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You can download the sources of this presentation here:
github.com/severin-lemaignan/lecture-hri-symbolic-reasoning



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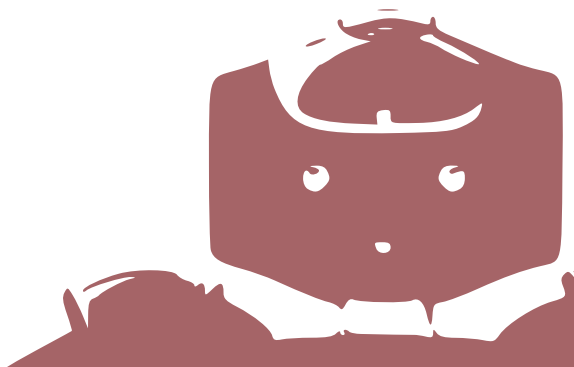
University of
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Symbolic Reasoning for HRI

Séverin Lemaignan

Bristol Robotics Lab

University of the West of England



IN THIS LECTURE

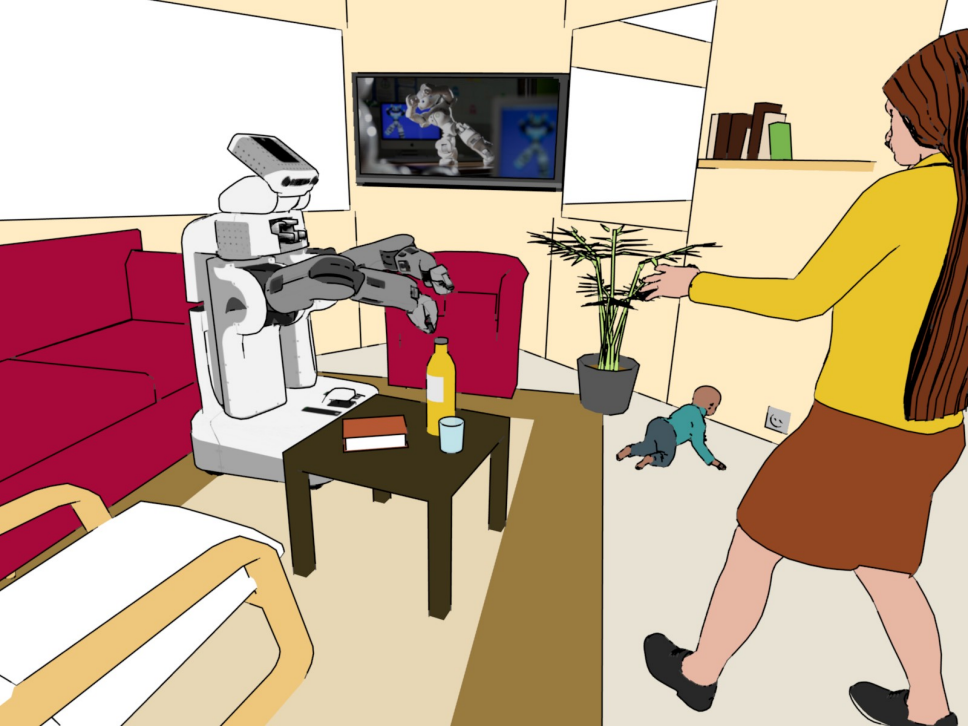
- Last week: NLP down to syntax parsing

IN THIS LECTURE

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- Today: **meaning** (both semantics and pragmatics)

IN THIS LECTURE

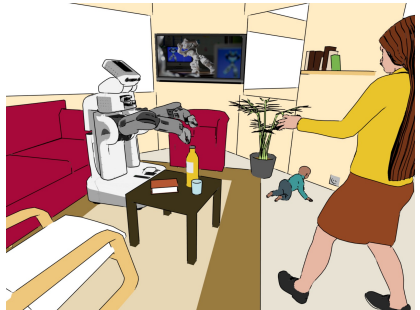
- Last week: NLP down to syntax parsing
- Today: **meaning** (both semantics and pragmatics)
 - How to attach *meaning* to perceptions & natural language?
 - What are ontologies?
 - How is 'meaning' represented and used within the robot?
 - How does it relate to *mental models*?



