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

- Fuzzy Logic (Zadeh, 1966)
- Frames (Minsky, 1975)
- Scripts (Shank & Abelson, 1977)
- Circumscription (McCarthy, 1980, 1986)

Machine-oriented Heuristics

- Newell Simon, GPS (1962)
- Semantic Networks (Collins and Quillian, 1969)
- Default Logic (Reiter, 1980)
- Qualitative Repres. (Forbus, 1984)

Conceptual Spaces (Gärdenfors, 2000)
Cognitive AI/Computational CogSci

Inspiration

Explanation
**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.

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**Functionalist Models**
- Evolutionistic Explanation
- Functional Explanation

**Structuralist Models**
- Teleological Explanation
- IBE
- Mechanistic Explanation
- Causal Explanation

*continuum*
Cognitive Design for Artificial Minds

Antonio Lieto

Commonsense reasoning

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

- induction
- abduction
- default reasoning
- ...

Commonsense reasoning

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- induction
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- ...

TYPICALITY
**Compositionality**

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

- A crucial generative requirement
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... \} 

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

Symbolic Layer: \( \forall x:\text{apple}(x) \Rightarrow \text{red}(x) \)

Conceptual Layer

Subsymbolic Layer: [0.42; -1.337]

Levels of Representations

Symbolic Layer

\[ \forall x : \text{apple}(x) \Rightarrow \text{red}(x) \]

Conceptual Layer

Subsymbolic Layer

[0.42; -1.337]

Dual PECCS

Typicality
Levels of Representations

Symbolic Layer: $\forall x: \text{apple}(x) \Rightarrow \text{red}(x)$

Conceptual Layer

Subsymbolic Layer: $[0.42; -1.337]$
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- Prototype and Exemplars Conceptual Categorization System

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.

<table>
<thead>
<tr>
<th>Type 1 Processes</th>
<th>Type 2 Processes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automatic</td>
<td>Controllable</td>
</tr>
<tr>
<td>Parallel, Fast</td>
<td>Sequential, Slow</td>
</tr>
<tr>
<td>Pragmatic/contextualized</td>
<td>Logical/Abstract</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
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</table>
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.

Ex. Heterogeneous Proxytypes at work

The different proposals that have been advanced can be grouped in three main classes: a) fuzzy approaches, b) probabilistic and Bayesian approaches, c) approaches based on non-monotonic formalisms.

Perceptual Stimulus

Stimulus α

Similarity comparison stimulus - representations

Working Memory

Penguin Exemplar

Proxification

Long-term Memory

BIRD Concept

Has component

BIRD Exemplars

BIRD Prototype

Concept (X)

Prototype (X)

Exemplar (X)

Theory (X)
Co-referring representational Structures via Wordnet

According to the hypotheses in composed in their turn by many sub-systems and processes. We assume that both systems can be phylogenetically older, unconscious, automatic, associative, Kahneman, 2011 ent types of cognitive systems.

cess theory, that postulates the co-existence of two differ-
ting, and makes no use of common-sense information. These
vention, and benefits from common-sense information associated
ments can be implemented in cognitive artificial systems
appropriate w.r.t. the sub-symbolic one.

hybrid knowledge base composed of computer and on
neurotypical proxytypes approach and on the dual process theory. As mentioned, the D
anisms for "proxyfying" conceptual representations can be
applied to be a case where symbolic and conceptual levels are more
ual (local) pattern of activation in a ANN. Finally, also for
nections in Artificial Neural Networks (ANNs). Similarly,
other hand, be represented as reinforced patterns of con-
tive, the prototypical knowledge concerning a concept can, on
ion concept (more on this aspect later);

The retrieval of such representations is driven by different

tative inference.

