Bounded and Resource-Rational Models for Integrated Intelligence

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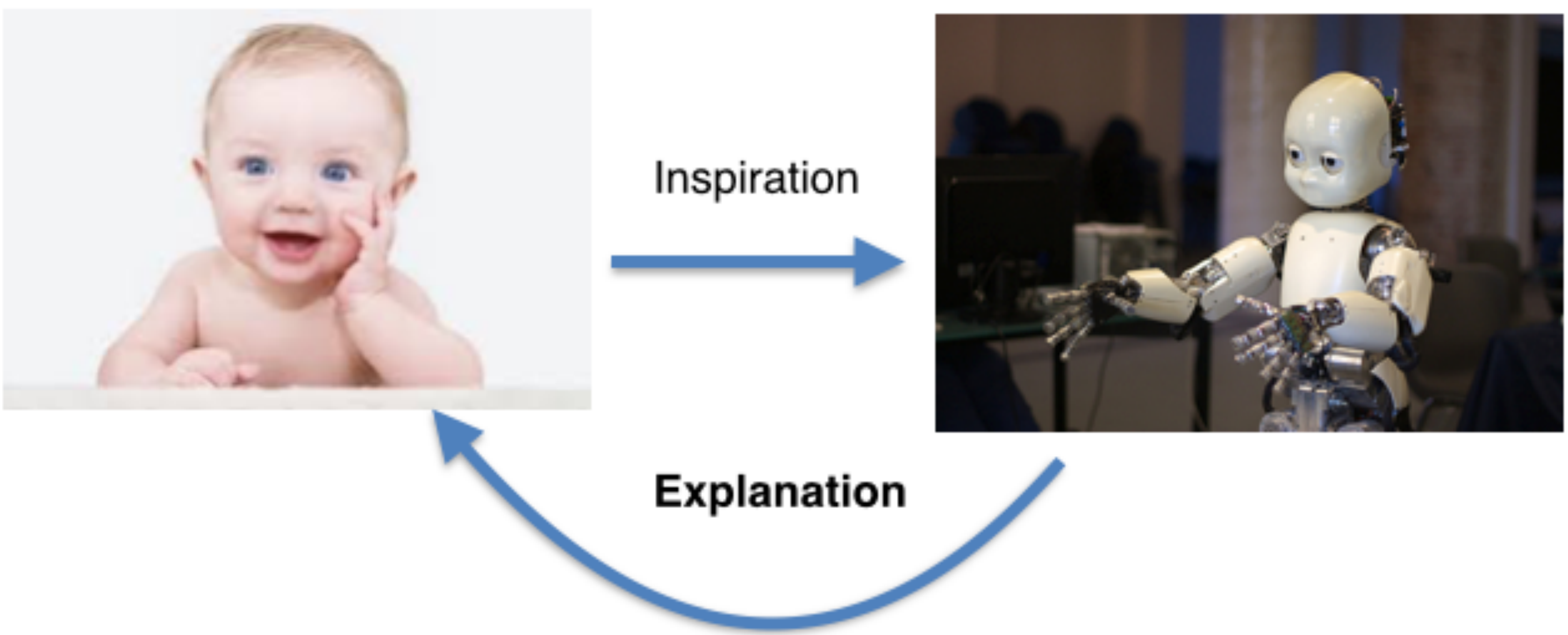
Overview

- Overall framework
- Models of rationality
- 2 case studies on commonsense reasoning

From human to artificial cognition (and back)



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

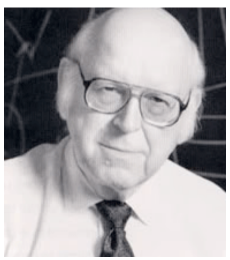
Mechanistic Explanation

“Natural/Cognitive” Inspiration and AI

Early AI

Cognitive or Biological Inspiration for the Design of “Intelligent Systems”

A. Newell

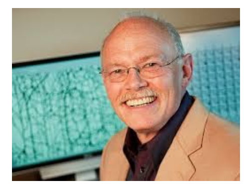


M. Minsky

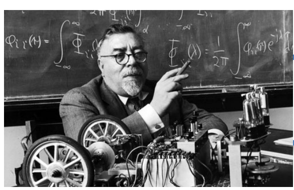
Modern AI

“Intelligence” in terms of optimality of a performance (narrow tasks)

J. McClelland



mid‘80s



N. Wiener

H. Simon

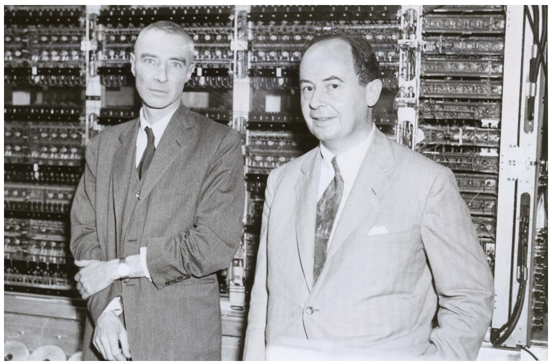
R. Shank

D. Rumhelart

Nowadays:
Renewed attention
“The gap between natural and artificial systems is still enormous” **(A. Sloman, AIC 2014).**

Models of Rationality

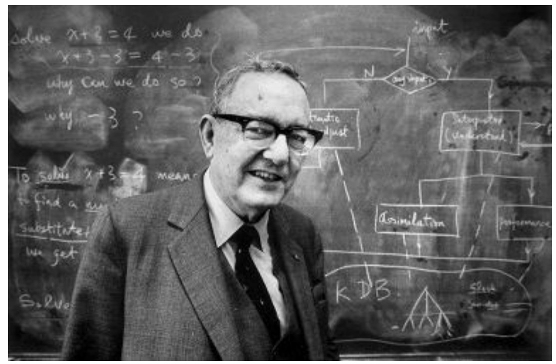
Morgenstern, Von Neumann



Expected Utility Theory

decision makers as optimizers

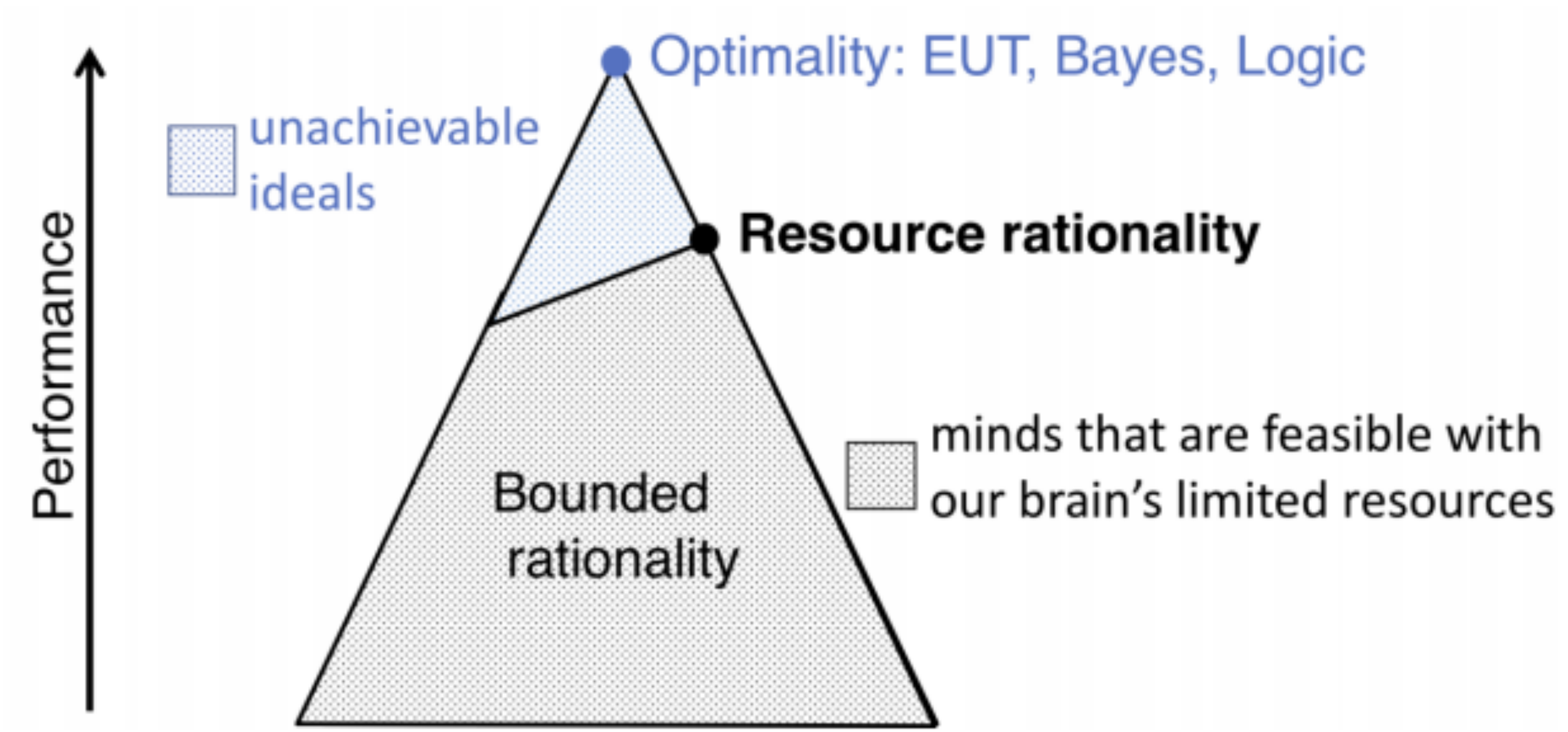
Simon



Bounded Rationality

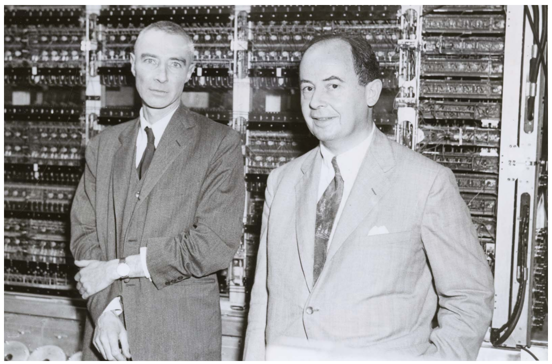
decision makers as “satisficers”

Bounded vs “olimpic" rationality



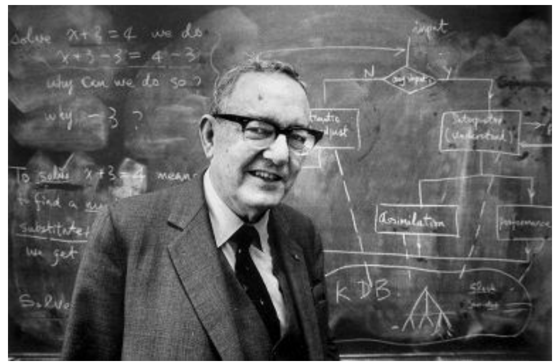
Models of Rationality

Morgenstern, Von Neumann



Expected Utility Theory

Simon



Bounded Rationality

Kahneman, Tversky

Cognitive Biases

Gigerenzer

Heuristics

Linda Problem

A version of the Linda example:

-Linda was young in the ‘70s
-Linda likes the color red
-Linda graduated in philosophy
- Linda is against nuclear power (“green” person)

Linda

<u>Linda is a bankteller</u>

<u>Linda is a feminist and bankteller</u>

Evolutionary shaped heuristics

The **conjunction fallacy** can be interpreted as an example of the strong tendency of human subjects to resort to prototypical information in categorization (**Non Monotonic Categorization**)

