



# **Progress Report: Active, Real-time Prototype Recognition in a Conceptual Network**

**Bowen Xu**  
**CIS, Temple University**  
**[bowen.xu@temple.edu](mailto:bowen.xu@temple.edu)**  
**May 2, 2024**

## Motivation

---

Modeling the sensorimotor procedure in a logical way



**Fig. 1.** Task-oriented Top-Down Attention. The eye trajectories vary in different task-hints [6].<sup>3</sup>

## Theory

---

### **Assimilation:**

- An intelligent system tries to explain and predict sensations via the existing concepts in its memory;
- the system tries to change its perceptive field via actions, for the sake of confirming its explanations and predictions, as well as achieving its desires.

### **Accommodation:**

- The system changes its memory to explain past experiences.

### **Working cycle:**

- The system accepts sensory input, processing it within a relatively constant time, and decides where to see next, subsequently executing an action to shift its perceptive field.

## Theory

---

- A **prototype** is a combination of compositions, each of whose locations can change slightly.
  - A special prototype (i.e., atomic prototype contains no composition inside it (in contrast to a compound prototype that contains at least two compositions), so that it can be the base of the recursive structure of prototypes and compositions
- A **composition** is a special concept composed of a prototype as part and a prototype as whole. A composition is attached with an attribute, *relative location*, which indicates the location of a part *relative* to its whole.
  - It is *relative* in the sense that the displacement between two locations can be computed without defining an absolute, original point.

## Theory

---

- **Implications**

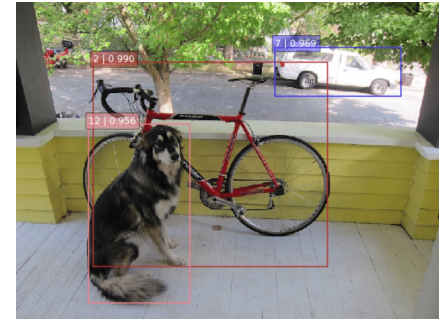
- The system works with an endless loop; there is no “final report” on “an image’s categorization(s)” .
- The system continuously perceives its sensations, so that different concepts may catch its attention at different moments.
- The system may gradually get a better and better understanding of scenery as time goes by, but it probably loses many details when it is in a hurry.

Different interpretations from traditional computer vision:

- **Feature** is the alias of *prototype*.
- An **object** is an instance of a prototype. In this sense, object here does not mean “a thing as it is”, but rather the summary of relations among prototypes.
- **Recognition** is the process in a system to retrieve its memory (i.e., the conceptual network) and pay attention to active concepts.

## Representation & Inference Rule

---



*Composition* has a different meaning from *intersection/union*.

- *E.g.*, A bicycle is composed of two wheels and a frame.
- Concept *bicycle* is not the intersection or union of concepts *wheel* and *frame*.
- Concept *bicycle* is the *extensional intersection* of concepts *vehicle* and *machine*.
- Concept *bicycle* is the *intentional intersection* of concepts *human-powered-vehicle* and *two-wheeled-vehicle*.

“ $P \mapsto W$ ” means  $P$  is a part of  $W$

- *Is transitivity* valid? – Can  $P \mapsto W, W \mapsto S$  derive  $P \mapsto S$ ?
- It may break the hierarchy.
- For example, when recognizing a bicycle, a bearing in a wheel does not directly contribute evidence to bicycle.
- *Deduction* here is not valid, but another type of ‘transitivity’ is valid (see next pages).

**Definition 1** If  $P$  and  $W$  are events, composition statement “ $P \mapsto W$ ” is true if and only if  $P$ ’s occurrence provides a piece of positive evidence for  $W$ ’s occurrence. The first term  $P$  is called *part*, and the second term  $W$  is called *whole*.

## Representation & Inference Rule

---

(IL)  $(P_i \mapsto W)[l_i] \wedge (P_j \mapsto W)[l_j]$  is true if and only if “ $(P_i, \uparrow \text{move}(l_j - l_i), P_j) \leftrightarrow W$ ” and “ $(P_j, \uparrow \text{move}(l_i - l_j), P_i) \leftrightarrow W$ ”, where  $l_i, l_j$  are local and *relative* to  $W$ .