Figure 1: Heterogeneous representation of the
typicality information (including both prototypes and ex-
reasoning frameworks used in our system, by focusing

Typicality-based knowledge

prototype of Tiger

is-a: feline
color: yellow
hasPart: fur
hasPart: tail
hasPart: stripes

... 

typical Tiger

white-tiger
is-a: feline
color: white
hasPart: fur
hasPart: tail
hasPart: stripes

... 

classical knowledge

classical information

Kingdom: Animalia
Class: Mammalia
Order: Carnivora
Genus: Panthera
Species: P. tigris

ontological representation

conceptual space representation

S1/S2 Categorization Algorithms

Algorithm 1: The S1-S2 categorization process.

Data: Linguistic $d$
Result: A class assignment, as computed by S1 and S2

1. TrialCounter ← 0;
2. closed$^{S1} = \{\emptyset\}$
3. while trialCounter < maxTrials do
   // conceptual spaces output
   4. c ← S1(d, closed$^{S1}$);
   5. if trialCounter == 0 then $c^* \leftarrow c$;
   // ontology based consistency check
   6. cc ← S2(d, conceptPointedBy(c));
   7. if cc equals(conceptPointedBy(c)) then
      return $\langle c^*, cc \rangle$;
   else
      closed$^{S1}$ add(conceptPointedBy(c))
   end
   9. ++trialCounter;
4. end
10. cc ← S2($\langle d, \text{Thing} \rangle$);
11. return $\langle c^*, cc \rangle$;

Algorithm 2: S1 categorization with prototypes and exemplars implementing the instruction in Algorithm 1: line 4.

Data: Linguistic description: $d$; list of inconsistent concepts: closed$^{S1}$.
Result: A typicality based representation of a category.

1. $S_{1_{EX}} \leftarrow \text{categorizeExemplars}(d)$;
2. if firstOf($S_{1_{EX}}, \text{closed}^{S1}$).distance($d$) < similarityThreshold then
   return firstOf($S_{1_{EX}}, \text{closed}^{S1}$);
3. else
   $S_{1_{PR}} \leftarrow \text{categorizePrototypes}(d)$;
   // in case of equal distance prefer exemplars
   typicalityCategorization ← sortResults($S_{1_{EX}}, S_{1_{PR}}$);
   return firstOf(typicalityCategorization, closed$^{S1}$);
4. end
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
- ...

Output S2 (CYC)
Ontological Repr.
- Whale NOT Fish
- Whale Shark OK

Output S1 + S2
Whale
Whale Shark
A bird that has large yellow eyes and hunts small animals at night; owl; PROTOTYPE
A big animal that lives in the desert and has two humps; camel; PROTOTYPE
A big animal with four legs, used to ride or to pull heavy things; horse; PROTOTYPE
A big black wild feline; panther; PROTOTYPE
A big fish with very sharp teeth; shark; PROTOTYPE
A big strong wild animal with thick fur; bear; PROTOTYPE
A big, black and white sea bird that swims and cannot fly; penguin; PROTOTYPE
A sea creature with ten legs and a circular body covered by a shell; crab; PROTOTYPE
A tall African animal with a very long neck and long, thin legs; giraffe; PROTOTYPE
An Australian animal like a small bear with grey fur which lives in trees; koala; PROTOTYPE
The big bird with hooked beak that eats carrions; vulture; PROTOTYPE
The big carnivore with yellow fur and black stripes; tiger; PROTOTYPE
The big herbivore with antlers; deer; PROTOTYPE
The carnivore with brown fur and short tail and tufted ears; lynx; PROTOTYPE
The carnivore with mane and big jaws; lion; PROTOTYPE
The insect with sting and black and yellow striped body that produces honey; bee; PROTOTYPE
The little black amphibian with yellow spots; salamander; PROTOTYPE
The mammal bred for milk and for slaughter; cow; PROTOTYPE
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.

