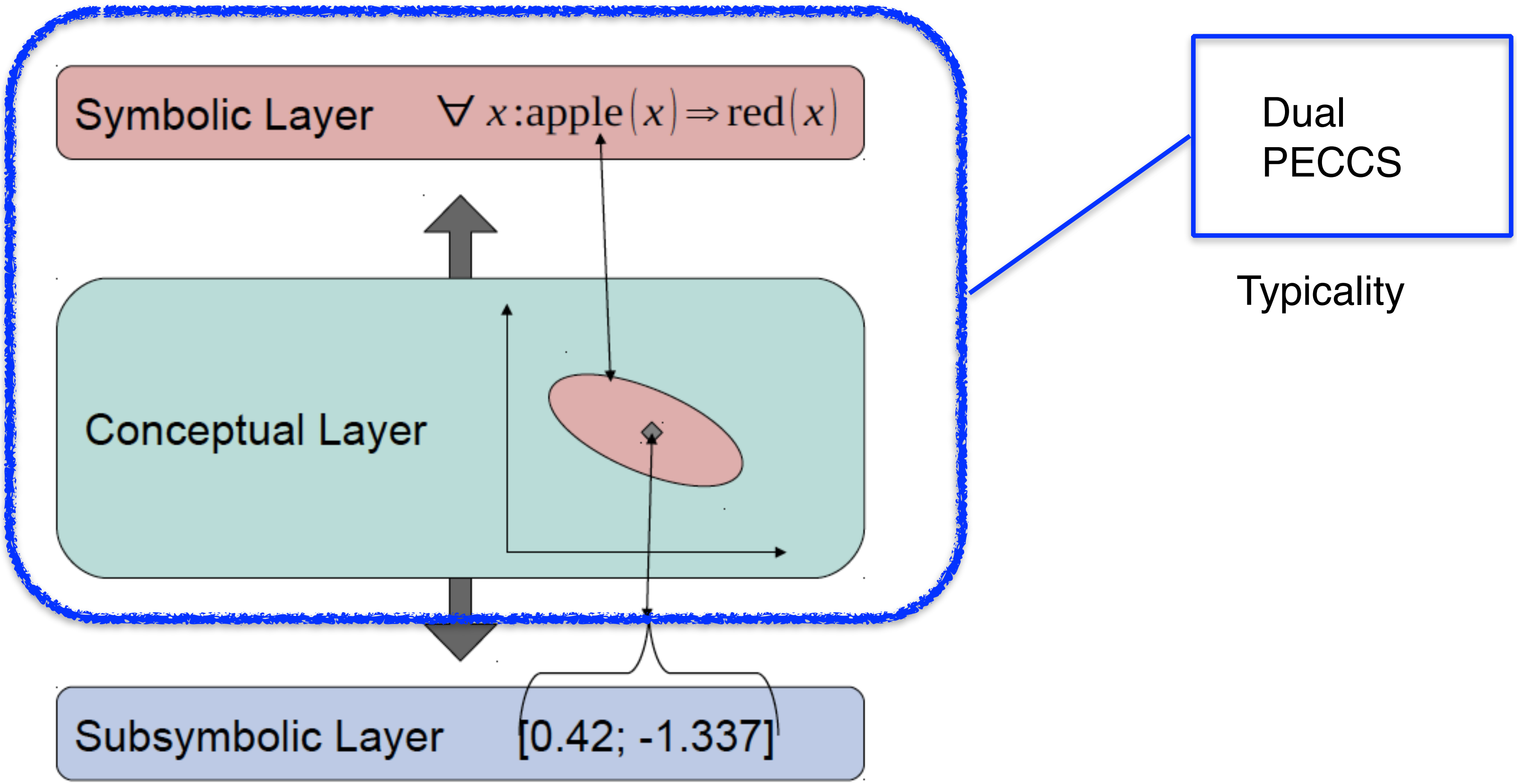
The resulting PET FISH concept is not merely composed by the additive inclusion of the typical features of the two composing concepts (i.e. PET and FISH).

Levels of Representations

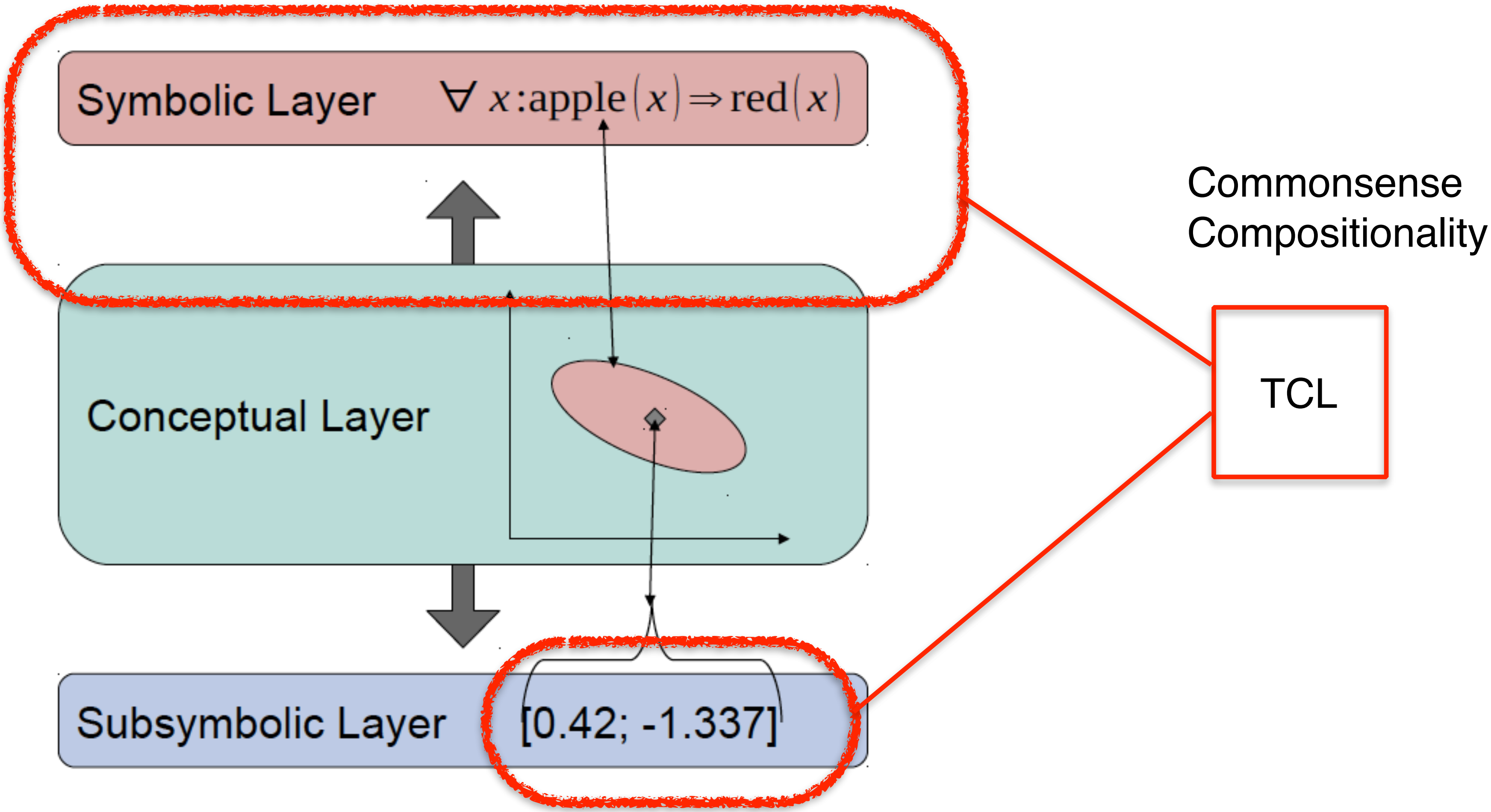


Lieto, Chella, Frixione, 2017. Conceptual Spaces for Cognitive Architectures: A Lingua Franca for Different Levels of Representations, Biologically Inspired Cognitive Architectures.