Situated dialogue effectively evidences the challenges

How can the robot make sense of and act upon a command like:

“Can you give me that book?”



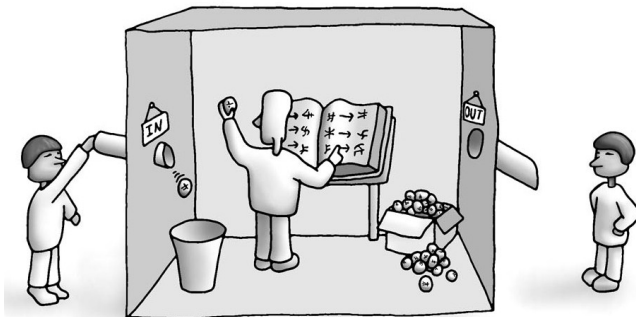
THE SYMBOL GROUNDING PROBLEM

How to attach meaning to a symbol?

THE SYMBOL GROUNDING PROBLEM

How to attach meaning to a symbol?

Searle's **Chinese Room Argument**



[Read more on Wikipedia](#)

THE SYMBOL GROUNDING PROBLEM

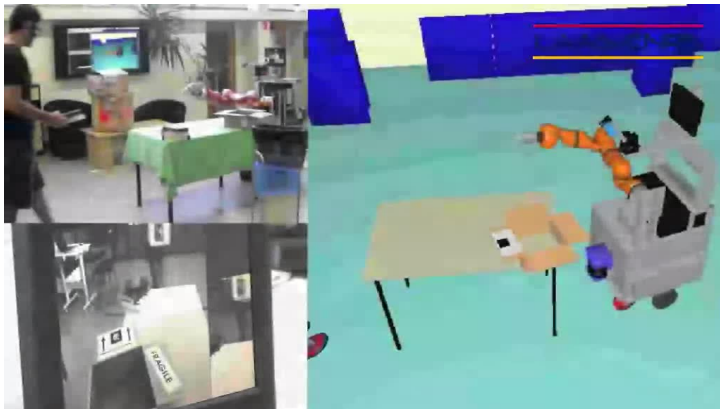
How to attach meaning to a symbol?
Is it possible at all?

THE SYMBOL GROUNDING PROBLEM

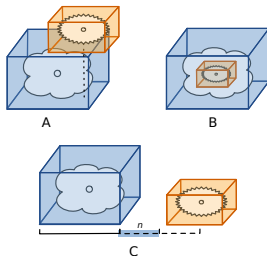
Embodiment is part of the answer. In robotics,
we talk of **Situated AI**.

SITUATED, GROUNDED, SYMBOLIC SOCIAL COGNITION

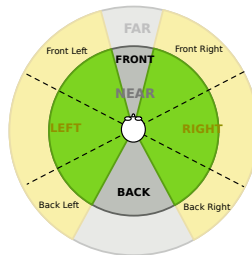
SITUATION ASSESSMENT



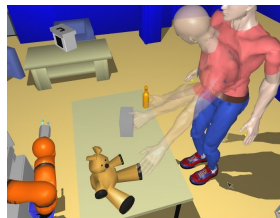
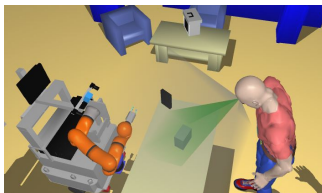
VISUAL PERSPECTIVE TAKING



allocentric



egocentric



Subject	Predicate	Object
Location	isAt	Location
	→ isOn	
	→ isIn	
	→ isNextTo	
Location	isAbove	Location
Location	isBelow	Location
Location	hasRelativePosition	Location
	→ behind	
	→ inFrontOf	
	→ leftOf	
	→ rightOf	
Object	farFrom	Agent
Object	near	Agent
Agent	looksAt	SpatialThing
Agent	sees	SpatialThing
SpatialThing	isInFieldOfView	xsd:boolean
Agent	pointsAt	SpatialThing
Agent	focusesOn	SpatialThing
Agent	seesWithHeadMovement	SpatialThing
Agent	canReach	Object

STATEMENT, BELIEFS

human_1 sees teddybear

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A **statement** is a true proposition (in a given model)

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teddybear isOn table_1

STATEMENT, BELIEFS

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A **statement** is a true proposition (in a given model) \equiv **belief**

teddybear type Toy

teddybear isOn table_1

human_1 hates robot_1 (in the human's model only!)