A version of the Linda example:

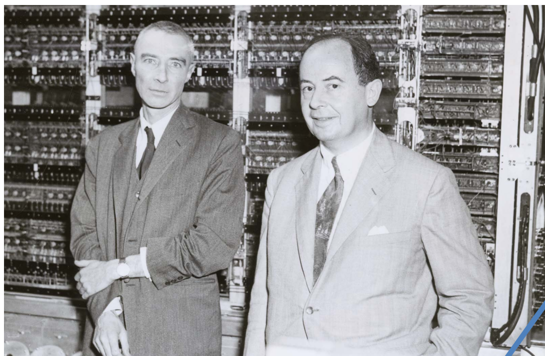
-Pippo weights 200 Kg
-Pippo is 2 metres tall
-Pippo growls and roars
-Pippo has robust teeths

Pippo is a mammal

Pippo is a mammal and he is wild and dangerous

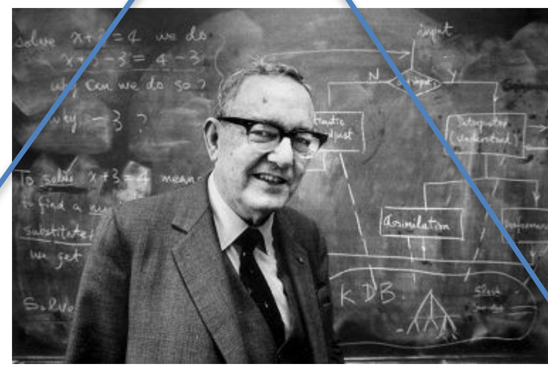
Models of Rationality

Morgenstern, Von Neumann



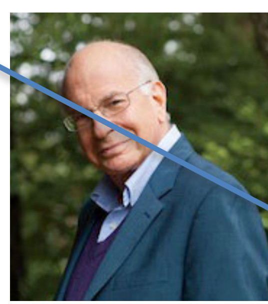
Expected Utility Theory

Simon



Bounded Rationality

Kahneman, Tversky



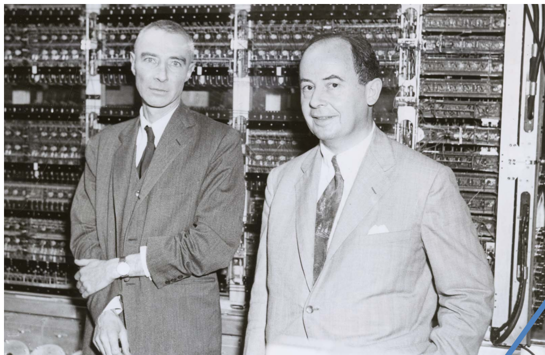
Cognitive Biases

Gigerenzer

Heuristics

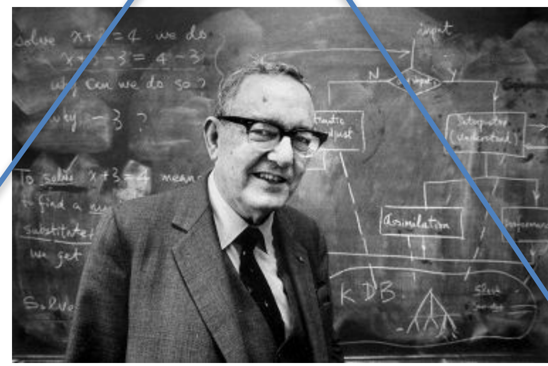
Models of Rationality

Morgenstern, Von Neumann



Expected Utility Theory

Simon



Bounded Rationality

Lieder, Griffiths

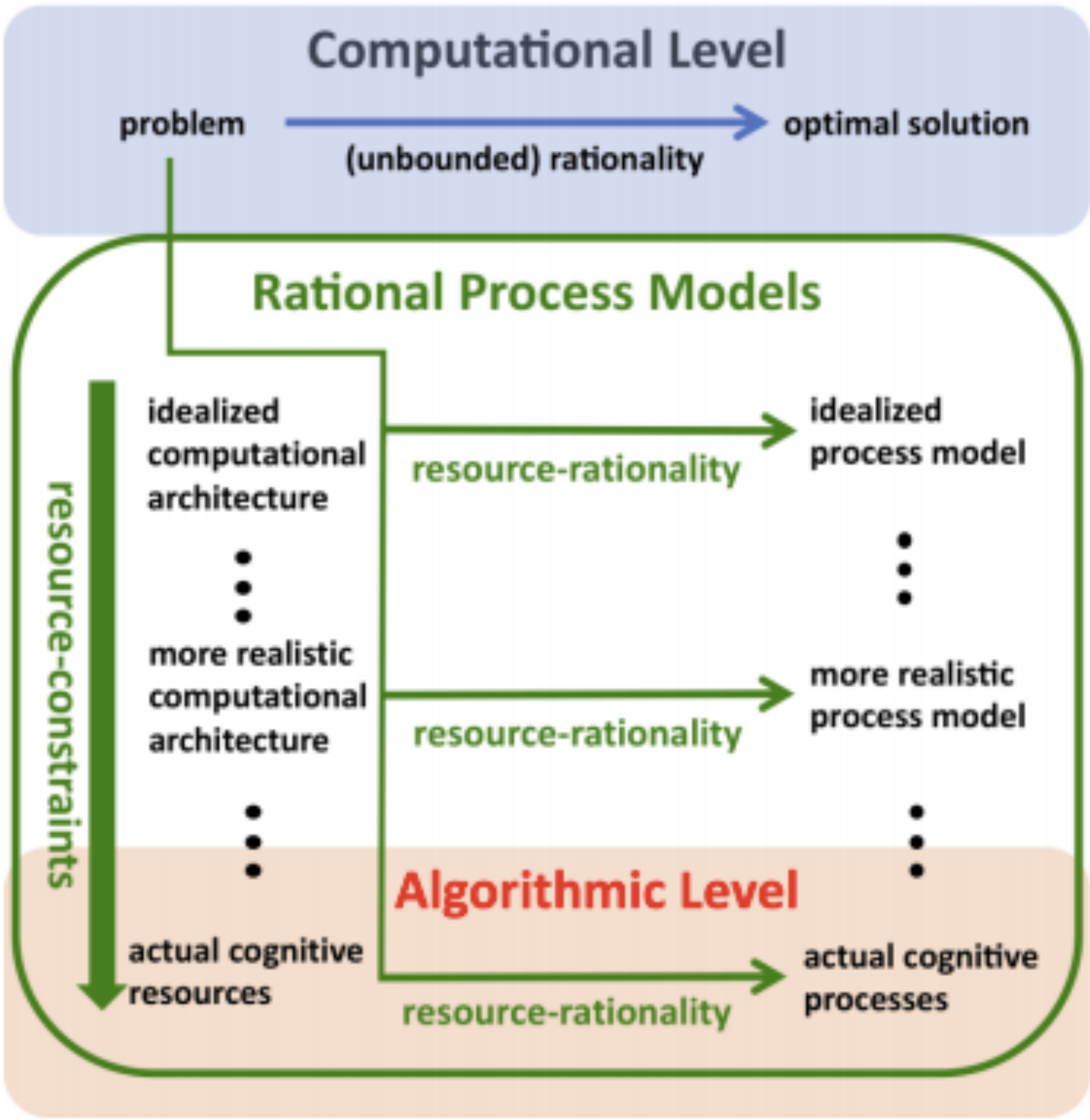
Bounded-Resource Rationality

Kahneman, Tversky

Cognitive Biases

Gigerenzer

Heuristics



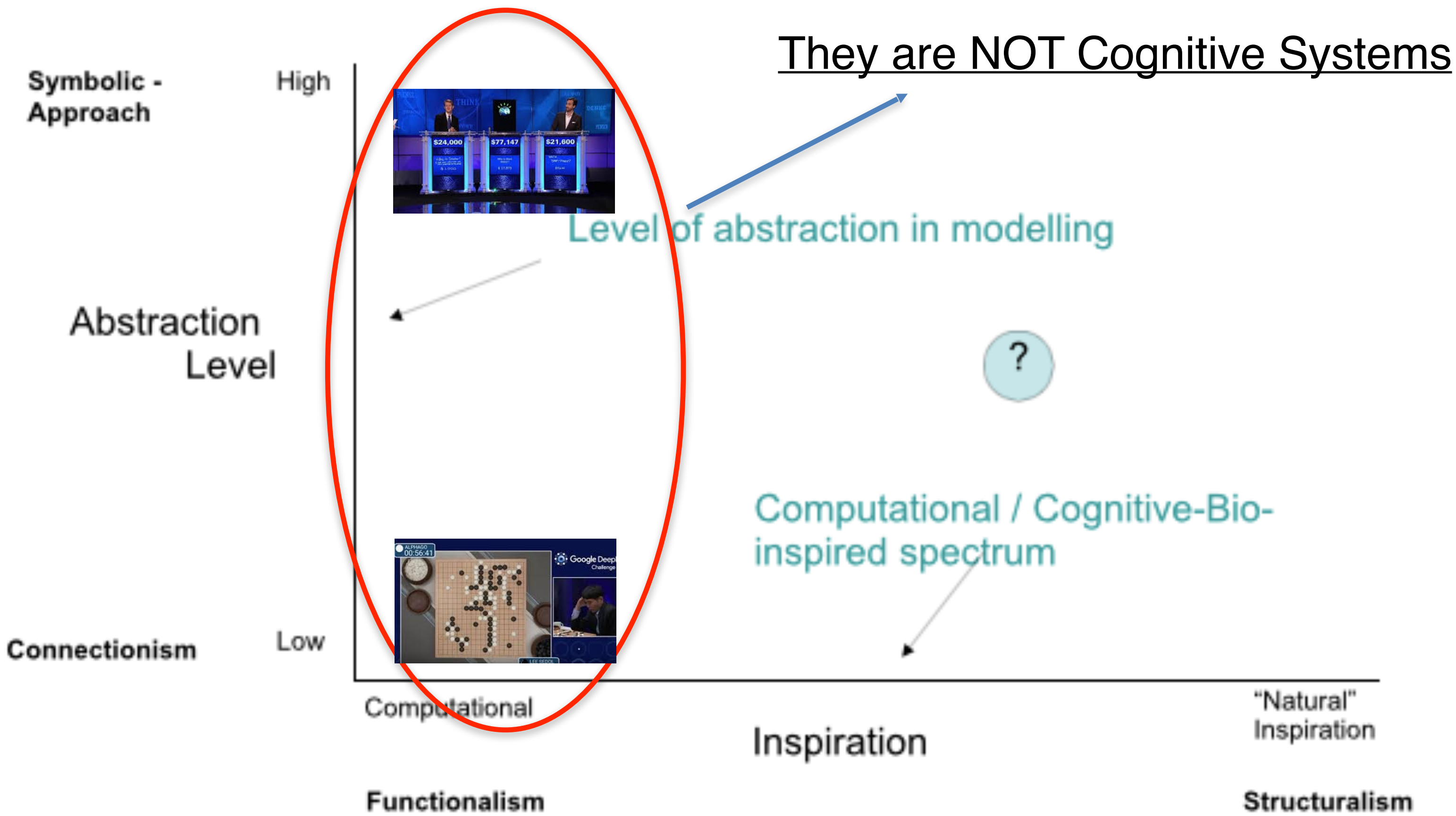
Computational Level
problem
optimal solution
(unbounded) rationality
Rational Process Models
resource-constraints
idealized computational architecture
resource-rationality
idealized process model
more realistic computational architecture
resource-rationality
more realistic process model
Algorithmic Level
actual cognitive resources
resource-rationality
actual cognitive processes