$P_1 \mapsto W.[l_1]$  can be abbreviated as “ $W: \{ | P_1[l_1], \dots, P_n[l_n] | \}$ ”, meaning that  $W$  is composed of  
...  
 $P_n \mapsto W.[l_n]$   $P_1, \dots, P_n$  attached with their corresponding *relative* locations  $l_1, \dots, l_n$ .

Implication:

- Spatial representation in an intelligent system is *relative* rather than absolute.
  - *The origin of a coordinate is meaningless (in the meta-level).*
  - *The distance between any two points/locations is determined.*

## Representation & Inference Rule

$$\{P \mapsto W, P\} \vdash W. F_{prt} \Rightarrow \{P \mapsto W, W \mapsto S, P\} \vdash S. F_{prt} F_{prt} \Rightarrow \{P \mapsto W, W \mapsto S\} \vdash P \mapsto S. \widehat{F}_{prt}$$

(C, P, Q are events)

$$\{(P \mapsto W)[l_1], P[l_2]\} \vdash W[l_2]. F_{spj} F_{prt}$$

$$F_{spj} F_{prt}: \\ f, c' = F_{prt}(f_1, f_2, c_1, c_2) \\ c = F_{spj}(c', l_1, l_2)$$

$$\{W[l_1], W[l_2]\} \vdash W[l]. F_{srv} F_{rev}$$

$$F_{srv} F_{rev}: \\ f, c = F_{rev}(f_1, f_2, c_1, c_2) \\ l = F_{srv}(f_1, f_2, c_1, c_2, l_1, l_2)$$

type	inference	name	function (a tentative proposal)
<i>weak syllogism</i>	<i>part-whole</i>	$F_{prt}$	$f = and(f_1, f_2)$ $w = and(f_1, f_2, c_1, c_2)$ <span style="color: red; font-size: small;">similar to deduction, but provides no more than 1 piece of evidence</span>
<i>immediate inference</i>	<i>spatial projection</i>	$F_{spj}$	$c = bell(l_1 - l_2) \times c'$
<i>local inference</i>	<i>spatial revision</i>	$F_{srv}$	$l = (l_1 f_1 c_1 + l_2 f_2 c_2) / (f_1 c_1 + f_2 c_2 + \epsilon)$



## Representation & Inference Rule

---

Is NAL1-9 enough to represent the *composition* relation?

$(P \times W) \rightarrow \text{partof}.$

$P.$

-----

$((P \times W) \rightarrow \text{partof}) \wedge W. F_{int}$

$((\$P \times \$W) \rightarrow \text{partof}) \wedge \$P \Rightarrow \$W.$

$((P \times W) \rightarrow \text{partof}) \wedge P.$

-----

$W. F_{ded}$

*strong syllogism*

deduction

$F_{ded}$

$f = \text{and}(f_1, f_2)$

$c = \text{and}(f_1, f_2, c_1, c_2)$

*term composition*

intersection

$F_{int}$

$f = \text{and}(f_1, f_2)$

$c = \text{and}(c_1, c_2)$

## Representation & Inference Rule

---

Is NAL1-9 enough for representing a prototype? Yes.

$$W \leftrightarrow (P_1, \uparrow \text{move}(l_2 - l_1), \dots, \uparrow \text{move}(l_n - l_{n-1}), P_n)$$
$$W \leftrightarrow W_1, \dots, W \leftrightarrow W_m$$