STATEMENT, BELIEFS (2)

human_1 sees teddybear

Triplet $\langle \mathbf{S}, \mathbf{P}, \mathbf{O} \rangle$: subject, predicate, object

STATEMENT, BELIEFS (2)

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P is a predicate of **arity** 2: $P(S, O)$

STATEMENT, BELIEFS (2)

human_1 sees teddybear

Triplet $\langle S, P, O \rangle$: subject, predicate, object

P is a predicate of **arity** 2: $P(S, O)$

Some logic language (like Prolog) allows arbitrary arities:

give(robot_1, human_1, teddybear)

STATEMENT, BELIEFS (2)

human_1 sees teddybear

Triplet $\langle S, P, O \rangle$: subject, predicate, object

P is a predicate of **arity** 2: $P(S, O)$

Many do not (like the OWL language). In this case, **reification**:

give_act_1 type Give

give_act_1 performedBy robot_1

give_act_1 receivedBy human_1

give_act_1 actsOnObject teddybear

TOWARDS ONTOLOGIES

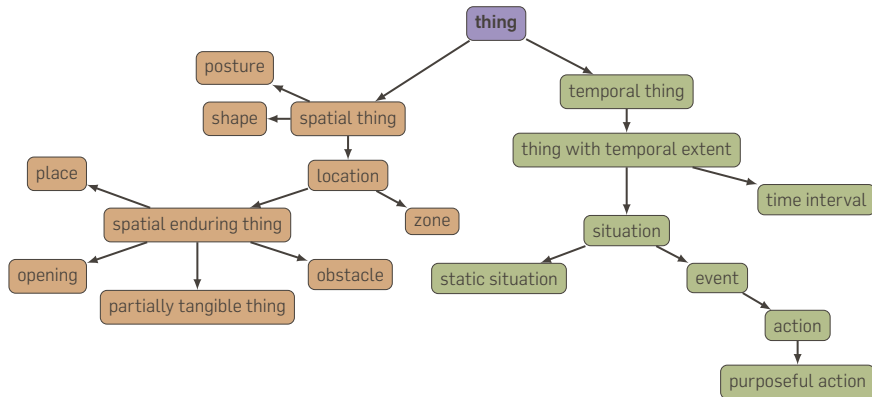
The robot's newly acquired beliefs typically have to be **anchored** in pre-existing knowledge.

→ We usually endow the robot with **background knowledge** (also known as **common-sense knowledge** with statements like:

```
Object rdfs:subclassOf PhysicalThing
```

```
Location rdfs:subclassOf SpatialThing
```

TOWARDS ONTOLOGIES



Example of an **upper ontology**

ONTOLOGIES

An **ontology** encompasses a representation, formal naming, and definition of the categories, properties, and relations between the concepts, data, and entities that substantiate one, many, or all domains.

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Ontologies often have close relationships with **first-order logic (FOL)** – more about that later.

ONTOLOGIES

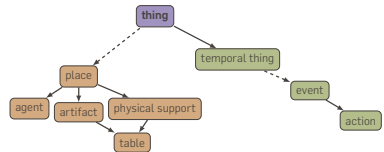
- **T-box** statements: the *conceptualisation* of the domain, for instance in terms of *categories* (classes): `Dog`
`rdfs:subClassOf Animal`
- **A-box** statements: (T-box compliant) statements about *individuals* (instances) in the ontology: `SPOT rdf:type Dog`

ONTOLOGIES

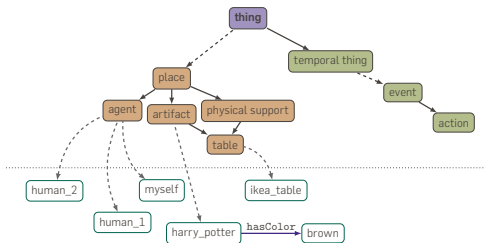
- **T-box** statements: the *conceptualisation* of the domain, for instance in terms of *categories* (classes): `Dog`
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Ontologies are represented using a **knowledge description** language. The **Web Ontology Language (OWL)** is a very common choice that uses a XML encoding.