<table>
<thead>
<tr>
<th>Stimulus</th>
<th>Expected Concept</th>
<th>Expected Proxy-Representation</th>
<th>Type of Proxy-Representation</th>
</tr>
</thead>
<tbody>
<tr>
<td>...</td>
<td>...</td>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td><em>The primate with red nose</em></td>
<td><em>Monkey</em></td>
<td><em>Mandrill</em></td>
<td>EX</td>
</tr>
<tr>
<td><em>The feline with black fur that hunts mice</em></td>
<td><em>Cat</em></td>
<td><em>Black cat</em></td>
<td>EX</td>
</tr>
<tr>
<td><em>The big feline with yellow fur</em></td>
<td><em>Tiger</em></td>
<td><em>Prototypical Tiger</em></td>
<td>PR</td>
</tr>
</tbody>
</table>
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.

<table>
<thead>
<tr>
<th>test</th>
<th>CC-ACC</th>
<th>P-ACC</th>
</tr>
</thead>
<tbody>
<tr>
<td>with no IE</td>
<td>89.3% (100/112)</td>
<td>79.0% (79/100)</td>
</tr>
<tr>
<td>with IE</td>
<td>77.7% (87/112)</td>
<td>71.3% (62/87)</td>
</tr>
</tbody>
</table>
Commonsense Compositionality
A non monotonic Description Logic of typicality (TCL), 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)

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:

\[
\text{extension of ALC by inclusions } p :: T(C) \subseteq D
\]

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 $C \subseteq CH \cap CM$

The compound concept $C$ as the combination of the HEAD (CH) and the MODIFIER (CM)
(T\text{CL}) \text{ at work - Pipeline}

1. KB with real data
2. Probabilistic Scenarios
3. Selection of the most appropriate scenarios

**INITIAL KNOWLEDGE BASE**

**RIGID PROPERTIES**
Fish \sqsubset \neg \text{livesIn. Water}

**PROTOTYPE OF HEAD**
- 0.7 :: T(Fish) \sqsubset \neg \text{Affectionate}
- 0.8 :: T(Fish) \sqsubset \neg \text{Warm}
- 0.6 :: T(Fish) \sqsubset \text{Greyish}
- 0.9 :: T(Fish) \sqsubset \text{Scaly}

**PROTOTYPE OF MODIFIER**
- 0.9 :: T(Pet) \sqsubset \text{livesIn. Water}
- 0.8 :: T(Pet) \sqsubset \text{Affectionate}
- 0.8 :: T(Pet) \sqsubset \text{Warm}

**SCENARIOS**

**PROTOTYPE OF COMBINED CONCEPT**
- 0.8 :: T(Pet \sqcap \text{Fish}) \sqsubset \neg \text{Warm}
- 0.8 :: T(Pet \sqcap \text{Fish}) \sqsubset \neg \text{Affectionate}
- 0.6 :: T(Pet \sqcap \text{Fish}) \sqsubset \text{Scaly}

**REVISED KNOWLEDGE BASE**
Fish \sqsubset \neg \text{livesIn. Water}

- 0.7 :: T(Fish) \sqsubset \neg \text{Affectionate}
- 0.8 :: T(Fish) \sqsubset \neg \text{Warm}
- 0.9 :: T(Fish) \sqsubset \text{Scaly}
- 0.6 :: T(Fish) \sqsubset \text{Greyish}

- 0.9 :: T(Pet) \sqsubset \text{livesIn. Water}
- 0.8 :: T(Pet) \sqsubset \text{Affectionate}
- 0.8 :: T(Pet) \sqsubset \text{Warm}

- 0.8 :: T(Pet \sqcap \text{Fish}) \sqsubset \neg \text{Warm}
- 0.8 :: T(Pet \sqcap \text{Fish}) \sqsubset \neg \text{Affectionate}
- 0.6 :: T(Pet \sqcap \text{Fish}) \sqsubset \text{Scaly}
- 0.9 :: T(Pet \sqcap \text{Fish}) \sqsubset \text{Red}

in T\text{CL} we assume a hybrid KB (Rigid and Typical Roles)
Applications

• Computational Creativity
• Characters Generation
• Novel Genre Generation
• Recommender Systems (Chiodino et al, ECAI 2020)