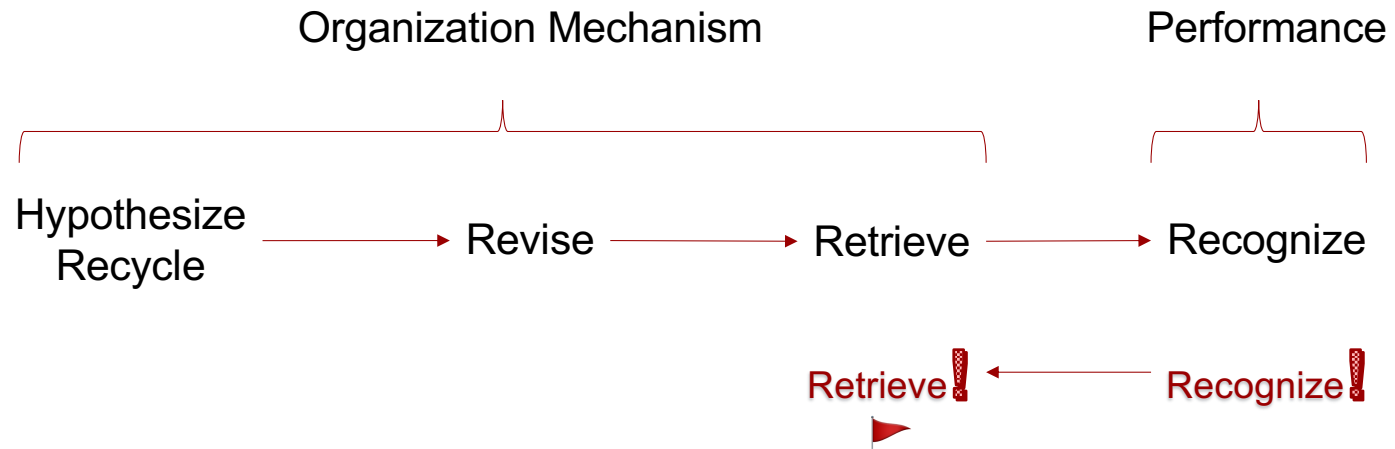
It is trajectory-dependent – a good attribute.

It is trajectory-dependent only – a bad attribute since humans can generalize to objects following an unusual and even novel observational trajectory. In this case, a trajectory-independent representation is more appropriate. Both coexist in the system.

I argue that trajectory matters and it is more relevant to the control mechanism.