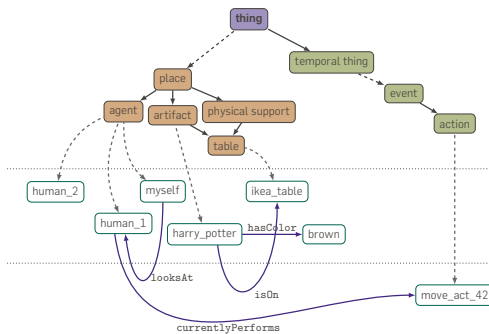
ONLINE INSTANCIATION



ONLINE INSTANTIATION



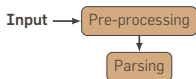
ONLINE INSTANTIATION



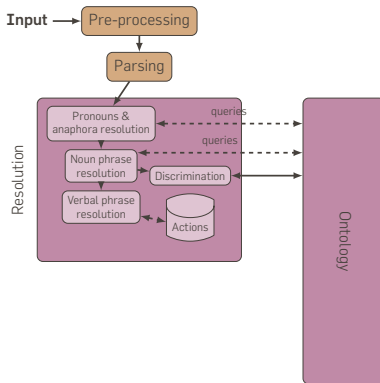
Back to our initial example:

Give me that book!

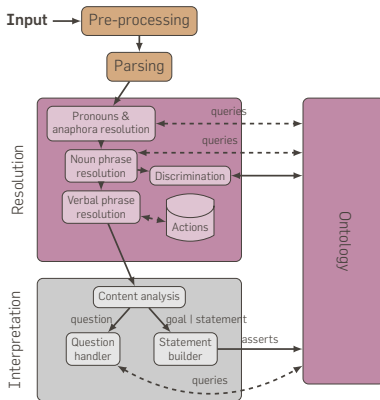
DIALOGUE GROUNDING



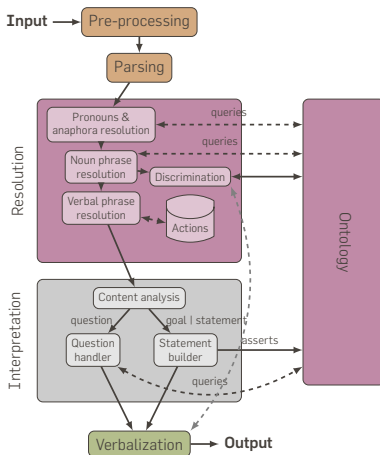
DIALOGUE GROUNDING



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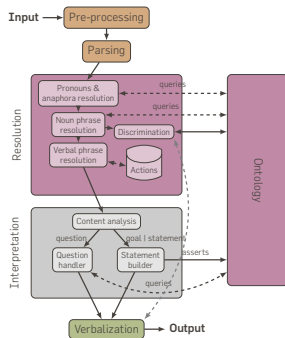


DIALOGUE GROUNDING



DIALOGUE GROUNDING

“Give me the book on the table”



DIALOGUE GROUNDING

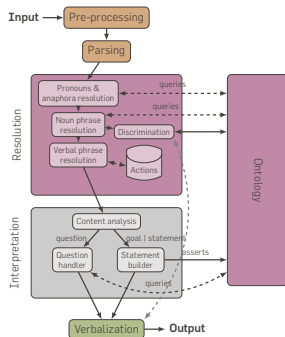
“Give me the book on the table”



me → human_1

find(?obj type Table) → ikea_table

find(?obj type Book, ?obj isOn ikea_table) →
harry_potter



DIALOGUE GROUNDING

“Give me the book on the table”



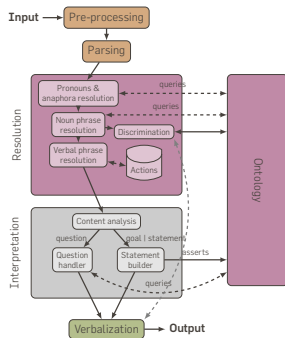
me → human_1

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human_1 desires give_act_1,
give_act_1 type Give,
give_act_1 performedBy myself,
give_act_1 actsOnObject harry_potter,
give_act_1 receivedBy human_1



MULTI-MODAL INTERACTION



What about
“Give me that book”?
(or even: **“Give me that!”**)

LAAS-CNRS



EXAMPLE OF FIRST-ORDER LOGIC REASONING

"Where is the other tape?"