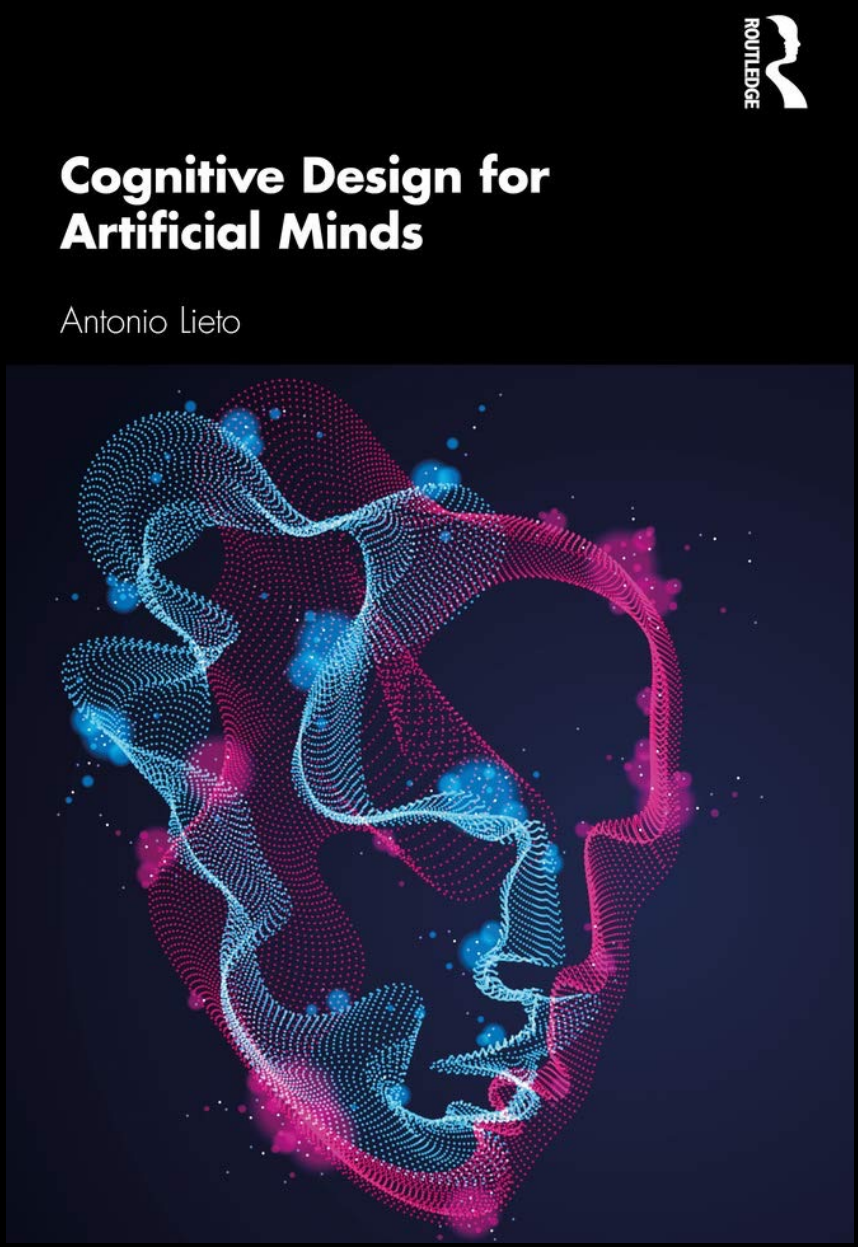
Minimal Cognitive Grid

"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)

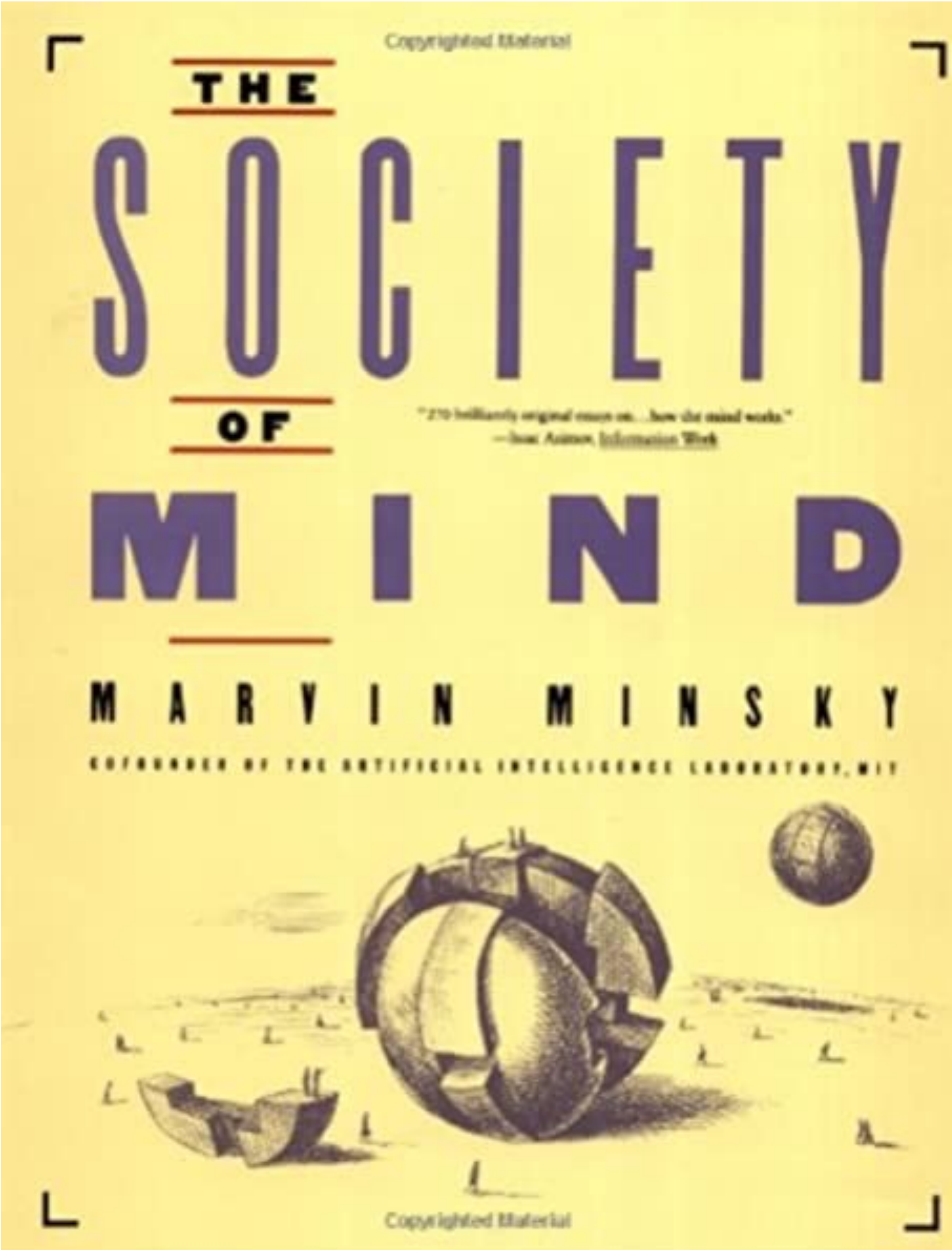
Functional/Structural Ratio
Generality
Performance match (including errors and psychometric measures)

Functionalist Models - Structuralist Models


They are NOT Cognitive Systems
Symbolic - Approach
High
Level of abstraction in modelling
Abstraction Level
?
Computational / Cognitive-Bio-inspired spectrum
Connectionism
Low
Computational
Inspiration
"Natural" Inspiration
Functionalism
Structuralism



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



Commonsense knowledge as grounding element of layers of growing thinking capabilities

Commonsense knowledge and reasoning capabilities

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:

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- …

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

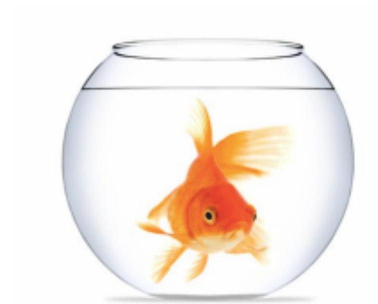
Commonsense Compositionality

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

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

+

=

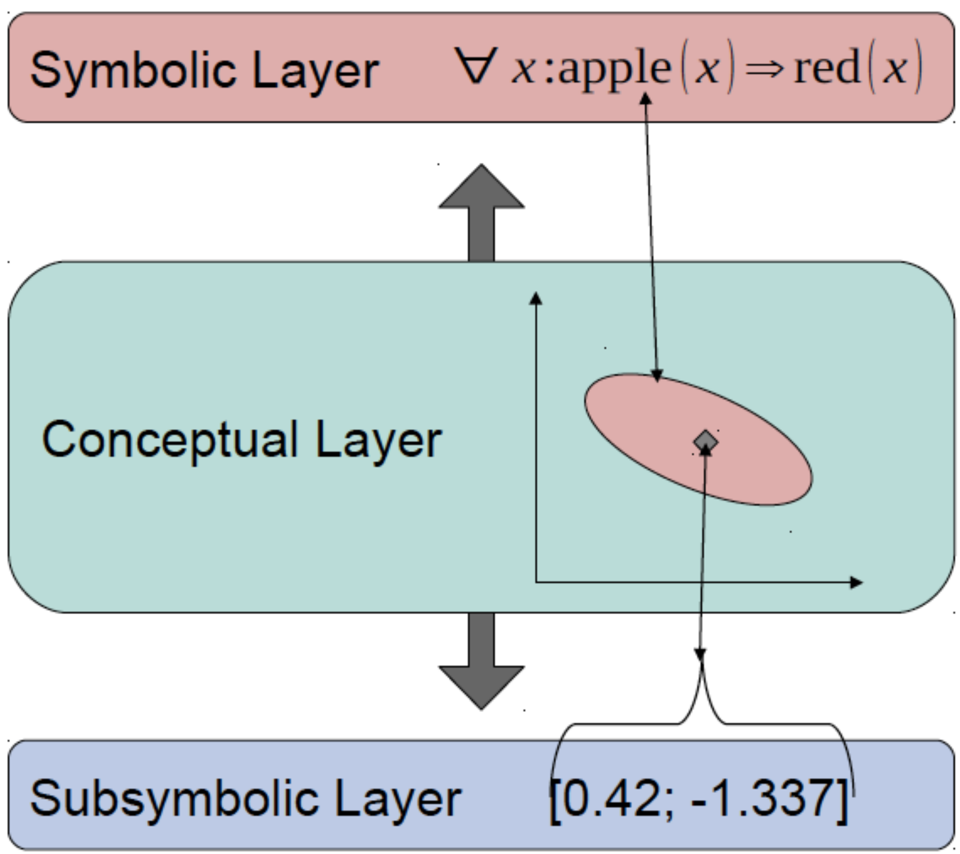


PET Fish =
{Lives-in Water, not Warm, Red.. }

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

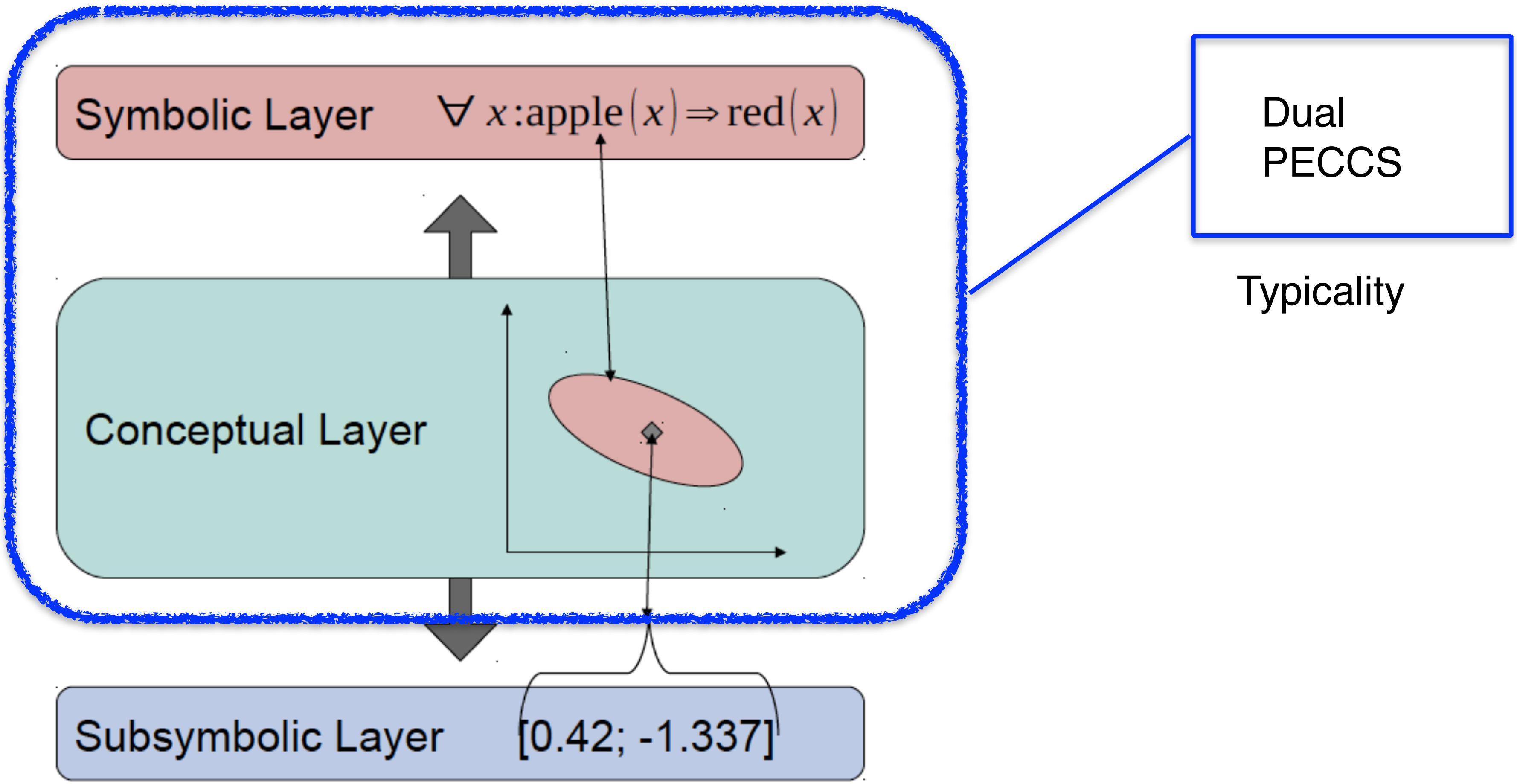
The resulting PET FISH concept is not merely composed by the additive inclusion of the typical features of the two composing concepts (i.e. PET and FISH).

Levels of Representations

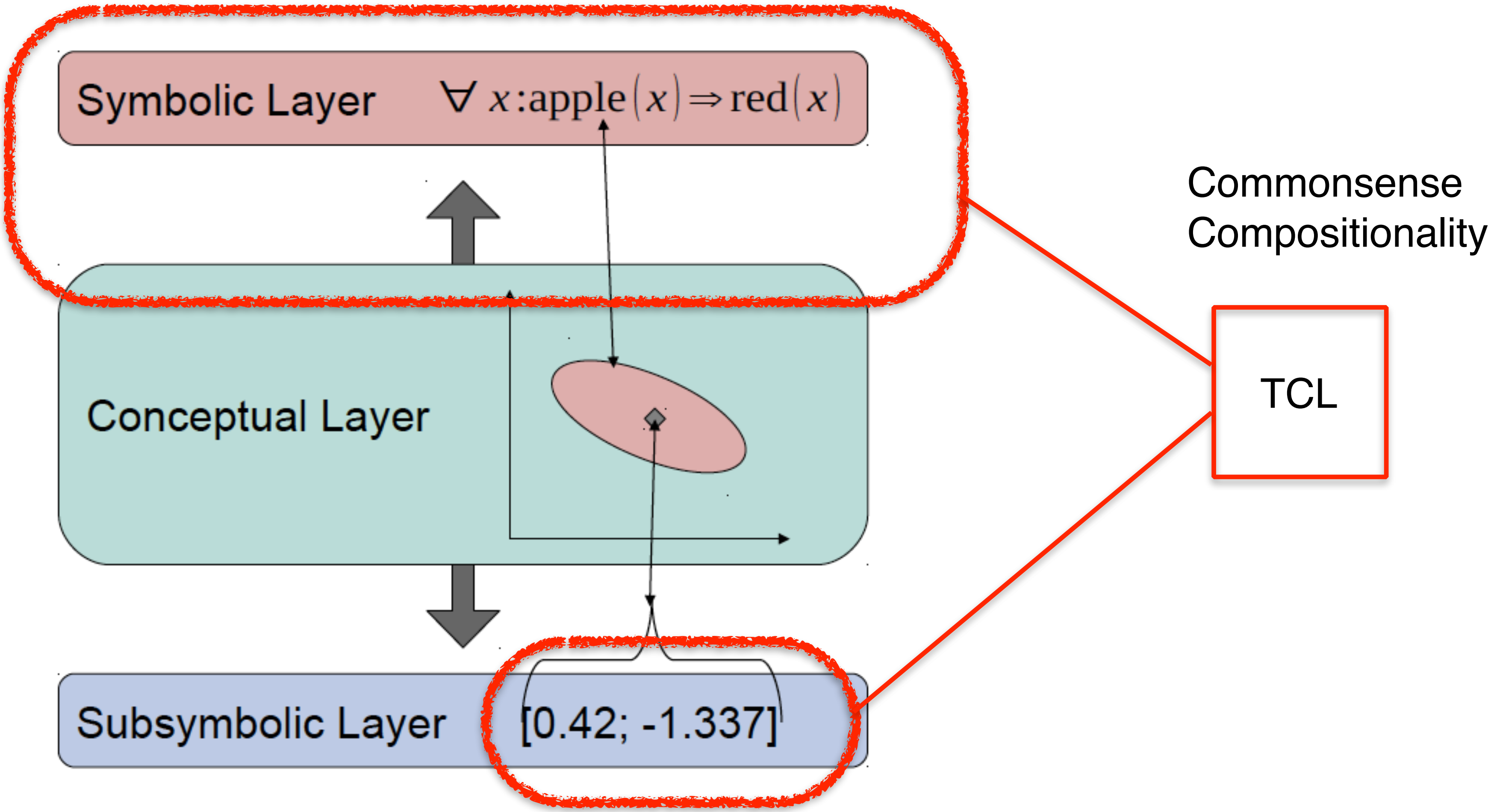


Lieto, Chella, Frixione, 2017. Conceptual Spaces for Cognitive Architectures: A
Lingua Franca for Different Levels of Representations, Biologically Inspired Cognitive Architectures.