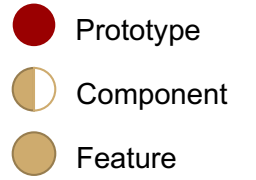
# Control

---

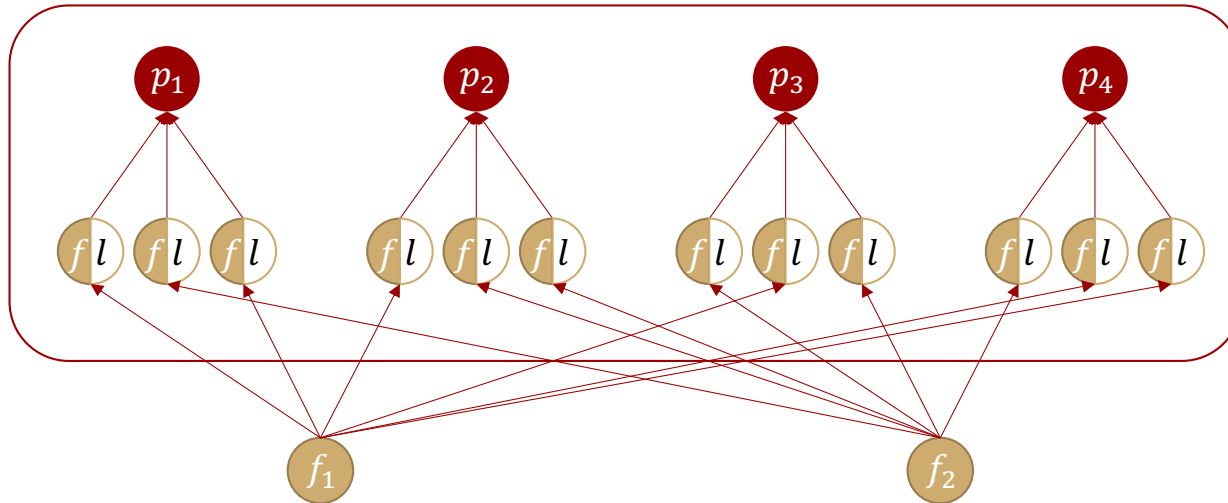


# Control

- Memory

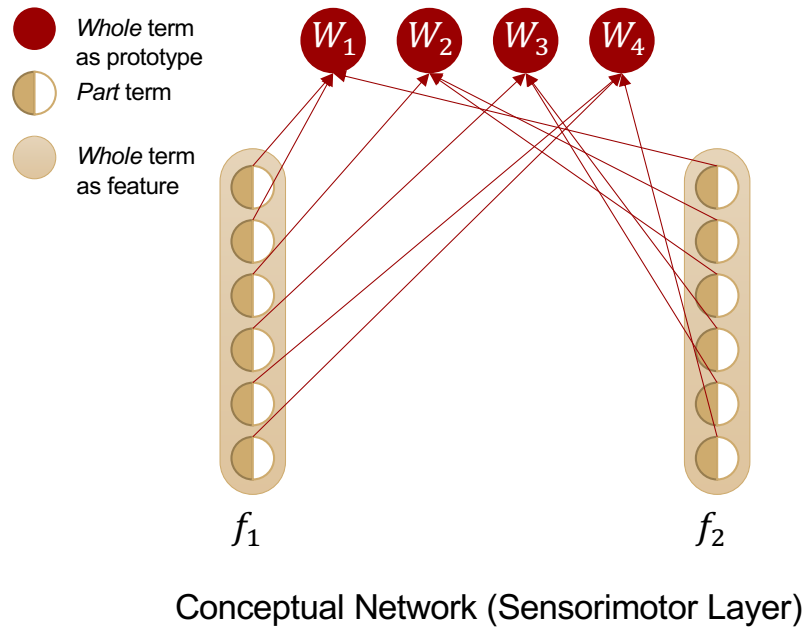


Conceptual Network (Sensorimotor Layer)



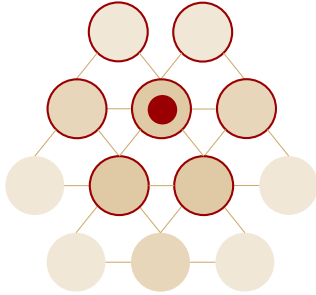
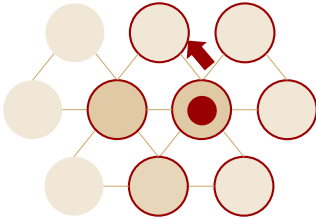
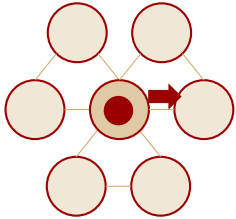
# Control

- Memory

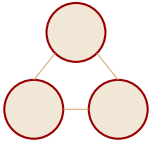


# Control

---



Task:

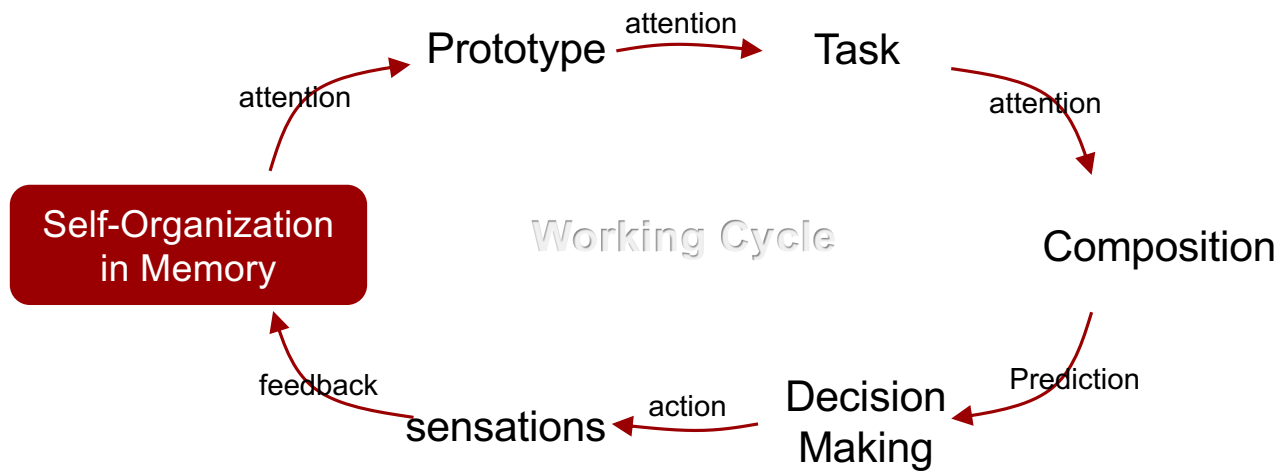


Current Location: ●

Action: ➡

# Control

- Working Cycle



# Working Example

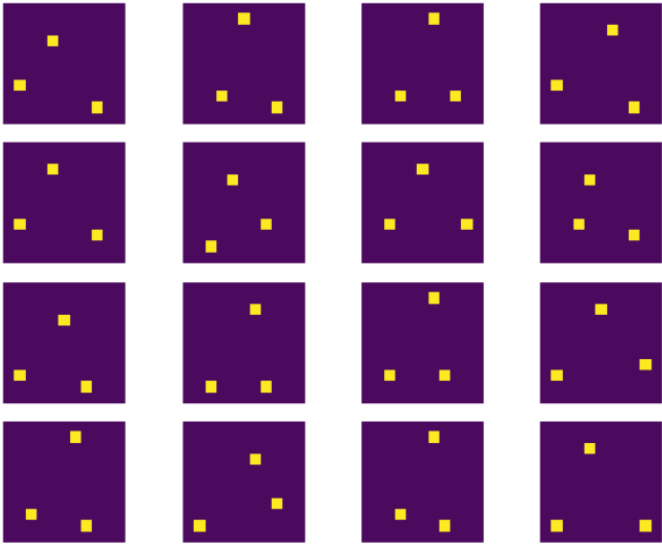
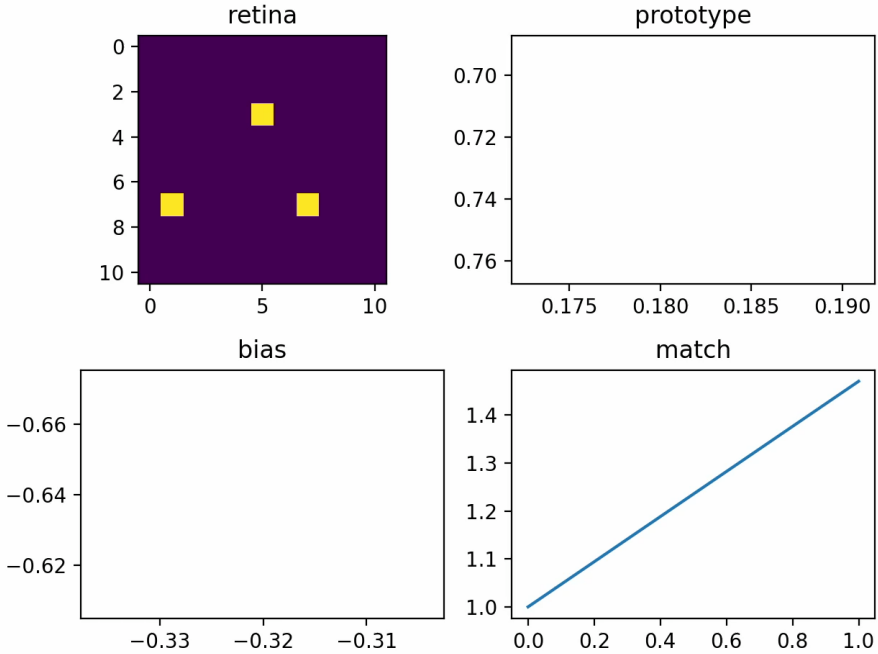
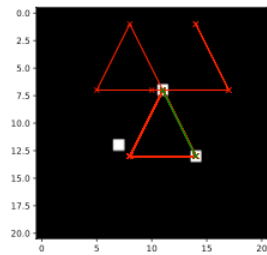