`find(?obj isAt ?loc, ?obj type VideoTape, ?obj differentFrom WALL_E)`

EXAMPLE OF FIRST-ORDER LOGIC REASONING

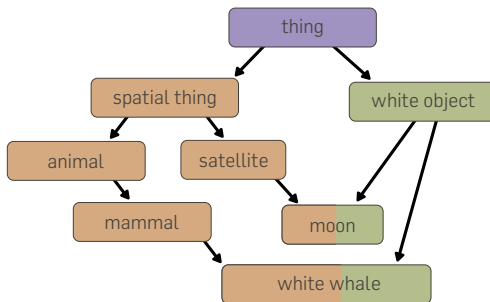
“Where is the other tape?”



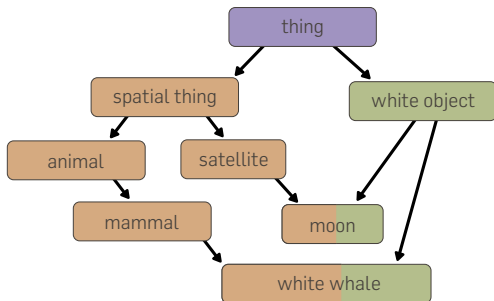
`find(?obj isAt ?loc, ?obj type VideoTape, ?obj differentFrom WALL_E)`

Symbolic approaches effective at dealing with this kind of
constraints

REASONING EXAMPLE: BEST DESCRIPTOR FOR A CONCEPT



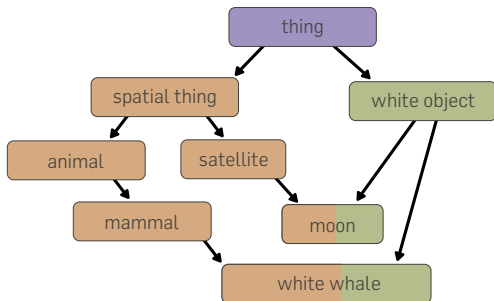
REASONING EXAMPLE: BEST DESCRIPTOR FOR A CONCEPT



Algorithm 2.1: CommonAncestors(*concept1*, *concept2*)

$$\begin{cases} \mathcal{I} \leftarrow \text{Superclasses}(\textit{concept1}) \cap \text{Superclasses}(\textit{concept2}) \\ \textbf{return } \{c \in \mathcal{I} \mid \text{Subclasses}(c) \cap \mathcal{I} = \emptyset\} \end{cases}$$

REASONING EXAMPLE: BEST DESCRIPTOR FOR A CONCEPT



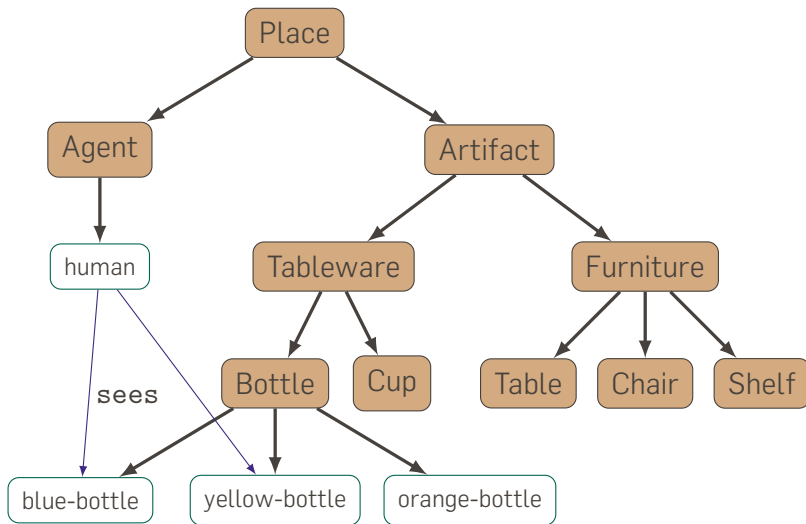
Algorithm 2.2: FirstDifferentAncestors(*concept1*, *concept2*)

$$\begin{cases} \mathcal{C} \leftarrow \text{CommonAncestors}(\textit{concept1}, \textit{concept2}) \\ \mathcal{S} \leftarrow \text{Superclasses}(\textit{concept1}) \cup \text{Superclasses}(\textit{concept2}) \\ \textbf{return } (\forall c \in \mathcal{C}, \text{DirectSubclasses}(c) \cap \mathcal{S}) \end{cases}$$