Levels of Representations



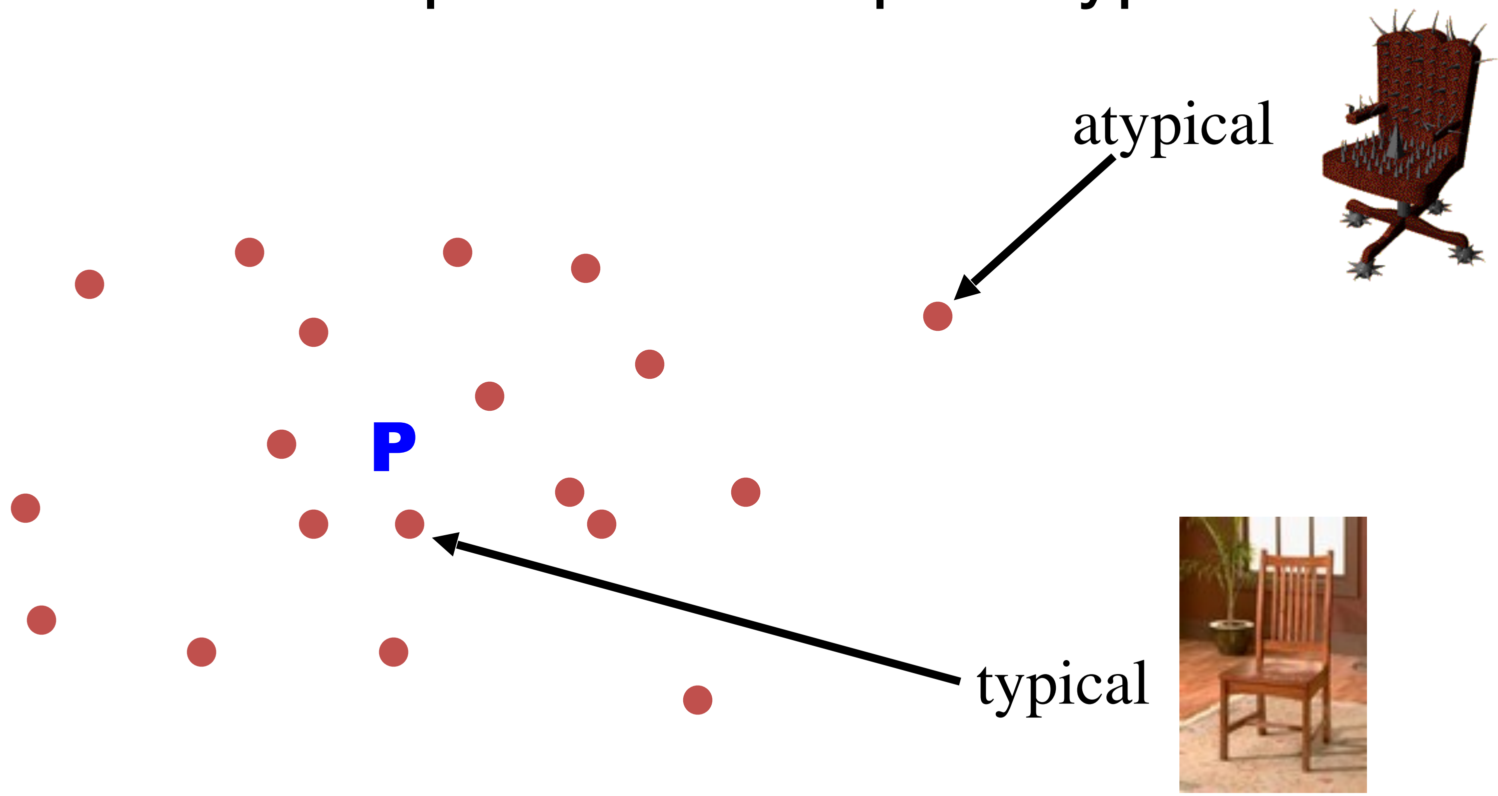
Levels of Representations



Typicality

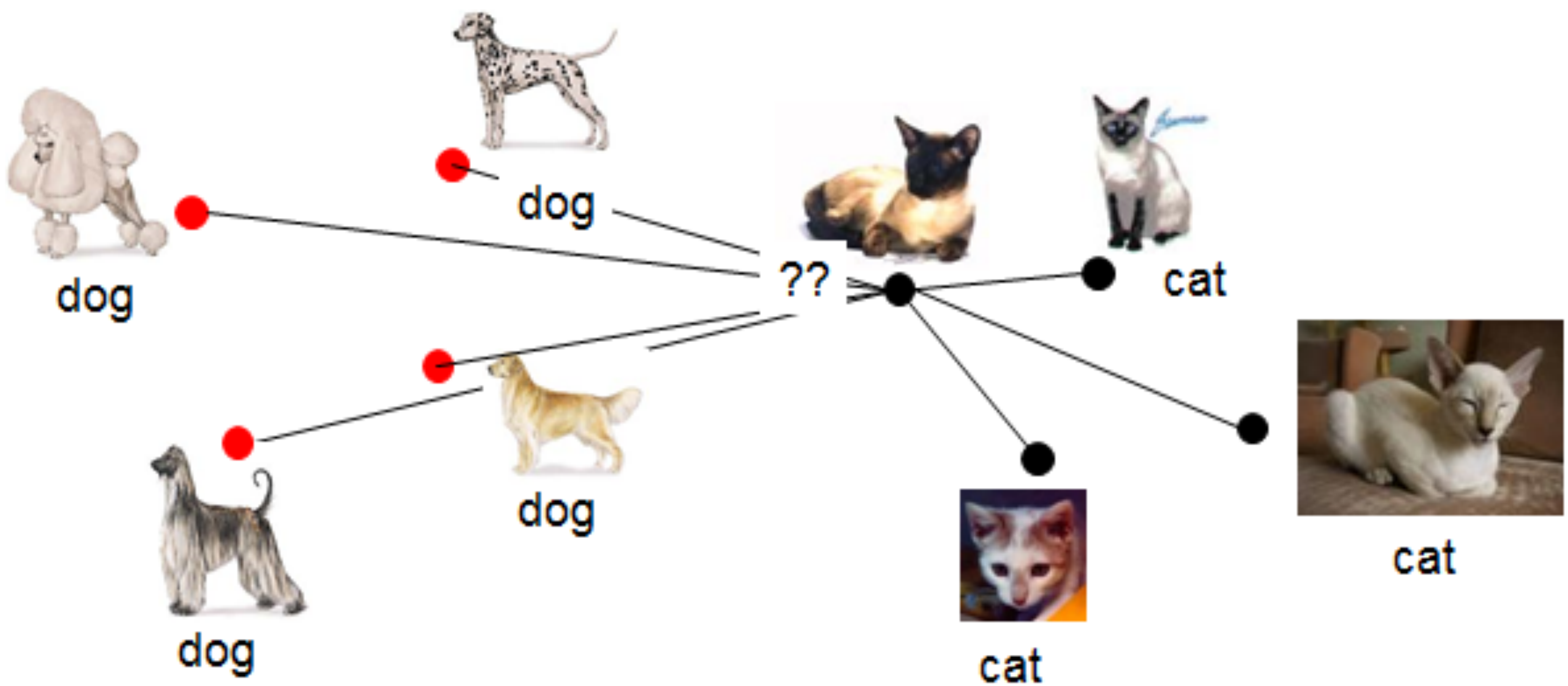
Prototypes and Prototypical Reasoning

- 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

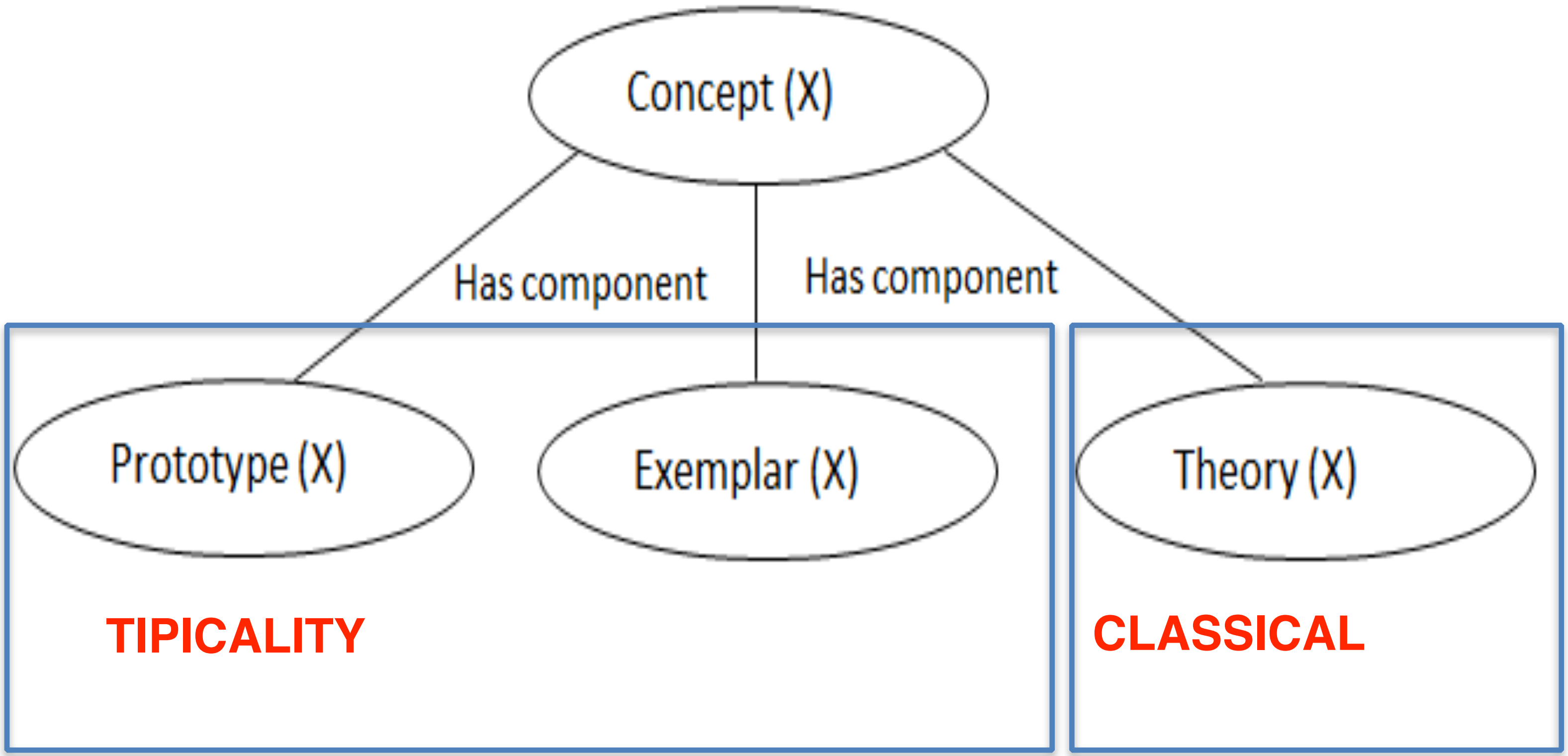
1) **Multiple representations for the same concept**