Levels of Representations



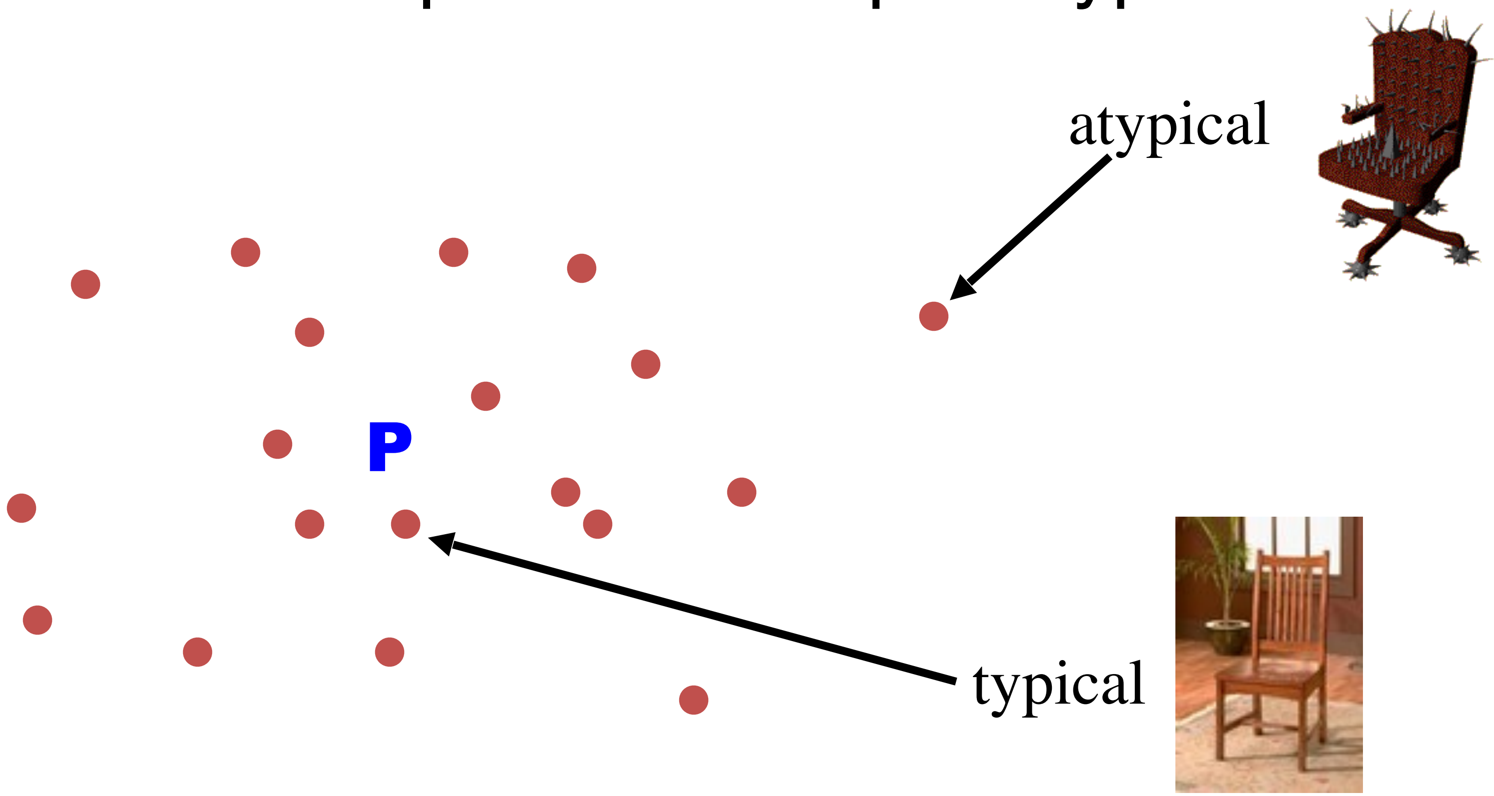
Levels of Representations



Typicality

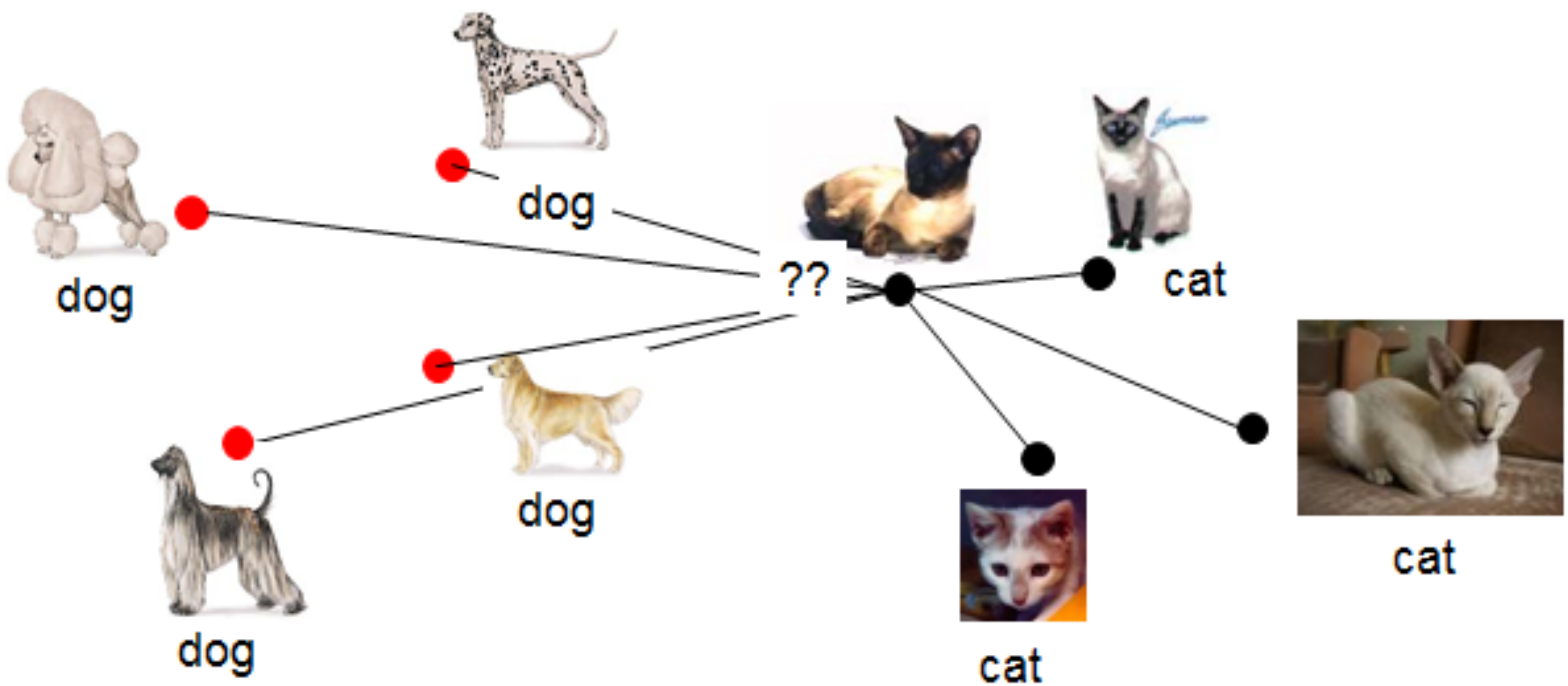
Prototypes and Prototypical Reasoning

- 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)

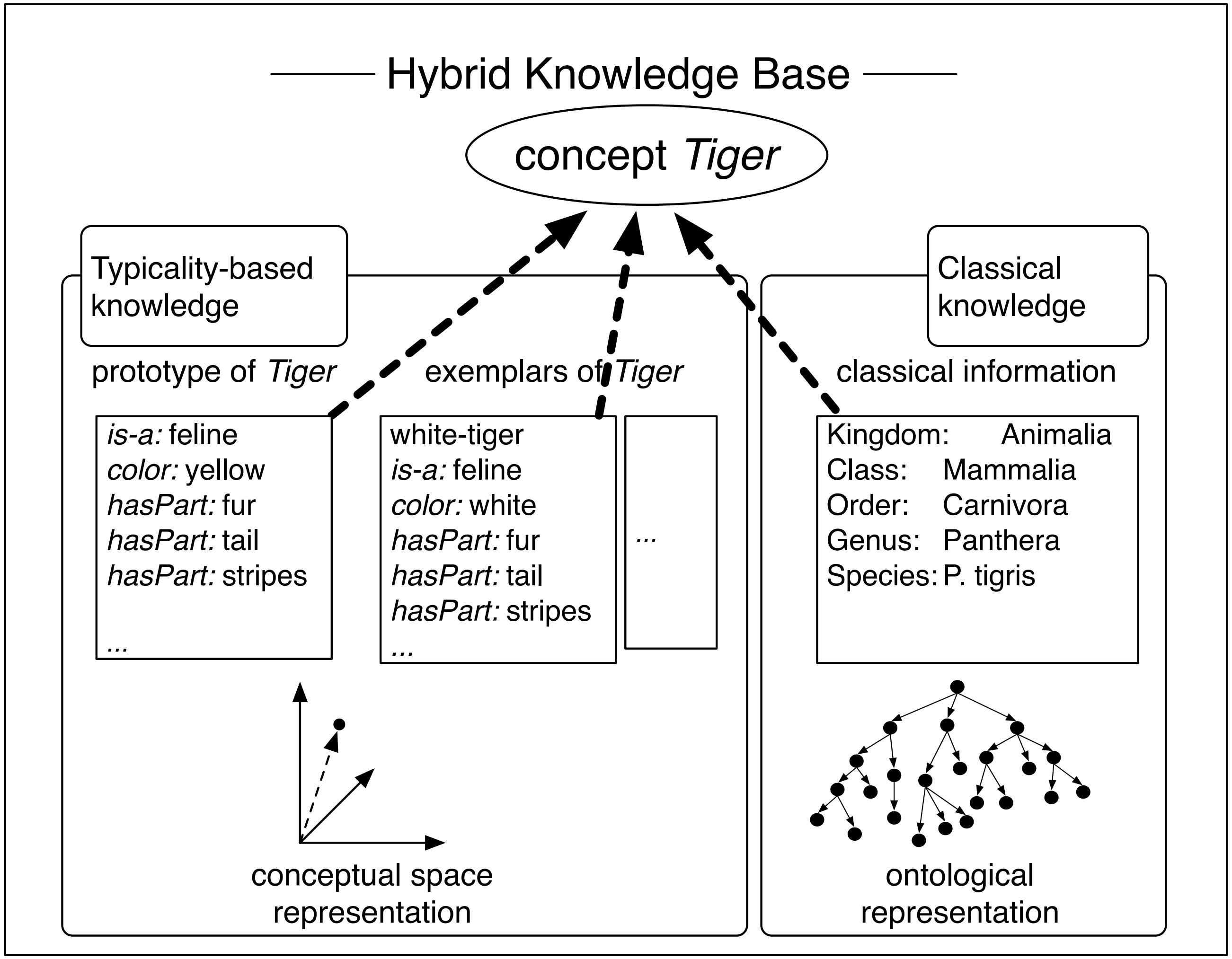
2 Cognitive Assumptions

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.

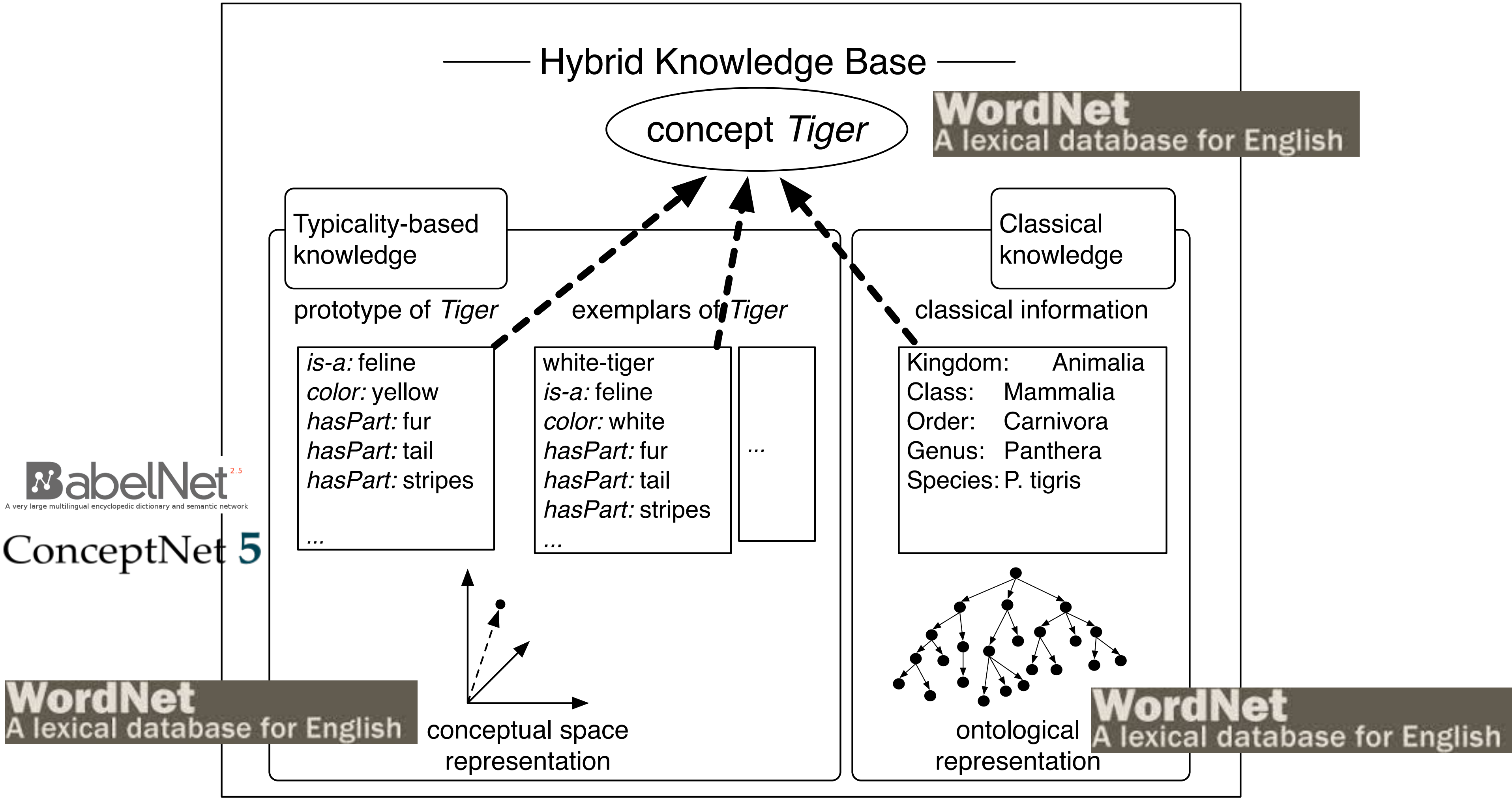
Type 1 Processes	Type 2 Processes
Automatic	Controllable
Parallel, Fast	Sequential, Slow
Pragmatic/contextualized …	Logical/Abstract …