Fig. 4. Input Examples

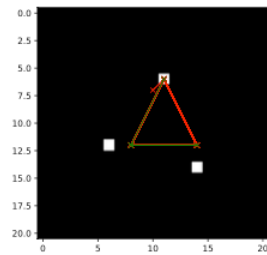




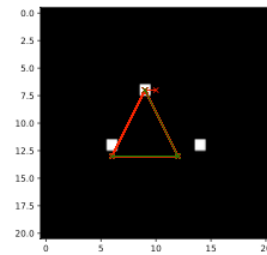
# Working Example



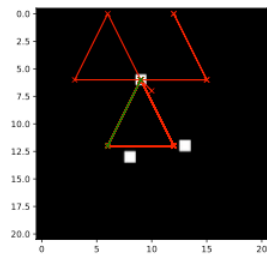
(a)



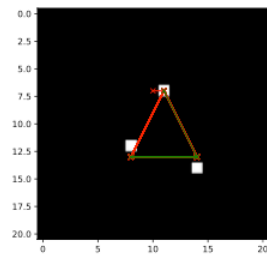
(b)



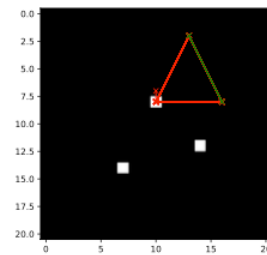
(c)



(d)



(e)

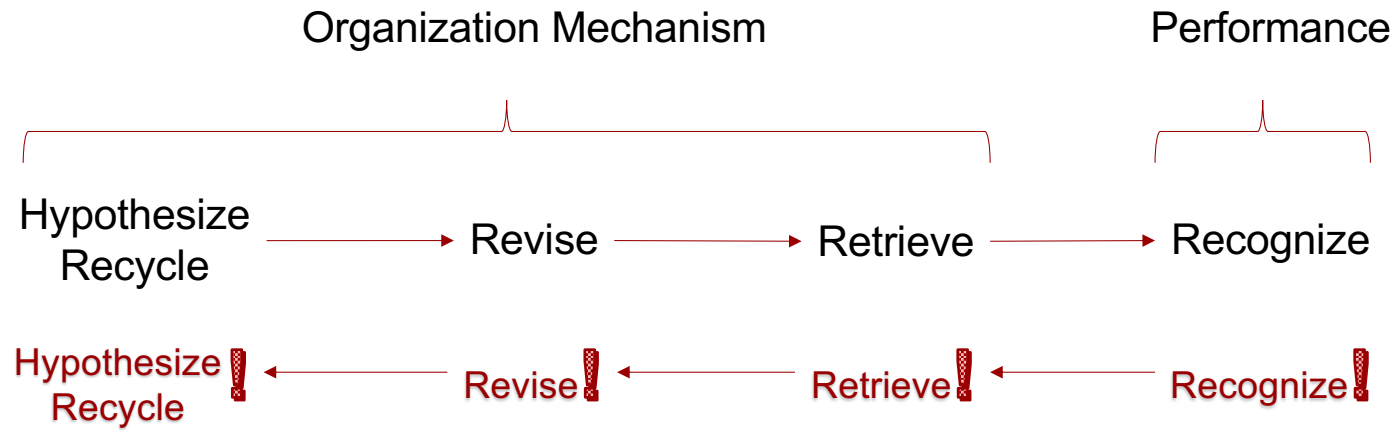


(f)

**Fig. 6.** (a)~(d) success examples; (f) a failure example

## Future Work

---



Single layer → Multiple layers

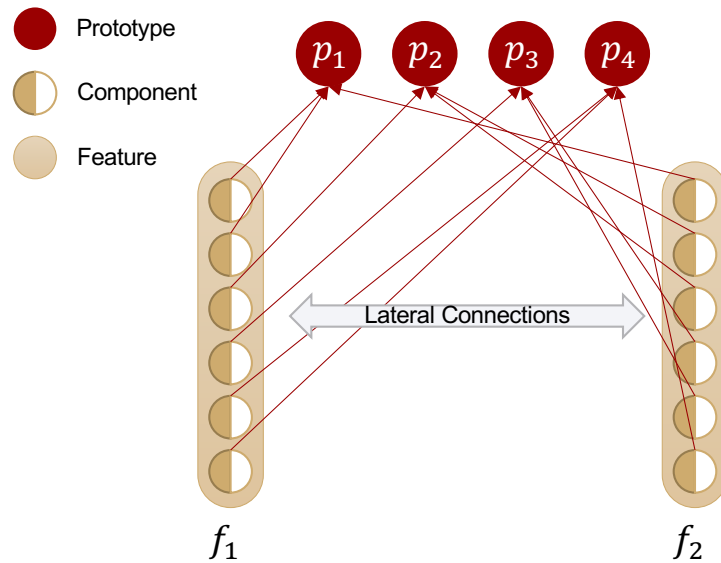
## Future work

---

Given a large amount of spatiotemporal information as input,

- how to actively organize them into memory and recall knowledge efficiently
- how to achieve goals