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 …

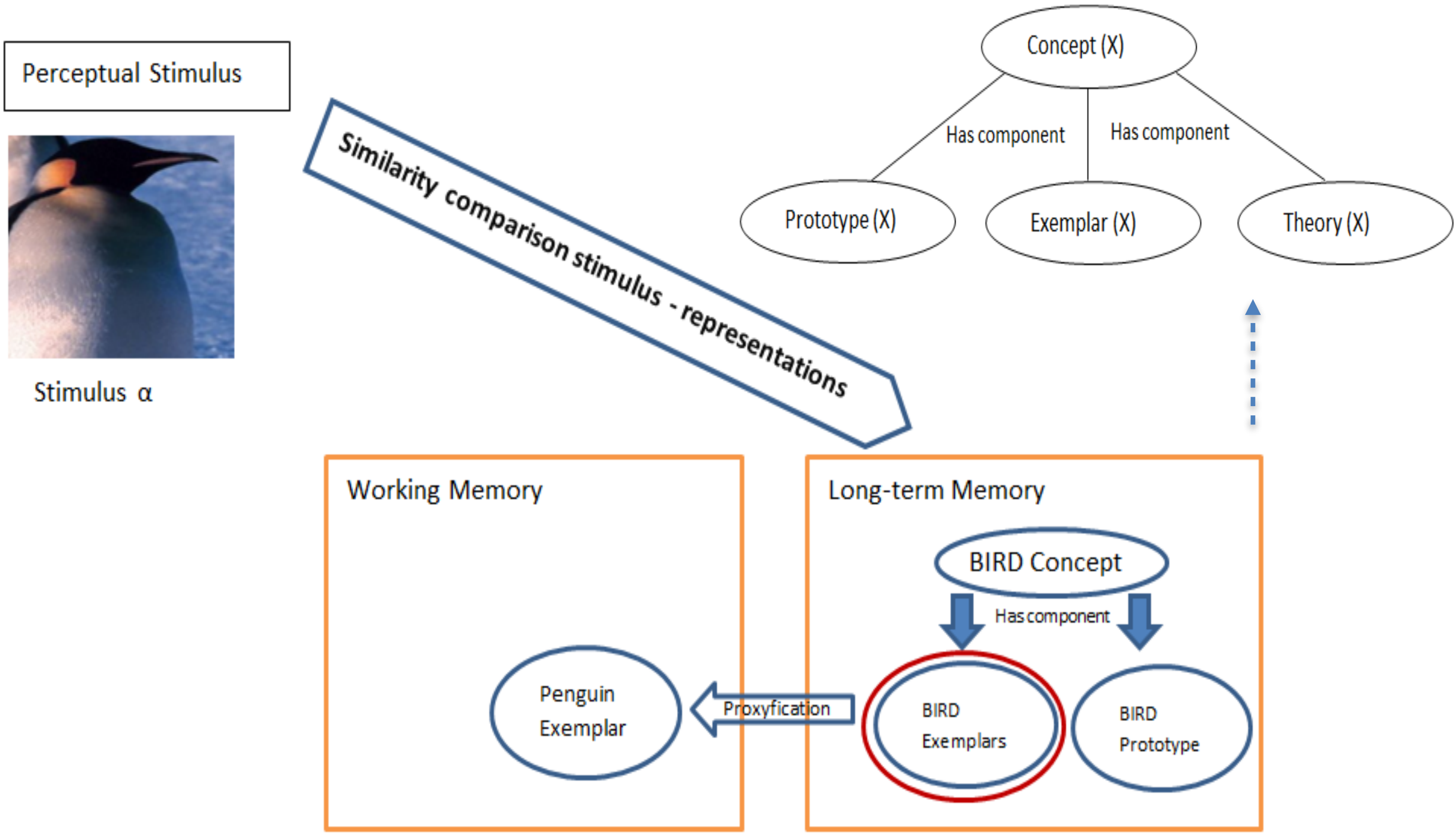
Heterogeneous Proxytypes Hypothesis

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.

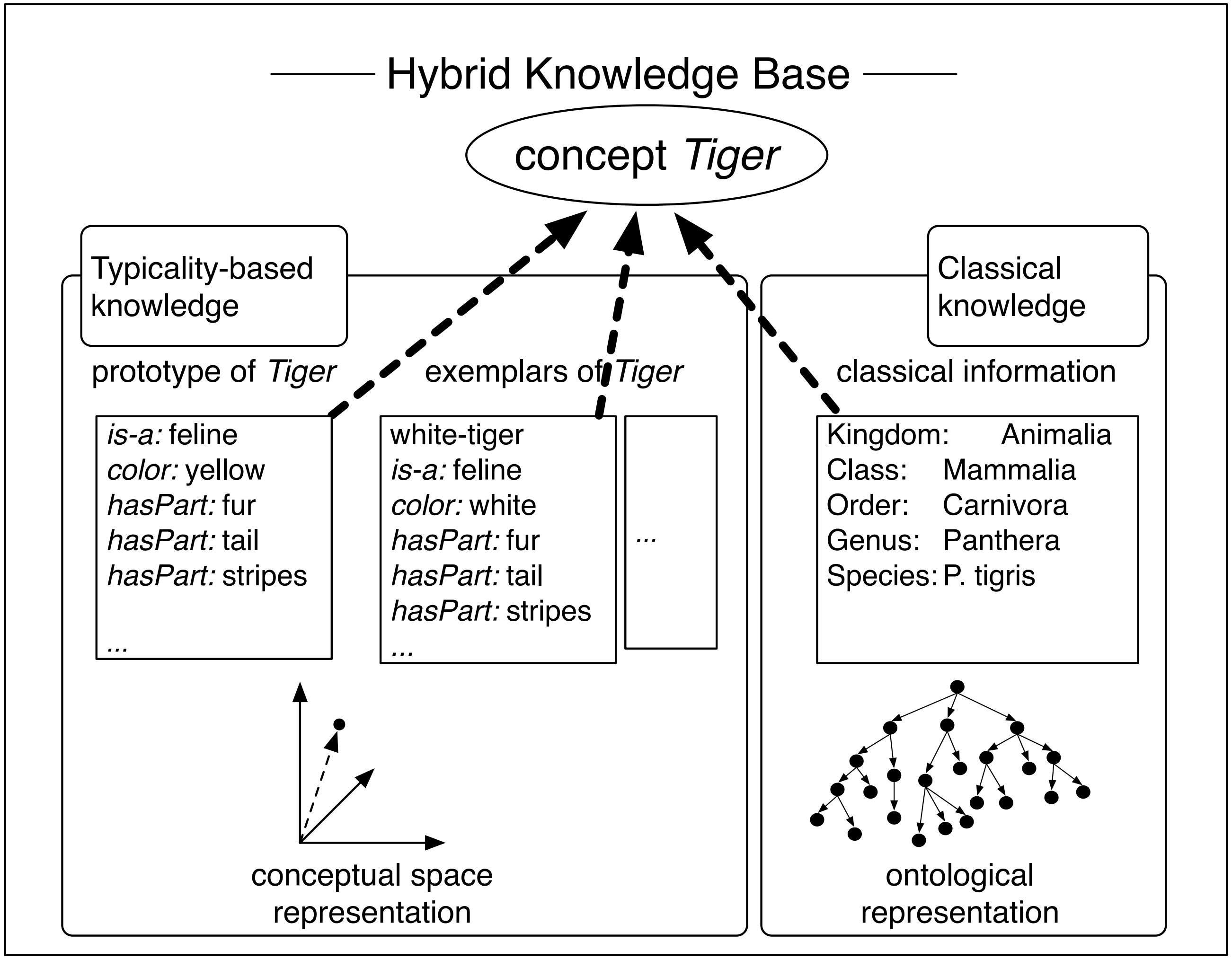


(Lieto, A. ***A Computational Framework for Concept Representation in Cognitive Systems and Architectures: Concepts as Heterogeneous Proxytypes***, Proc. of BICA 2014)

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.