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 $\mathcal{S}2$

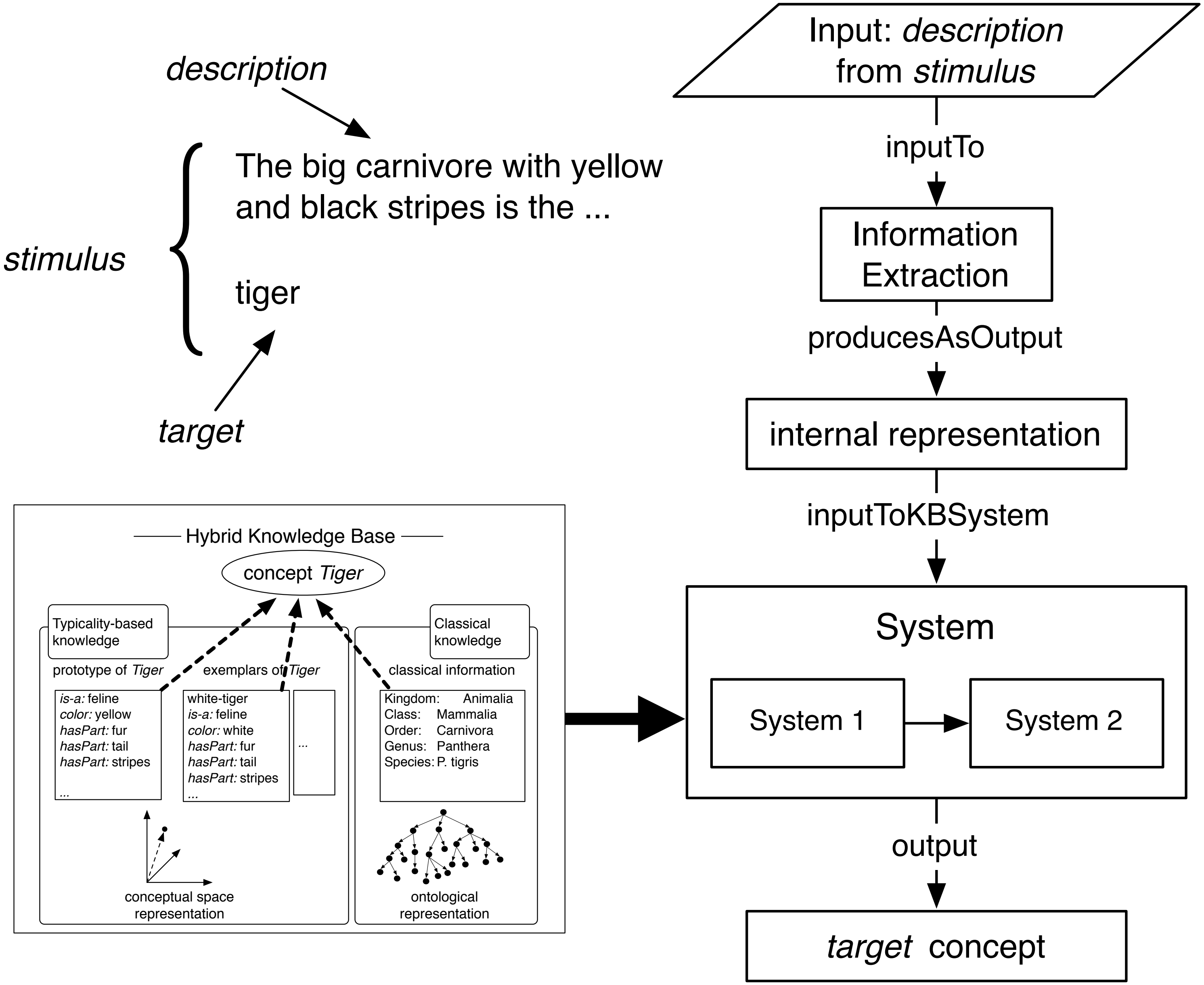
1 *trialCounter* $\leftarrow 0$;
2 *closed*$^{\mathcal{S}1} = \{\emptyset\}$
3 **while** *trialCounter* $<$ *maxTrials* **do**
    `// conceptual spaces output`
4   c $\leftarrow \mathcal{S}1(d, closed^{\mathcal{S}1})$;
5   **if** *trialCounter* $== 0$ **then** c* $\leftarrow$ c ;
    `// ontology based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

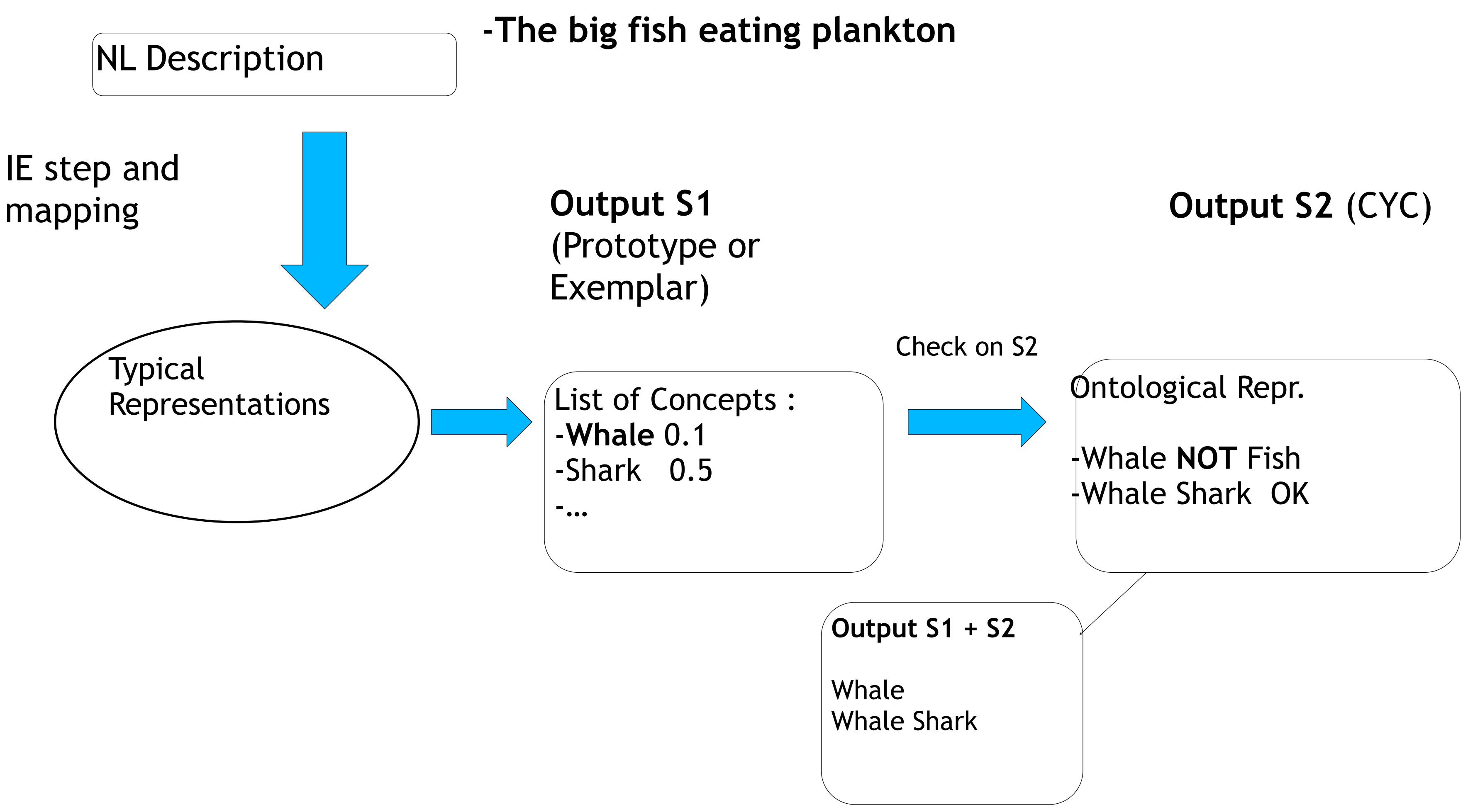
1 $\mathcal{S}1_{\text{EX}} \leftarrow$ *categorizeExemplars*(d);
2 **if** *firstOf*$(\mathcal{S}1_{\text{EX}}, closed^{\mathcal{S}1})$*.distance*$(d) <$ *similarityThreshold* **then**
3   **return** *firstOf*$(\mathcal{S}1_{\text{EX}}, closed^{\mathcal{S}1})$;
4 **else**
5     $\mathcal{S}1_{\text{PR}} \leftarrow$ *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.

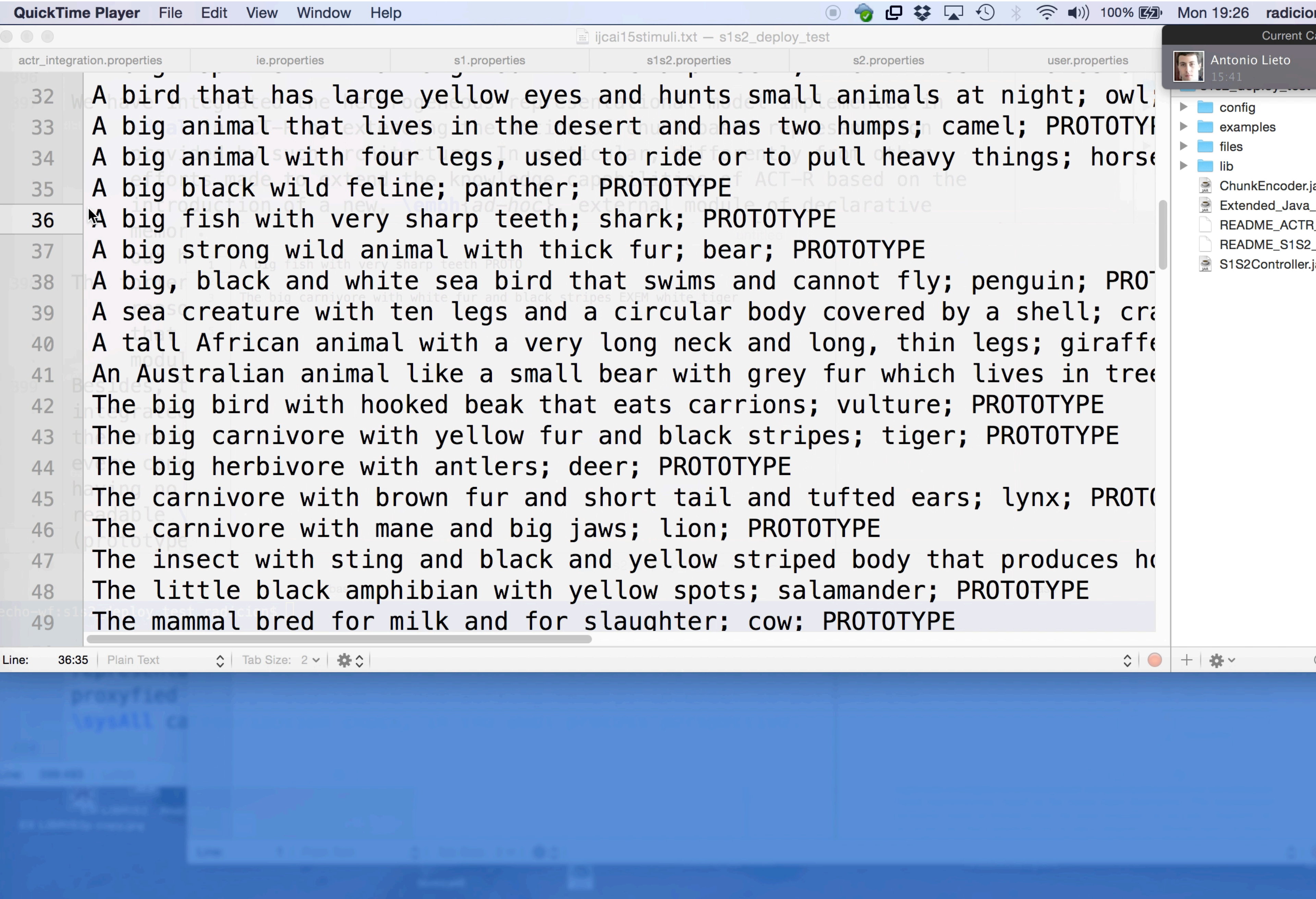


description
The big carnivore with yellow and black stripes is the ...
stimulus
tiger
target
Input: *description* from *stimulus*
inputTo
Information Extraction
producesAsOutput
internal representation
inputToKBSystem
System
System 1
System 2
output
target concept
Hybrid Knowledge Base
concept *Tiger*
Typicality-based knowledge
Classical knowledge
prototype of *Tiger*
exemplars of *Tiger*
classical information
is-a: feline
color: yellow
hasPart: fur
hasPart: tail
hasPart: stripes
...
white-tiger
is-a: feline
color: white
hasPart: fur
hasPart: tail
hasPart: stripes
...
...
Kingdom: Animalia
Class: Mammalia
Order: Carnivora
Genus: Panthera
Species: P. tigris
conceptual space representation
ontological representation