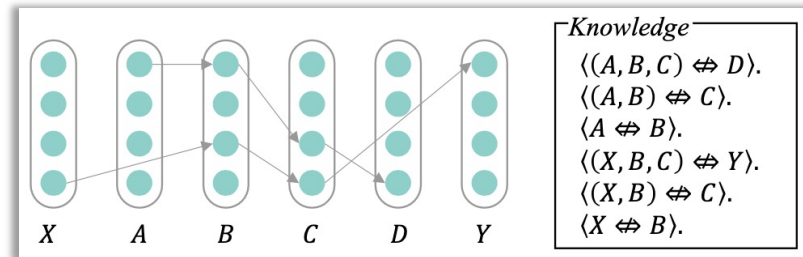
# Future Work



Conceptual Network (Sensorimotor Layer)

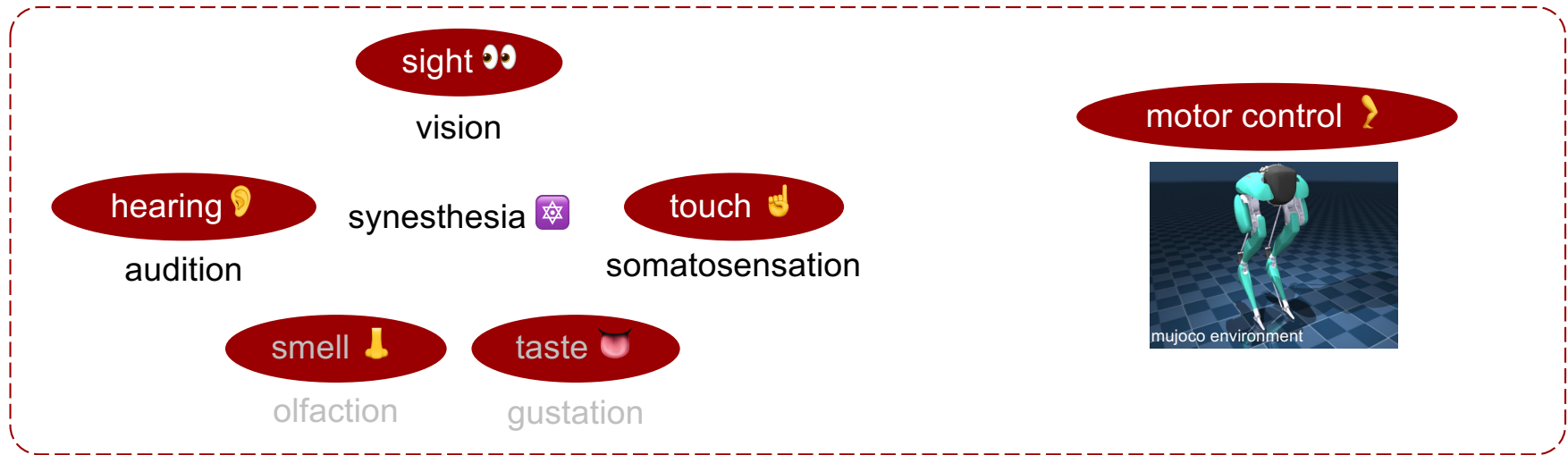


The unity of the two types of representation



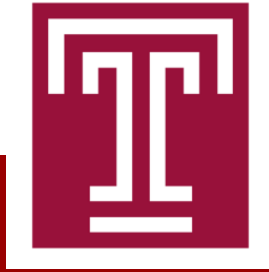
Sequence Learning Model (Xu, 2023)

# Future Work



control mechanism

NAL + Narsese



**Thank you!**