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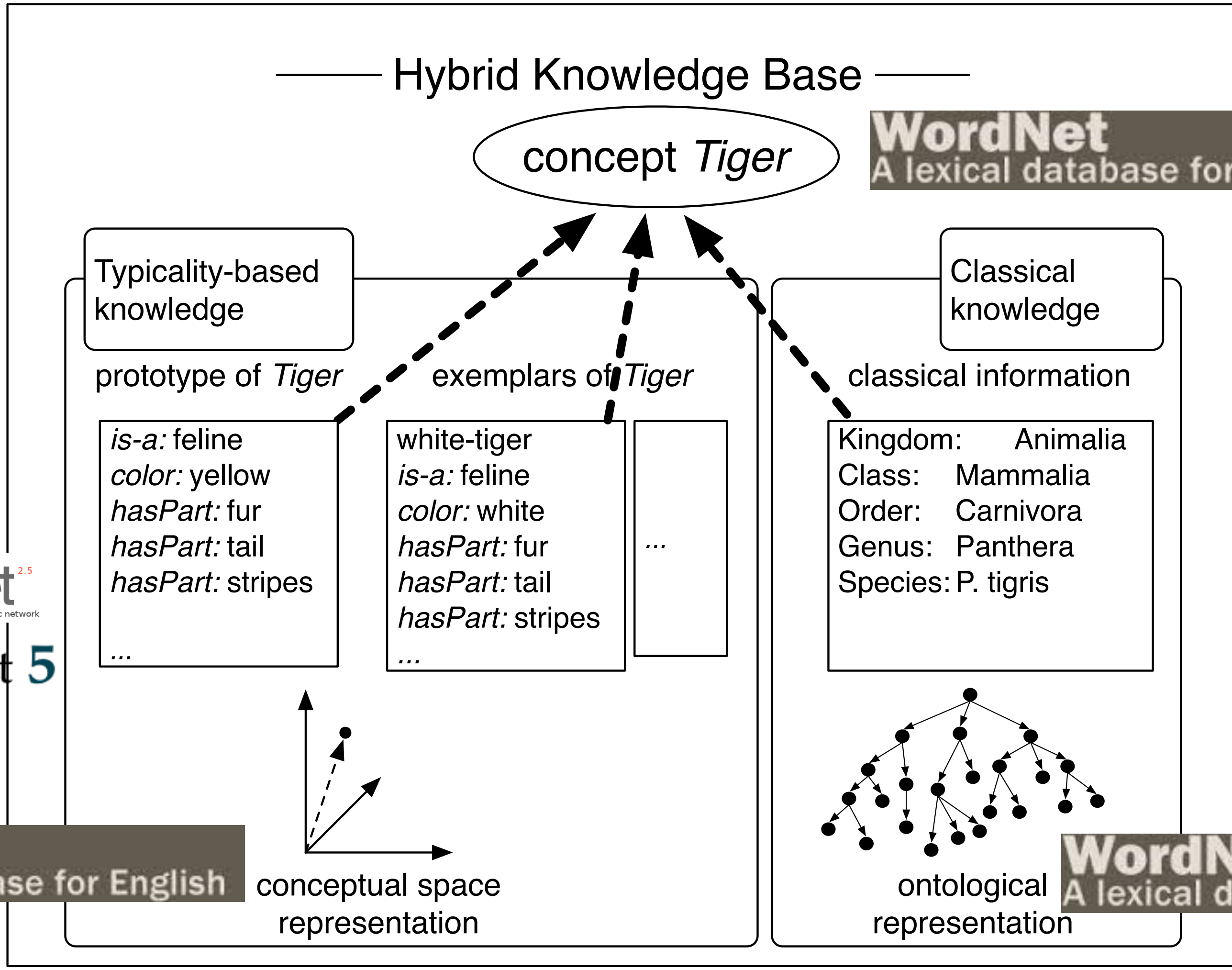


Lieto, A., Mensa, E,, Radicioni, D., 2016. **A resource-driven approach for anchoring linguistic resources conceptual spaces**. In Conference of the Italian Association for Artificial Intelligence (pp. 435-449). Springer, Cham.

S1/S2 Categorization Algorithms

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

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

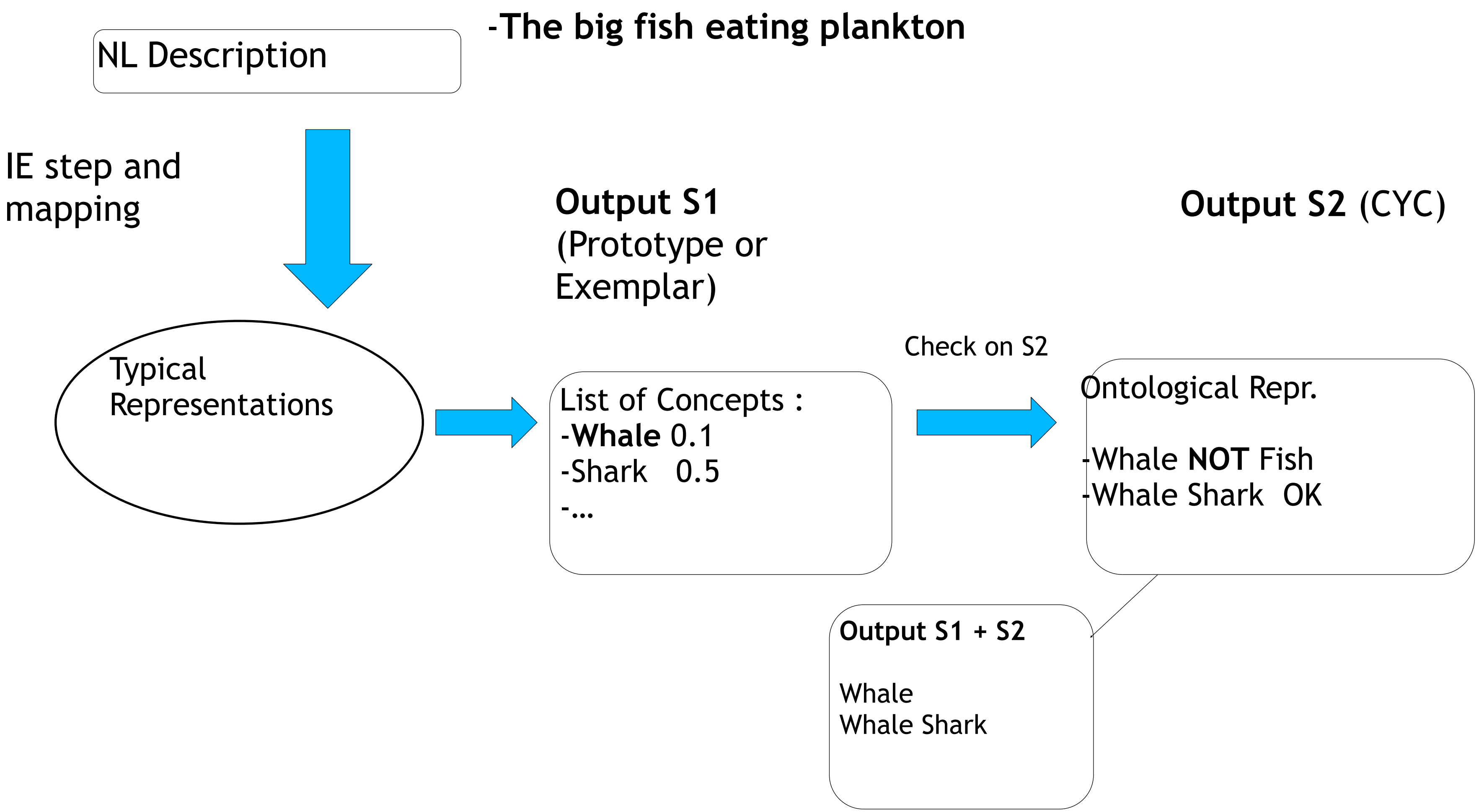
Algorithm 1: The $\mathcal{S}1$-$\mathcal{S}2$ categorization process.

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

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

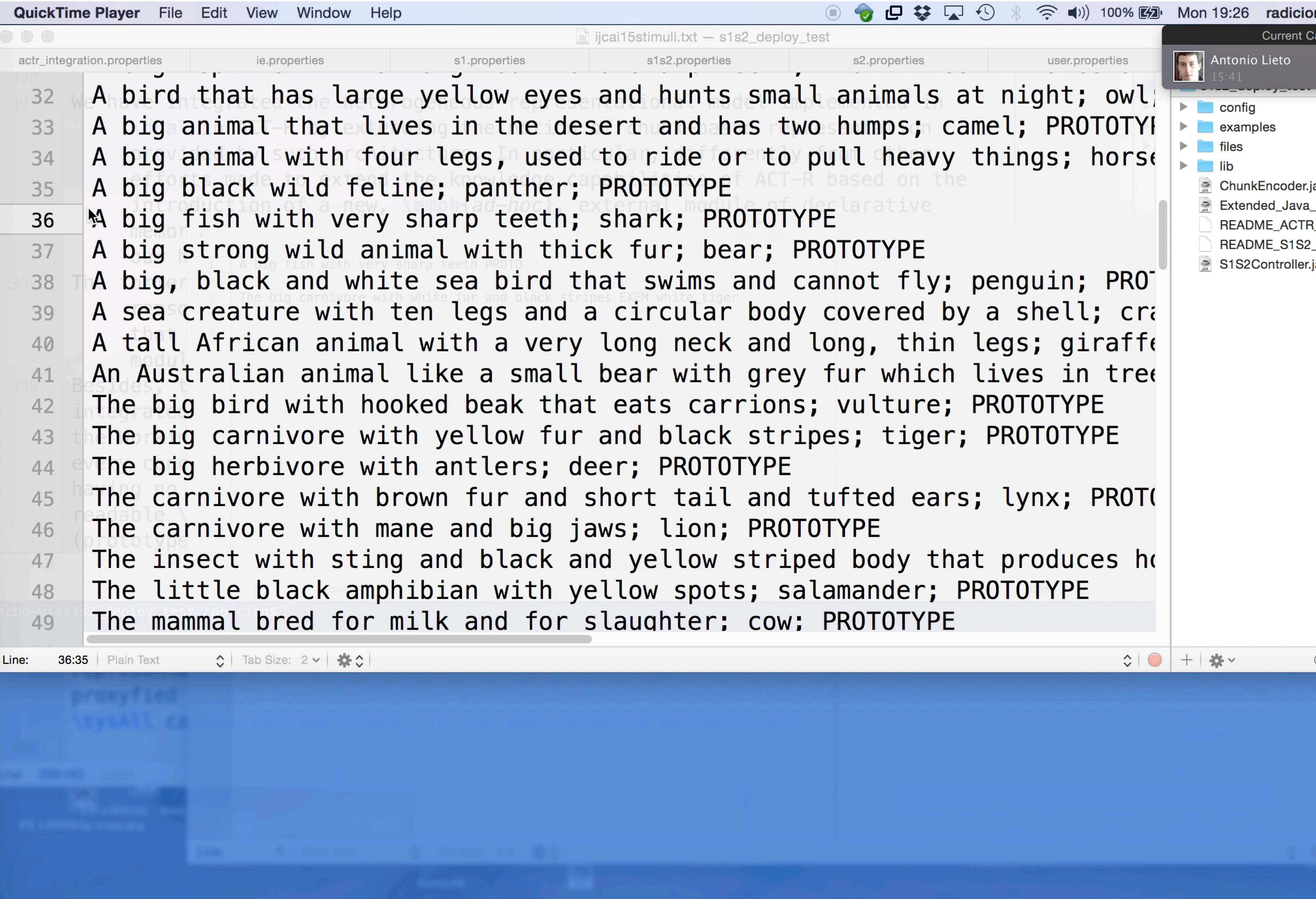
Algorithm 2: $\mathcal{S}1$ categorization with prototypes and exem plars implementing the instruction in Algorithm 1: line 4.