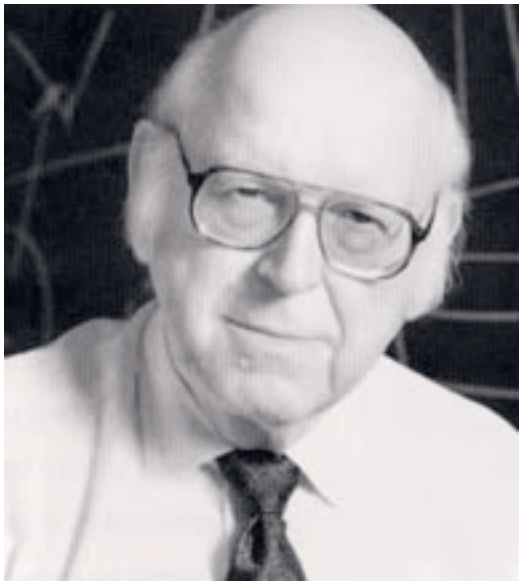
Overview


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



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

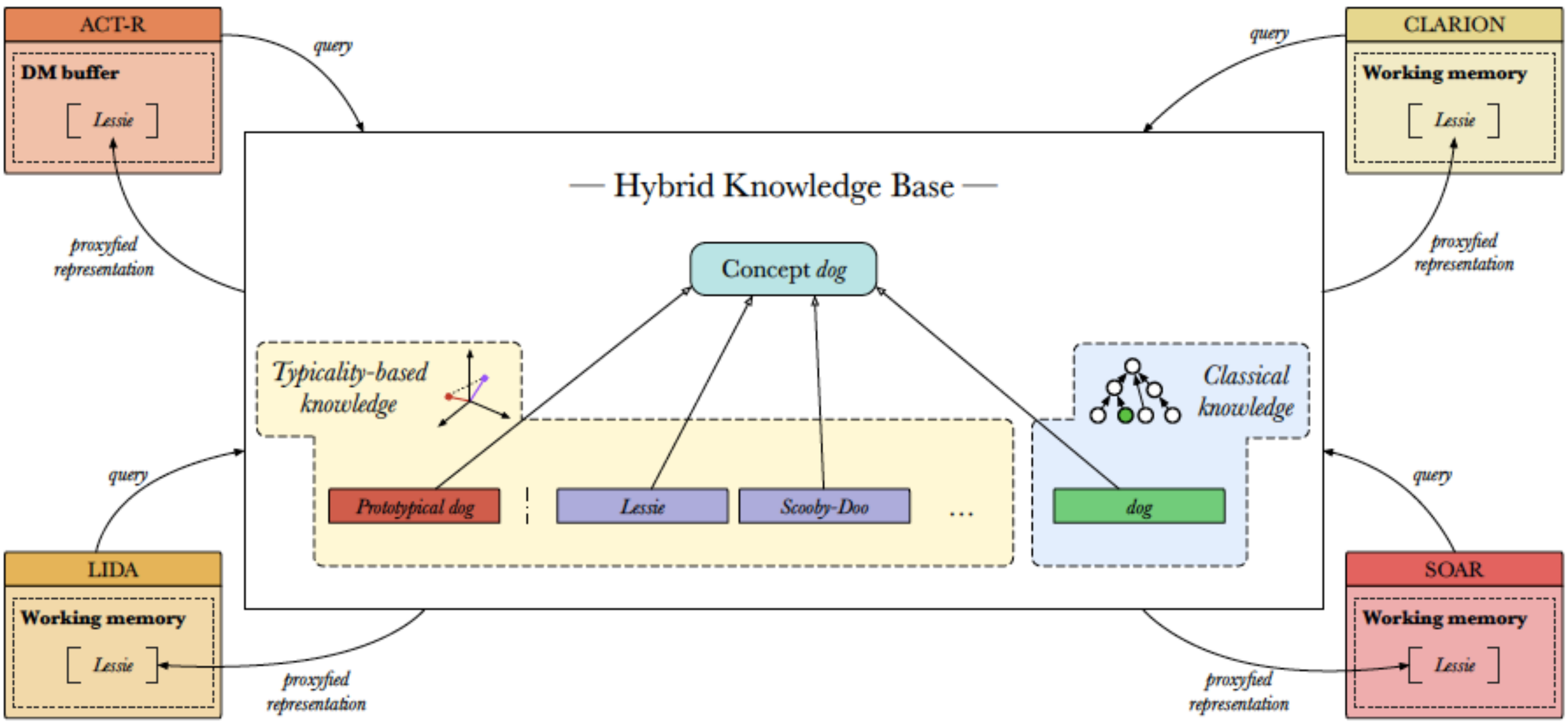
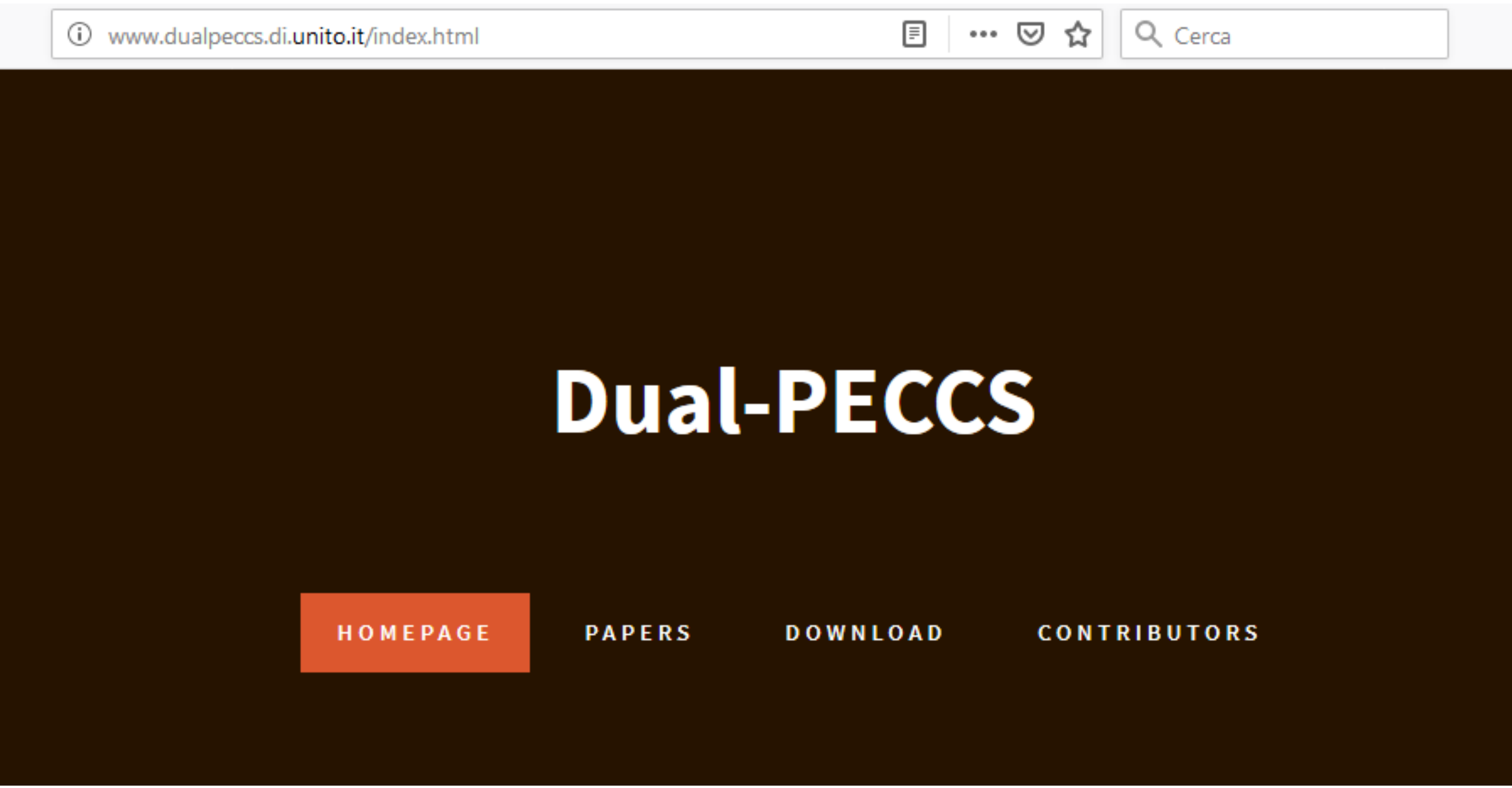


Fig. 3. General overview of the DUAL-PECCS integration within different cognitive architectures.

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*

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)

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.