Cognitive modelling
Linda problem; Lieto & Pozzato, JETAI 20

with Centro Ricerche RAI
Goal oriented Knowledge Generation

**Definition 1.** Given a knowledge base $K$ in the logic $T^{CL}$, let $G$ be a set of concepts $\{D_1, D_2, \ldots, D_n\}$ called goal.

$$G = \{\text{Property1, Property2, Property3…}\}.$$  

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

– for all $D_i \in G$, either $K \models C \sqsubseteq D$ or $K_0 \models T(C) \sqsubseteq D$ in the logic $T^{CL}$ or:

– $C$ corresponds to the **combination of at least two concepts** $C_1$ and $C_2$ occurring in $K$, i.e.

$$C \equiv C_1 \cap C_2,$$

and the $C$-revised knowledge base $K_c$ provided by the logic $T^{CL}$ is such that, for all $D_i \in G$, either $K_c \models C \sqsubseteq D$ or $K_c \models T(C) \sqsubseteq D$ in $T^{CL}$.
Concept composition

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

\[ G_1 = \{ \text{Object, Cutting, Graspable} \} , \]
\[ G_2 = \{ \text{Object, Graspable, LaunchingObjectsAtDistance} \} , \]
\[ G_3 = \{ \text{Object, Support, LiftingFromTheGround} \} , \]

GOALS

\[
\begin{align*}
\text{vase, object} & \quad \text{Vase} \sqsubseteq \text{Object} \\
\text{vase, high convexity} & \quad \text{Vase} \sqsubseteq \text{HighConvexity} \\
\text{vase, ceramic, 0.8} & \quad 0.8 :: \text{T(Vase)} \sqsubseteq \text{Ceramic} \\
\text{vase, to put plants, 0.9} & \quad 0.9 :: \text{T(Vase)} \sqsubseteq \text{ToPutPlants} \\
\text{vase, to contain objects, 0.9} & \quad 0.9 :: \text{T(Vase)} \sqsubseteq \text{ToContainObjects} \\
\text{vase, graspable, 0.9} & \quad 0.9 :: \text{T(Vase)} \sqsubseteq \text{Graspable}
\end{align*}
\]

KB T^{CL}
G = \{\text{Object, Graspable, Launching objects at distance}\}
Evaluation (30 subjects)

<table>
<thead>
<tr>
<th></th>
<th>$G_1$</th>
<th>$G_2$</th>
<th>$G_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>System</td>
<td><em>Stone □ Branch</em></td>
<td><em>Branch □ RubberBand</em></td>
<td><em>Shelf □ Stump</em></td>
</tr>
<tr>
<td>Human</td>
<td><em>Stone □ Branch</em> (KnifeWithHandle, 52%)</td>
<td><em>Branch □ RubberBand</em> (Slingshot, 42%)</td>
<td><em>Shelf □ Stump</em> (Table, 59%)</td>
</tr>
<tr>
<td>System</td>
<td>-</td>
<td><em>Book □ RubberBand</em></td>
<td><em>Stump □ SurfBoard</em></td>
</tr>
<tr>
<td>Human</td>
<td><em>Stone □ Towel</em> (13, 3%)</td>
<td><em>Towel □ RubberBand</em> (10, 8%)</td>
<td><em>Vase □ Shelf</em> (22, 5%)</td>
</tr>
</tbody>
</table>

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

$G_1 = \{\text{Object, Cutting, Graspable}\},$

$G_2 = \{\text{Object, Graspable, LaunchingObjectsAtDistance}\},$

$G_3 = \{\text{Object, Support, LiftingFromTheGround}\},$
SOAR Integration

“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)

**Minimal Cognitive Grid**

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

<table>
<thead>
<tr>
<th>Functionalist Models</th>
<th>Structuralist Models</th>
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<tbody>
<tr>
<td>TCL</td>
<td>Dual Peccs</td>
</tr>
</tbody>
</table>
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