Overview

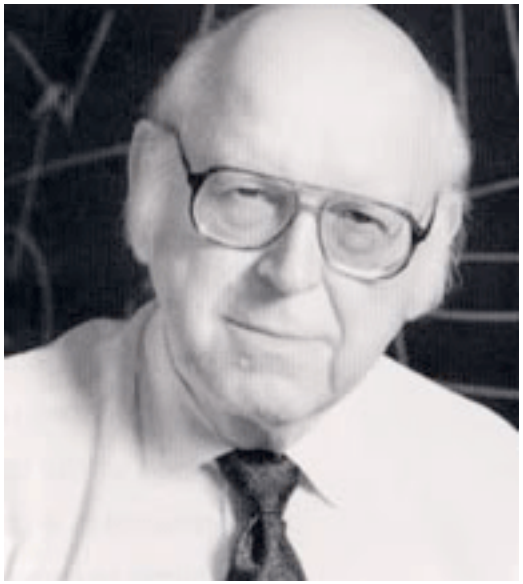


-The big fish eating plankton
NL Description
IE step and mapping
Typical Representations
Output S1 (Prototype or Exemplar)
List of Concepts :
-Whale 0.1
-Shark 0.5
-...
Check on S2
Output S2 (CYC)
Ontological Repr.
-Whale NOT Fish
-Whale Shark OK
Output S1 + S2
Whale
Whale Shark

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



Cognitive Architectures



A **cognitive architecture** (Newell, 1990) implements the **invariant structure of the cognitive system**.

The work on such systems started in the ‘80s (**SOAR** (Newell, Laird and Rosenbloom, 1982)

It captures the underlying **commonality** between different **intelligent agents** and provides a **framework** from which intelligent behavior arises.

The **architectural approach** emphasizes the **role of memor**y in the **cognitive process**.

Allen Newell (1990)
Unified Theory of Cognition

ACT-R, SOAR, CLARION and LIDA Extended Declarative Memories with DUAL-PECCS

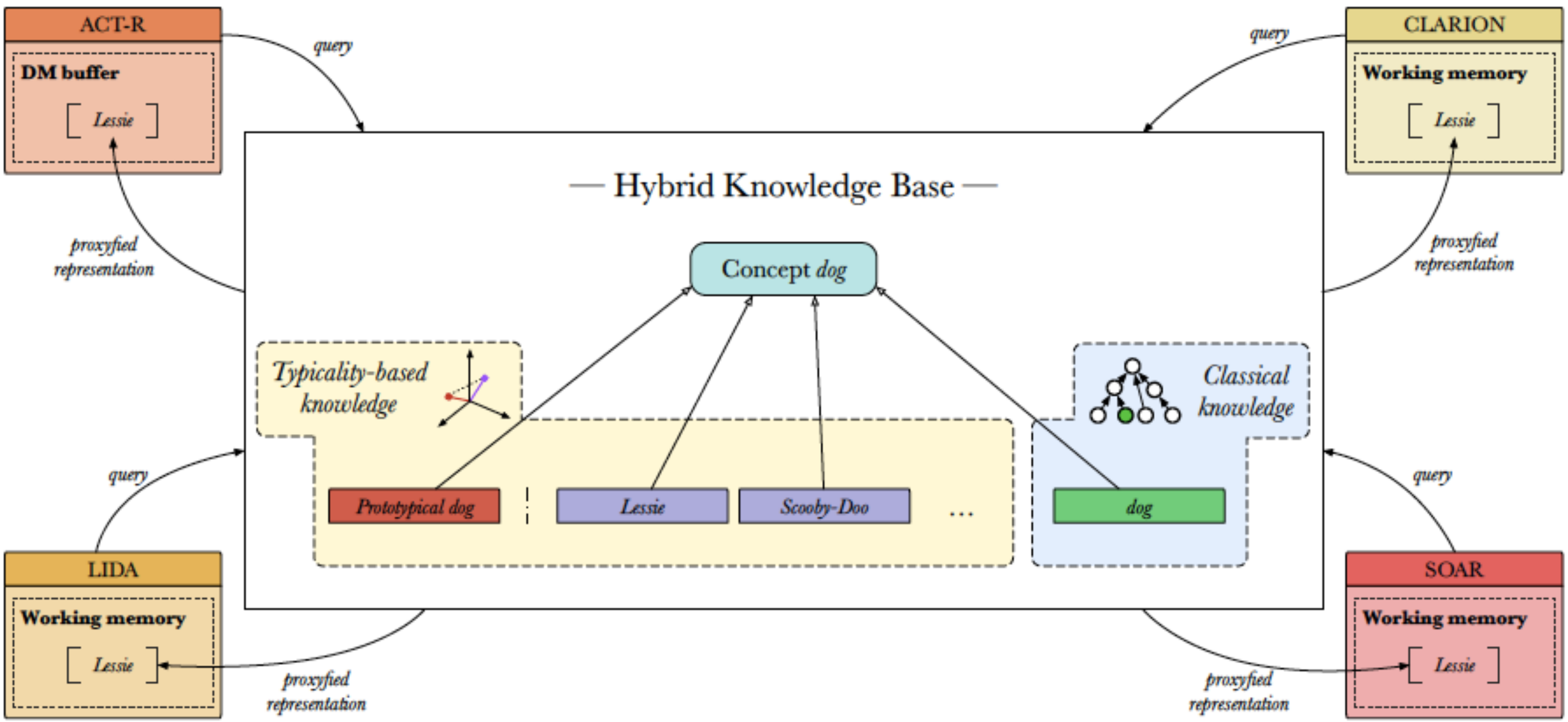
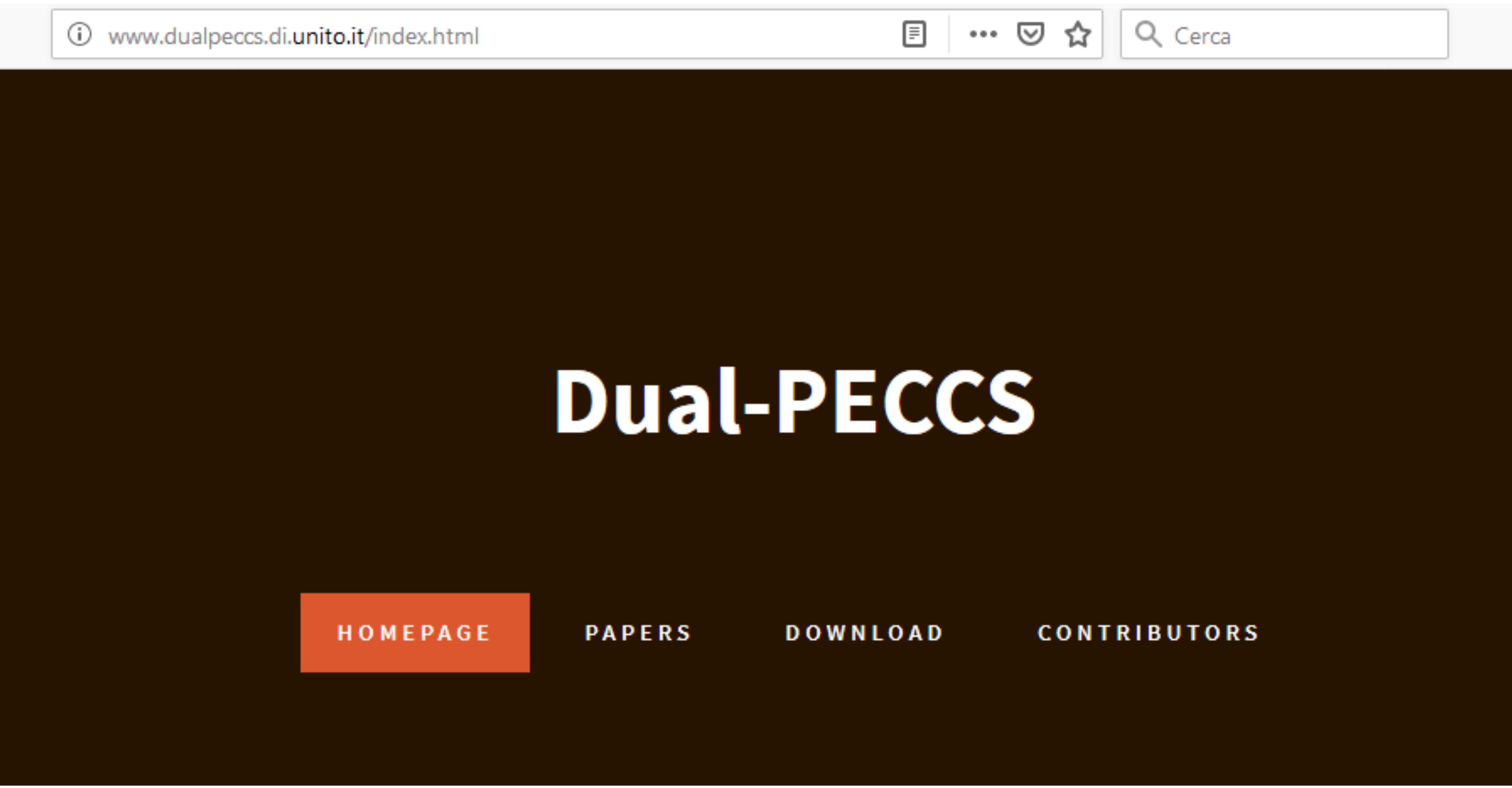