Commonsense Compositionality

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

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

A non monotonic Description Logic of typicality ($\mathbf{T}^{\mathbf{CL}}$), for typicality-based concept combination 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)

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

1. **KB with real data**

2.Probabilistic Scenarios

3. Selection of the most appropriate scenarios

INITIAL KNOWLEDGE BASE

RIGID PROPERTIES

$Fish \sqsubseteq \forall livesIn.Water$

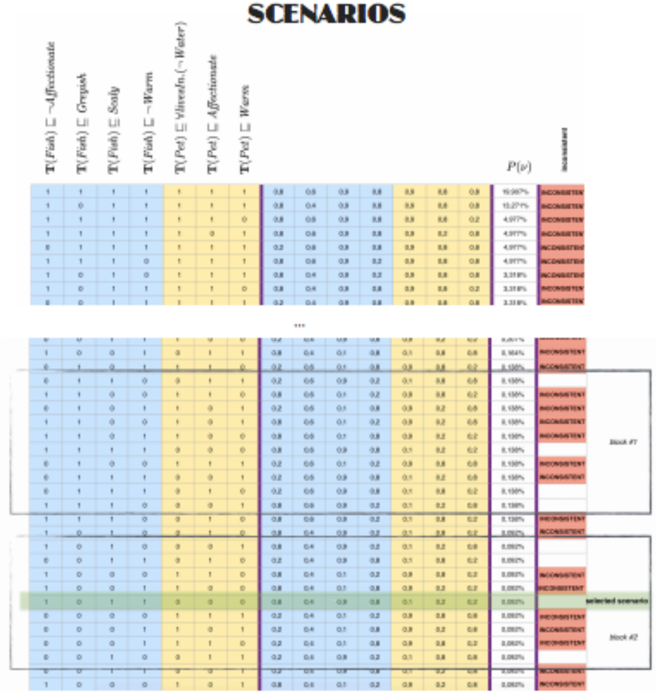
PROTOTYPE OF HEAD

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

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

$Fish \sqsubseteq \forall livesIn.Water$

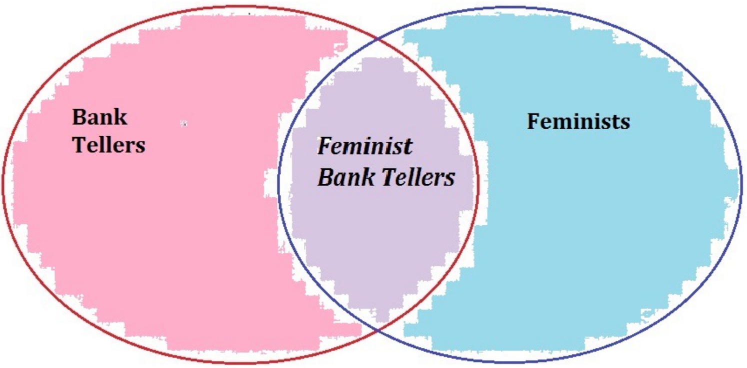
$0.7 :: \mathbf{T}(Fish) \sqsubseteq \neg Affectionate$
$0.8 :: \mathbf{T}(Fish) \sqsubseteq \neg Warm$ $\quad 0.9 :: \mathbf{T}(Fish) \sqsubseteq Scaly$
$0.6 :: \mathbf{T}(Fish) \sqsubseteq Greyish$

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

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

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

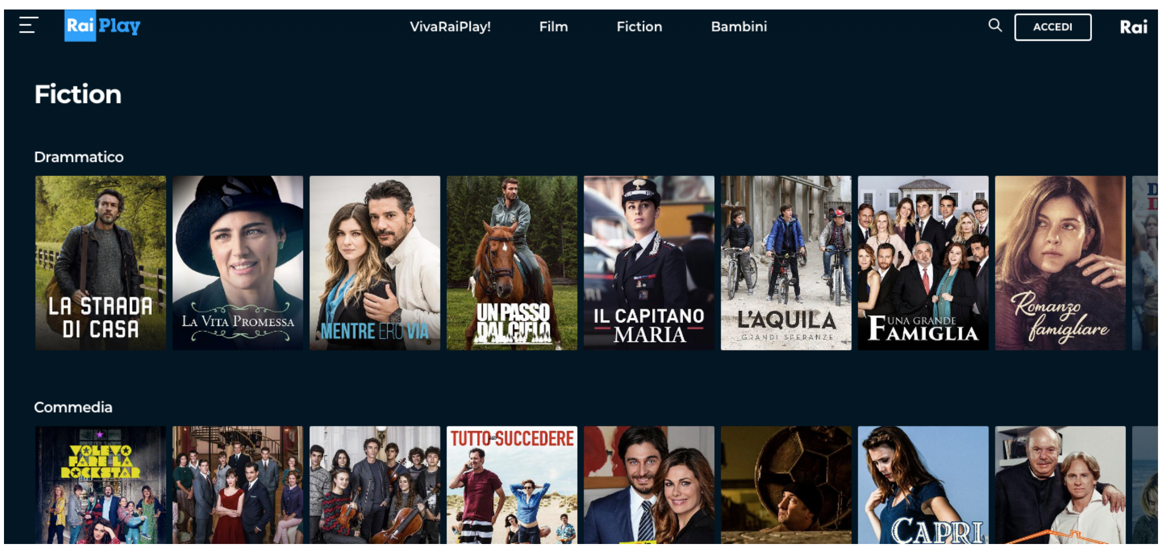
Applications



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

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

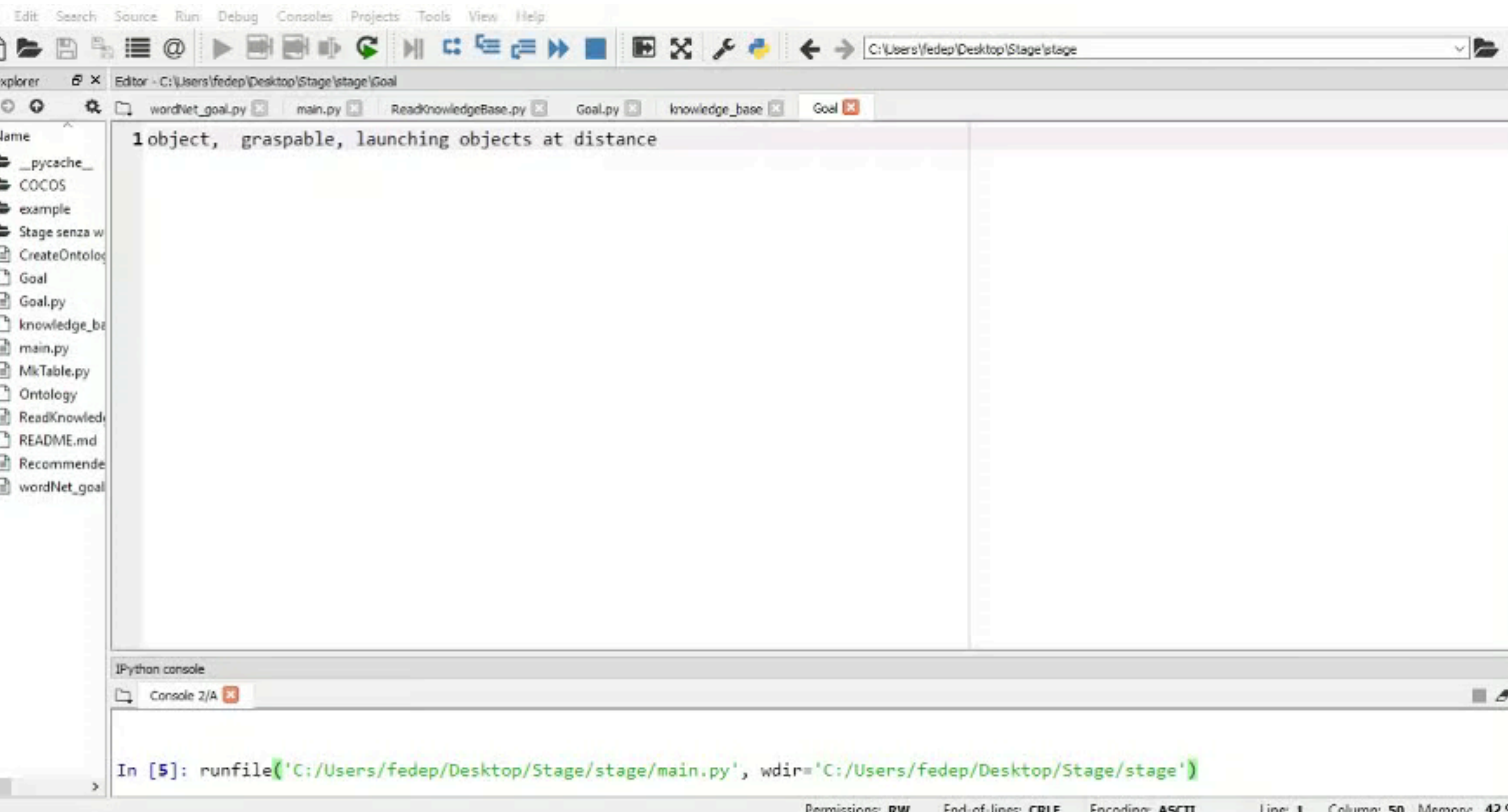
$$\mathcal{G}_2 = \{Object, Graspable, LaunchingObjectsAtDistance\},$$

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

KB 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.

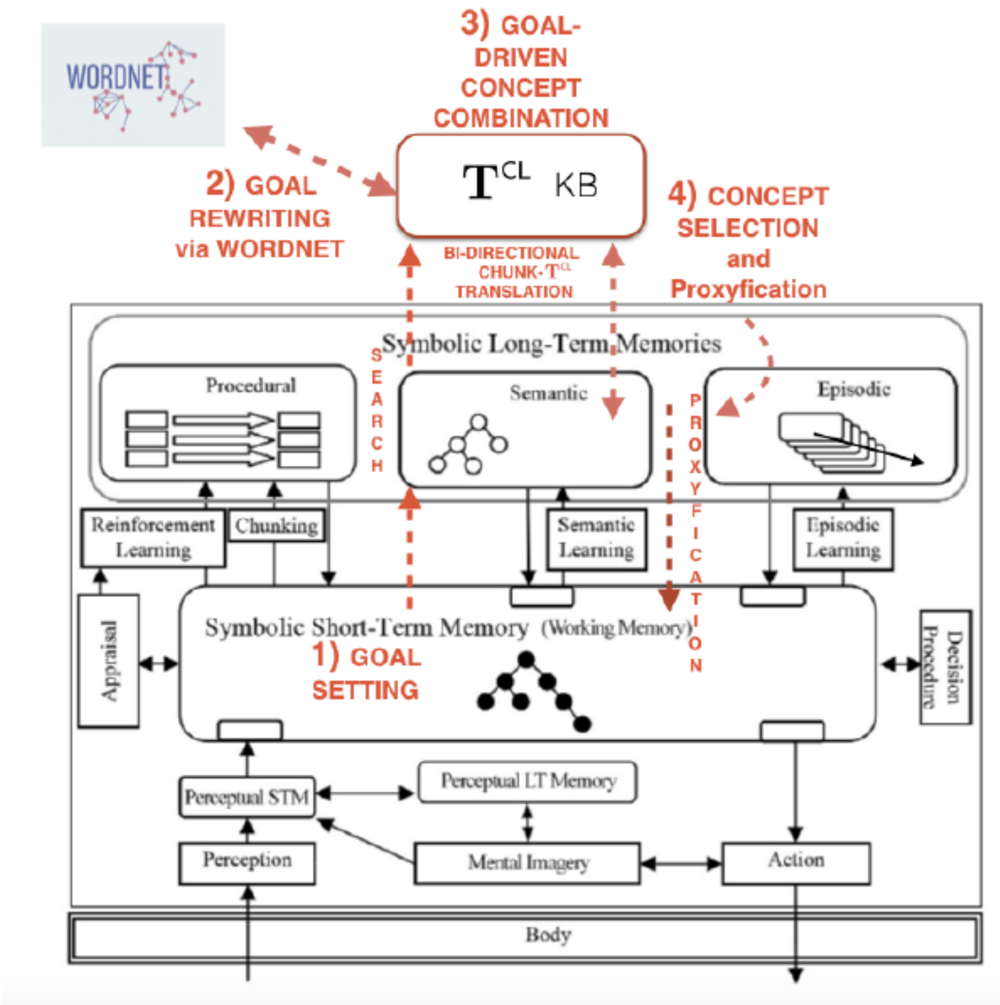
$$\mathcal{G}_1 = \{Object, Cutting, Graspable\},$$

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

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

SOAR Integration

•



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

- Cognitively Inspired AI can play a crucial for the development of the next generation of AI systems
- I have shown **two different types of cognitively inspired systems** addressing, at different levels of representation, some crucial **requirements** of commonsense reasoning
- Such structural systems have been integrated with different general cognitive architectures thus extending, de facto, their categorization and reasoning capabilities
- The kind of capabilities modeled in **DUAL-PECCS** and **TCL a**re crucial also in the context of multi-agent systems for coordination, cooperative problem solving etc.

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