INTERACTION EXAMPLE: I SPY WITH MY LITTLE EYE



INTERACTION EXAMPLE: I SPY WITH MY LITTLE EYE

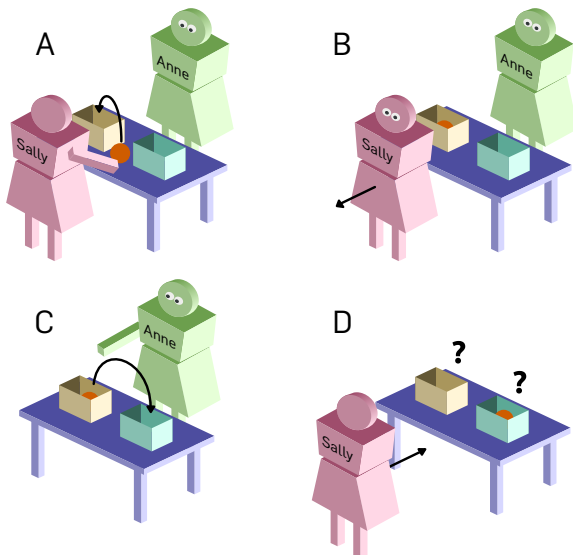


INTERACTION EXAMPLE: I SPY WITH MY LITTLE EYE

human		It is a tableware.
robot		<i>[retrieves possible objects: blue-bottle, yellow-bottle, orange-bottle, cup-with-handle]</i> <i>[keeps human-visible objects: blue-bottle, yellow-bottle, cup-with-handle]</i> <i>[obtains discriminants: type, color.]</i> Which type of object is: bottle or cup?
human		Bottle.
robot		<i>[obtains possible objects: blue-bottle, yellow-bottle.]</i> <i>[obtains discriminants: color.]</i> What color the object is: blue or yellow?
human		Blue.
robot		<i>[obtains possible objects: blue-bottle.]</i> The object is the blue-bottle!

ONE STEP FURTHER: THEORY OF MIND

1ST ORDER TOM: THE FALSE-BELIEF EXPERIMENT





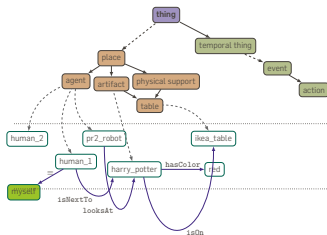
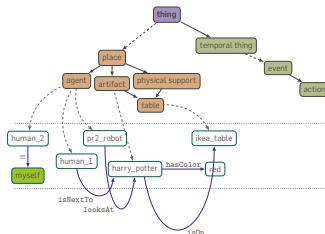
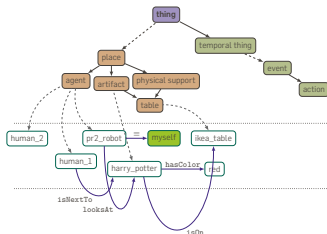
What if I ask for the video tape in the box, but the robot previously moved it somewhere else?



What if I ask for the video tape in the box, but the robot previously moved it somewhere else?

False-belief situation

PARALLEL MODELS: TOWARDS THEORY OF MIND



...

THE SYMBOLIC VS SUB-SYMBOLIC DEBATE

- Symbolic approaches assume a well-ordered, 'regular' world
→ not often the case + world full of exceptions! (`Bird`
`subclassOf FlyingThing?`)
- Symbolic learning is possible, but not nearly as powerful as
sub-symbolic machine learning
- How to bridge the epistemic gap between symbolic and
sub-symbolic AI?

That's all for today, folks!

Questions:

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Slides:

github.com/severin-lemaignan/lecture-hri-symbolic-reasoning