Fig. 3. General overview of the DUAL-PECCS integration within different cognitive architectures.

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*

Evaluation 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)

Lieto, A., Radicioni, D., Rho, V, (2017). **Dual PECCS: a cognitive system for conceptual representation and categorization, JETAI**, 29 (2), 433-452, Taylor and Francis..

Proxyfication Error

test	Proxyfication error		
	Ex-Proto	Proto-Ex	Ex-Ex
with no IE	21.0% (21/100)	0.0% (0/100)	0.0% (0/100)
with IE	28.8% (26/87)	0.0% (0/87)	5.8% (5/87)

- Three sorts of proxyfication errors were committed:
  - *Ex-Proto*, an exemplar is returned in place of a prototype;
  - *Proto-Ex*, we expected a prototype, but a prototype is returned;
  - *Ex-Ex*, an exemplar is returned differing from the expected one.

Analysis

- The comparison of the obtained results with human categorization is encouraging **77-89% (**results of other AI systems for such reasoning tasks are by far lower).

- The analysis of the results revealed that **it is not true that exemplars** (if similar enough to the stimulus to categorize) **are always preferred** w.r.t. the prototypes.

- Need of a more fine-grained theory explaining more in the details the interaction between co-existing representations in the heterogeneous hypothesis.

Theory-theory

Concepts themselves are identified with **micro-theories** of some sort.

- The use of micro-theories is important for categorization

- Keil experiment (1989): subjects were asked to make **categorization judgments** about the **biological membership of an animal** that had undergone unusual **transformations** (moving it from typical to atypical) => People confirms original categoriz.

Micro-theories are common-sense "relational" knowledge networks about a given concept. They lead to common-sense inferences.

Ex.: we typically associate to a **light switch** the **knowledge** that **IF** we turn it "on" **THEN t**he light will be provided (common-sense inf.).

Heterogeneous Proxytypes Extended: Integrating Theory-like Representations and Mechanisms with Prototypes and Exemplars

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DELTA: unifie**D** **C**at**E**gorization a**L**gorithm for he**T**erogeneous represent**A**tions

Data: Stimulus d; list of candidate representations: $closed^{\mathcal{S}1}$.
Result: A typicality based representation of a category.

$closed^{\mathcal{S}1} = \{\emptyset\}$
$\mathcal{S}1_{\mathrm{EX}} \leftarrow categorizeExemplars(d)$;
if $firstOf(\mathcal{S}1_{\mathrm{EX}}, closed^{\mathcal{S}1}).distance(d) < similarityThreshold$ **then**
    return $firstOf(\mathcal{S}1_{\mathrm{EX}}, closed^{\mathcal{S}1})$;
else
    $\mathcal{S}1_{\mathrm{PR}} \leftarrow categorizePrototypes(d)$ **return** $firstOf(\mathcal{S}1_{\mathrm{PR}}, closed^{\mathcal{S}1})$;
end
if $firstOf(\mathcal{S}1_{\mathrm{PR}}, closed^{\mathcal{S}1}).distance(d) > ConceptualCoherenceThreshold$ **then**
    return $firstOf(\mathcal{S}1_{\mathrm{PR}}, closed^{\mathcal{S}1})$;
else
    $\mathcal{S}1_{\mathrm{T}} \leftarrow categorizeTheory(d)$;
    return $firstOf(TheoryBasedCategorization, closed^{\mathcal{S}1})$;
end

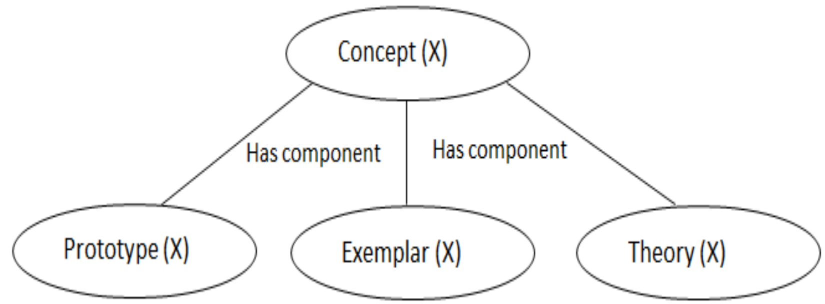
Algorithm 1: A Unified categorization algorithm for prototypes, exemplars and theory-like representations.

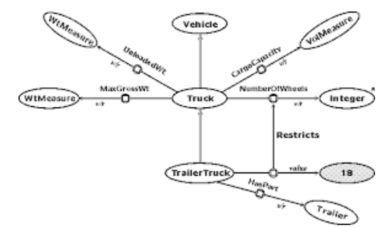
DELTA at work (an Example)

Stimulus (golden zebra)

1) Exemplar-based categorization

LTM





white horse
(Prototype)

horse “theory”

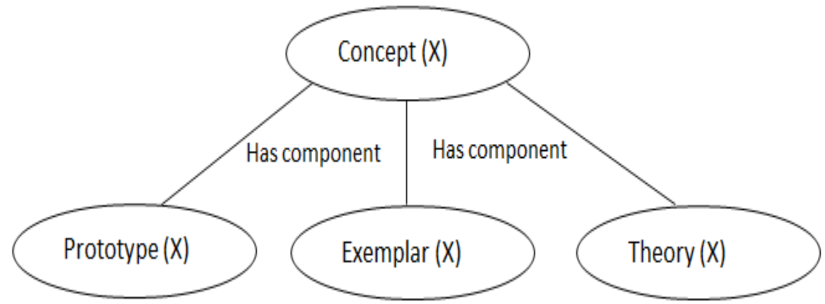
DELTA at work (an Example)

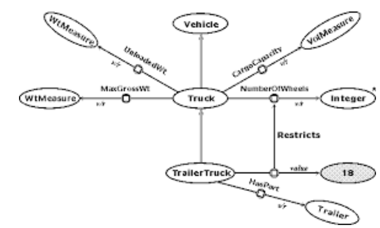
Stimulus (golden zebra)

1) Exemplar-based categorization

No exemplar

LTM





white horse (Prototype)

horse "theory"

DELTA at work (an Example)

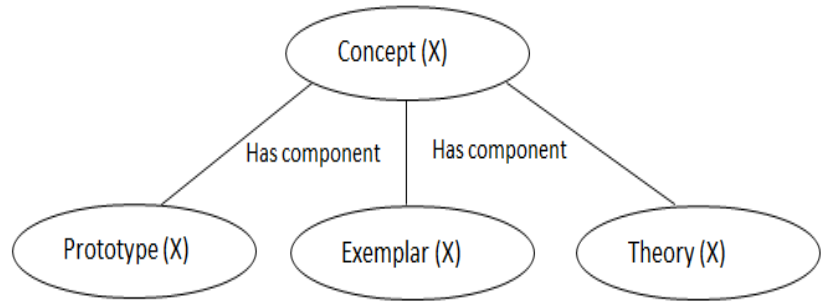
Stimulus (golden zebra)

1) Exemplar-based categorization

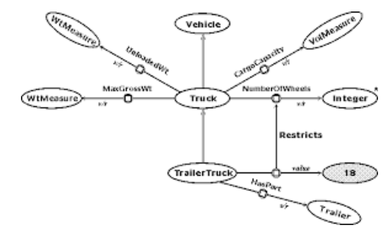
No exemplar

2) Prototype-based categorisation

LTM



white horse (Prototype)



horse "theory"

DELTA at work (an Example)

Stimulus (golden zebra)

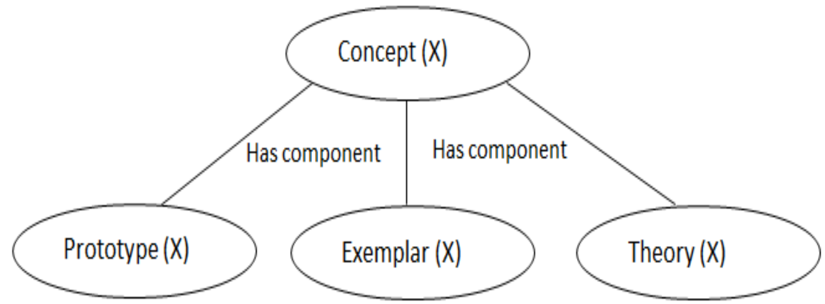
1) Exemplar-based categorization

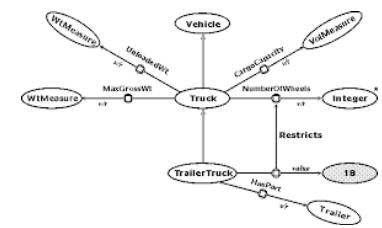
No exemplar

2) Prototype-based categorisation

white horse

LTM





white horse (Prototype)

horse "theory"

DELTA at work (an Example)

Stimulus (golden zebra)

1) Exemplar-based categorization

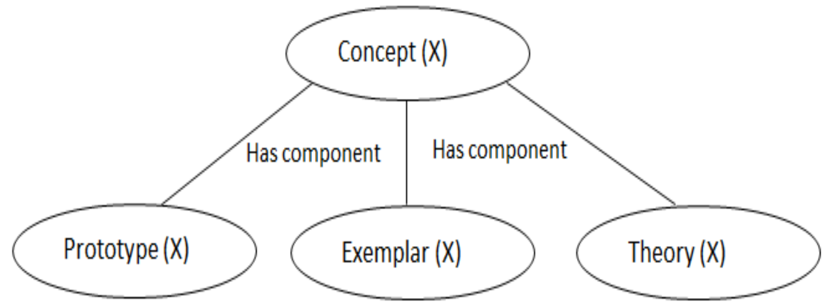
No exemplar

2) Prototype-based categorisation

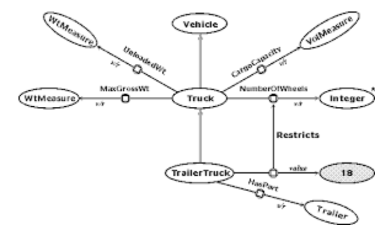
white horse

3) Conceptual Coherence Check of the Prototype (w.r.t. the Stimulus).

LTM



white horse (Prototype)



horse "theory"

DELTA at work (an Example)

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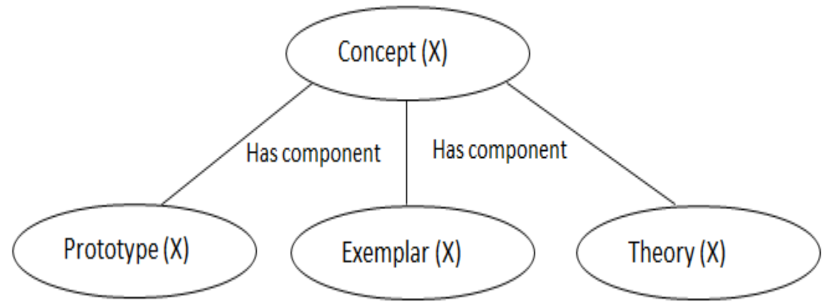
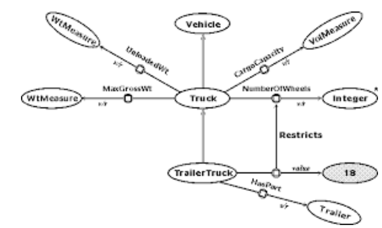




white horse (Prototype)

horse "theory"

E.g. the stimulus "lives in the Savannah" (and this contrasts with our "theory" about horses). Thus the prototypical answer can be overridden (as in the Klein cases)

Commonsense Compositionality

T^{CL}

A non monotonic Description Logic of typicality (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 $\mathbf{p :: T(C) \sqsubseteq D}$

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)

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

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

Pet Fish

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

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

Pet Fish - Different scenarios

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

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

Pet Fish - Inconsistent scenario

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

($\mathbf{T}^{\mathrm{CL}}$) 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: $(1 - 0.9) \times (1 - 0.8) \times 0.7 \times \cdots \times 0.8 = 0.1\%$

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

Pet Fish - Trivial scenario

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

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

Pet Fish - MODIFIER preferred to the HEAD

- $Fish \sqsubseteq \forall livesIn.Water$
- $0.9 :: \mathbf{T}(Pet) \sqsubseteq \forall livesIn.(\neg Water)$
- $0.8 :: \mathbf{T}(Pet) \sqsubseteq Affectionate$
- $0.7 :: \mathbf{T}(Fish) \sqsubseteq \neg Affectionate$
- $0.8 :: \mathbf{T}(Pet) \sqsubseteq Warm$
- $0.6 :: \mathbf{T}(Fish) \sqsubseteq Greyish$
- $0.9 :: \mathbf{T}(Fish) \sqsubseteq Scaly$
- $0.8 :: \mathbf{T}(Fish) \sqsubseteq \neg Warm$
- Probability: 0.05%

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

1. **KB with real data**

2.Probabilistic Scenarios

3. Selection of the most appropriate scenarios

INITIAL KNOWLEDGE BASE

RIGID PROPERTIES

$Fish \sqsubseteq \forall livesIn.Water$

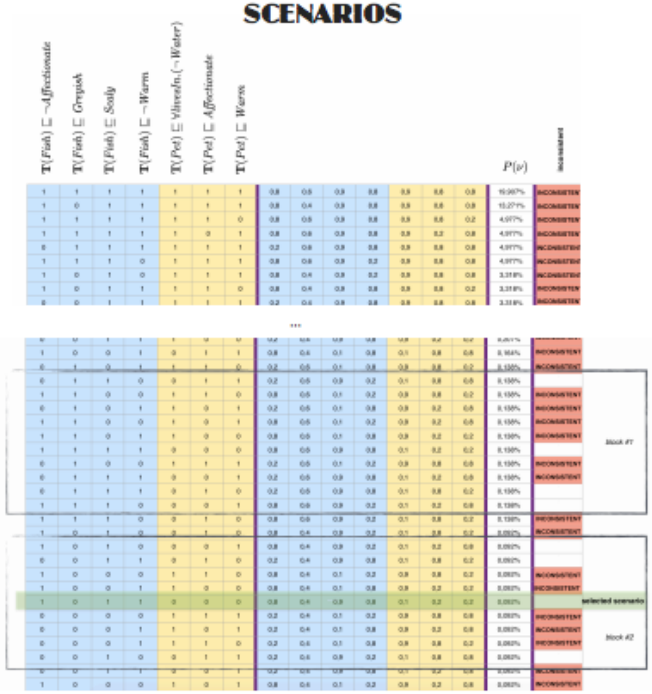
PROTOTYPE OF HEAD

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

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

$Fish \sqsubseteq \forall livesIn.Water$

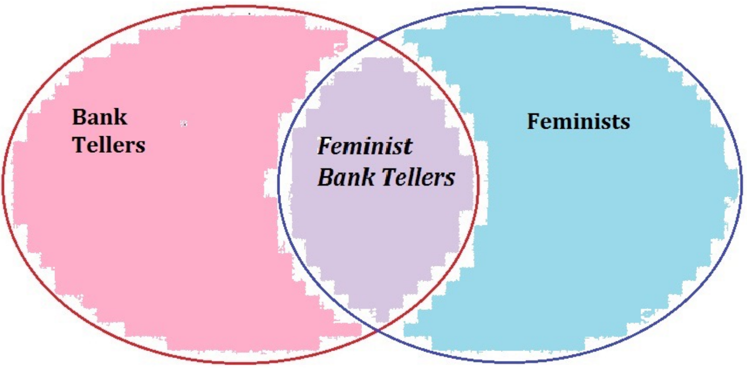
$0.7 :: \mathbf{T}(Fish) \sqsubseteq \neg Affectionate$
$0.8 :: \mathbf{T}(Fish) \sqsubseteq \neg Warm$ $0.9 :: \mathbf{T}(Fish) \sqsubseteq Scaly$
$0.6 :: \mathbf{T}(Fish) \sqsubseteq Greyish$

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

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

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

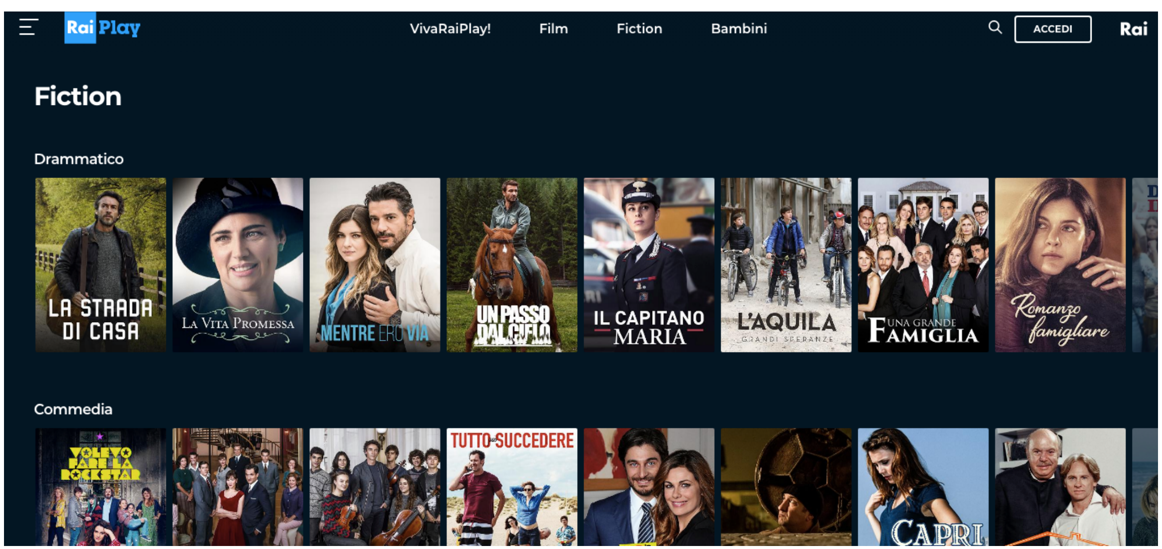
Applications



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 $\mathbf{T^{CL}}$, 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 $\sqsubseteq$ D or K0 |= T(C) $\sqsubseteq$ D in the logic $\mathbf{T^{CL}}$ 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 $\mathbf{T^{CL}}$ is such that, for all $D_i \in$ G, either K_c |= C $\sqsubseteq$ D or Kc |= T(C) $\sqsubseteq$ D in $\mathbf{T^{CL}}$

Concept composition

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

GOALS

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

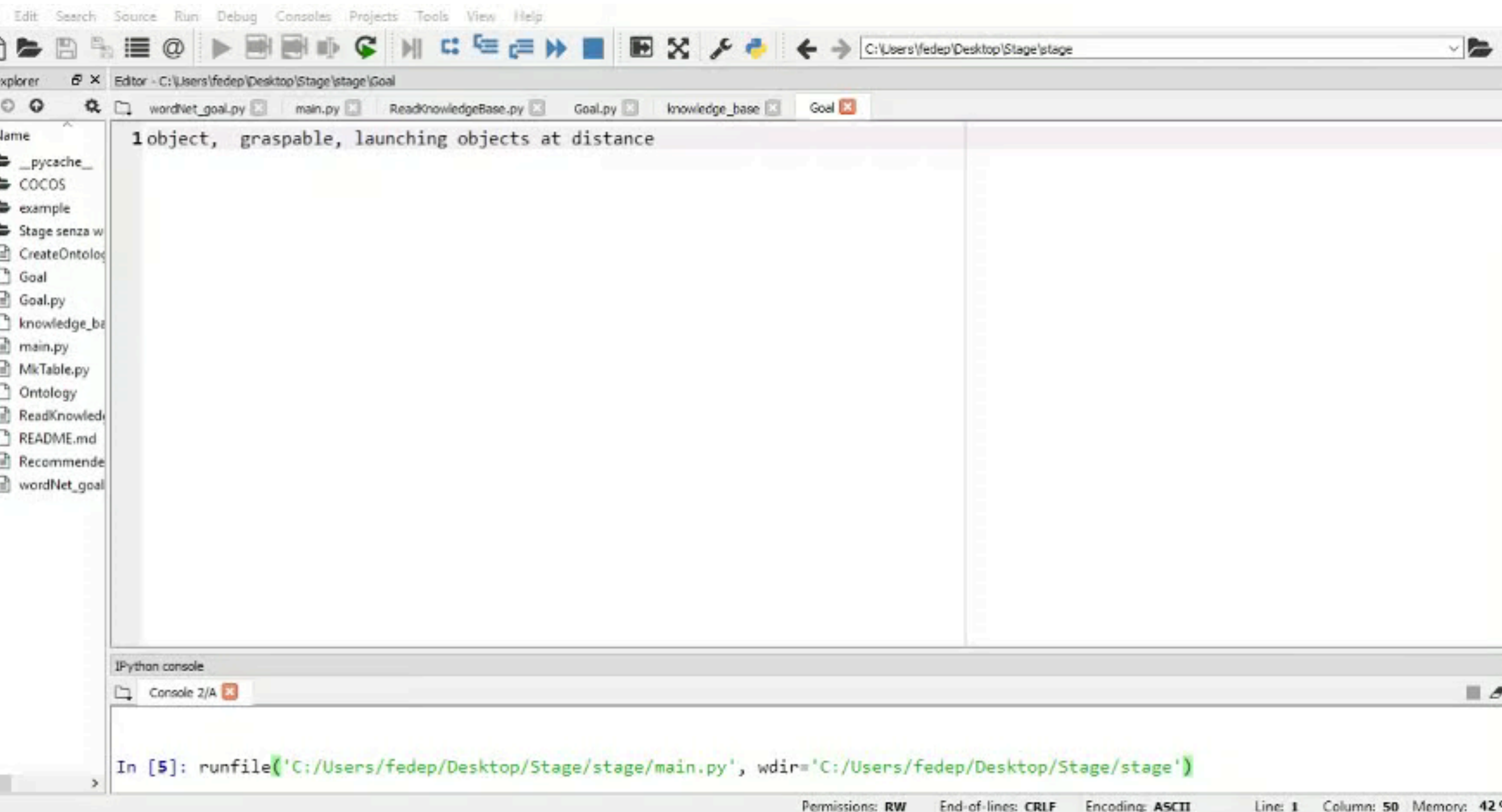
$$\mathcal{G}_2 = \{Object, Graspable, LaunchingObjectsAtDistance\},$$

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

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

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	$Stone \sqcap Towel$ $(13, 3\%)$	$Towel \sqcap RubberBand$ $(10, 8\%)$	$Vase \sqcap Shelf$ $(22, 5\%)$

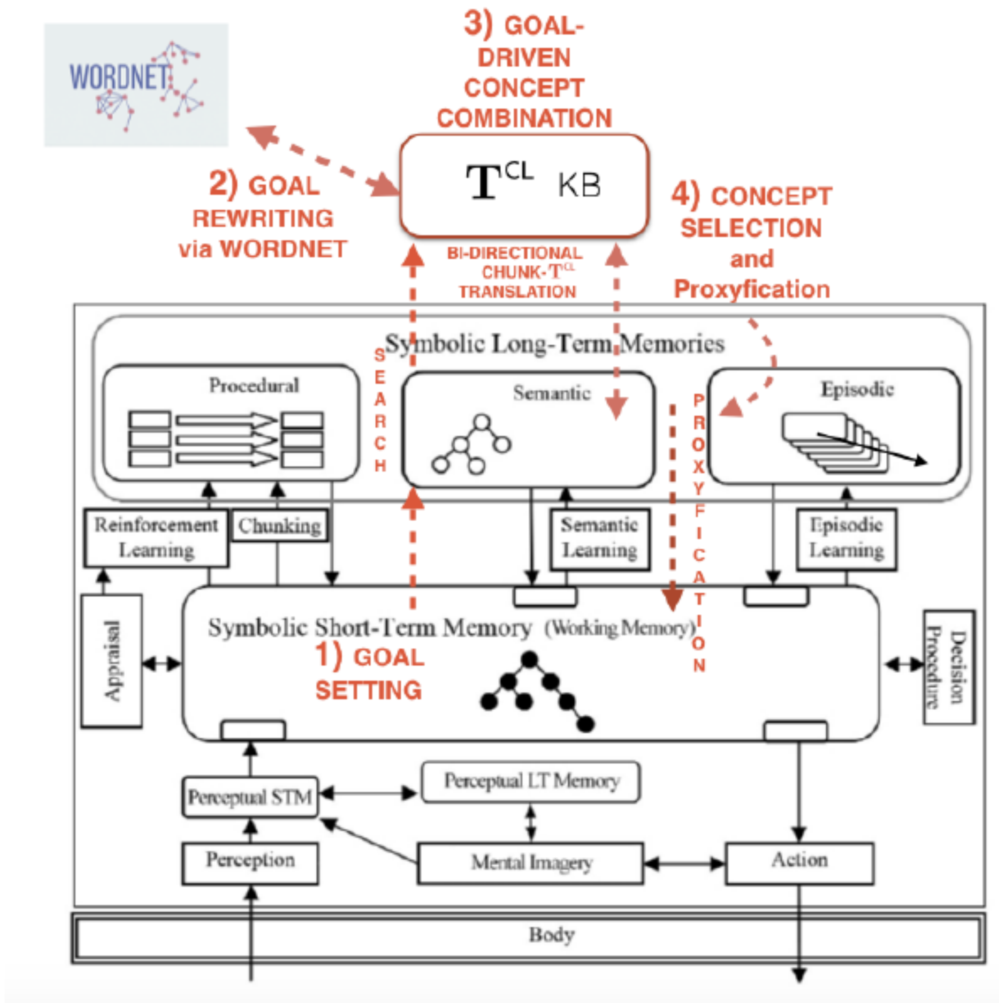
Figure 1: Comparison on Concept Composition in a Domestic Domain.

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

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

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

SOAR Integration



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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)

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