

Self-reflective Learning

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1. Human-Level AI and ML

Three AI Paradigms

~ 1985 ~



❑ Symbolic AI (1G)

- Rational/Deductive
- Logical
- System 2 (Kahneman)
- Propositional/Linguistic
- Thinking/Top-down
- Knowledge-Based
- **Reasoning Systems (Rules)**

~ 2015 ~



❑ Connectionist AI (2G)

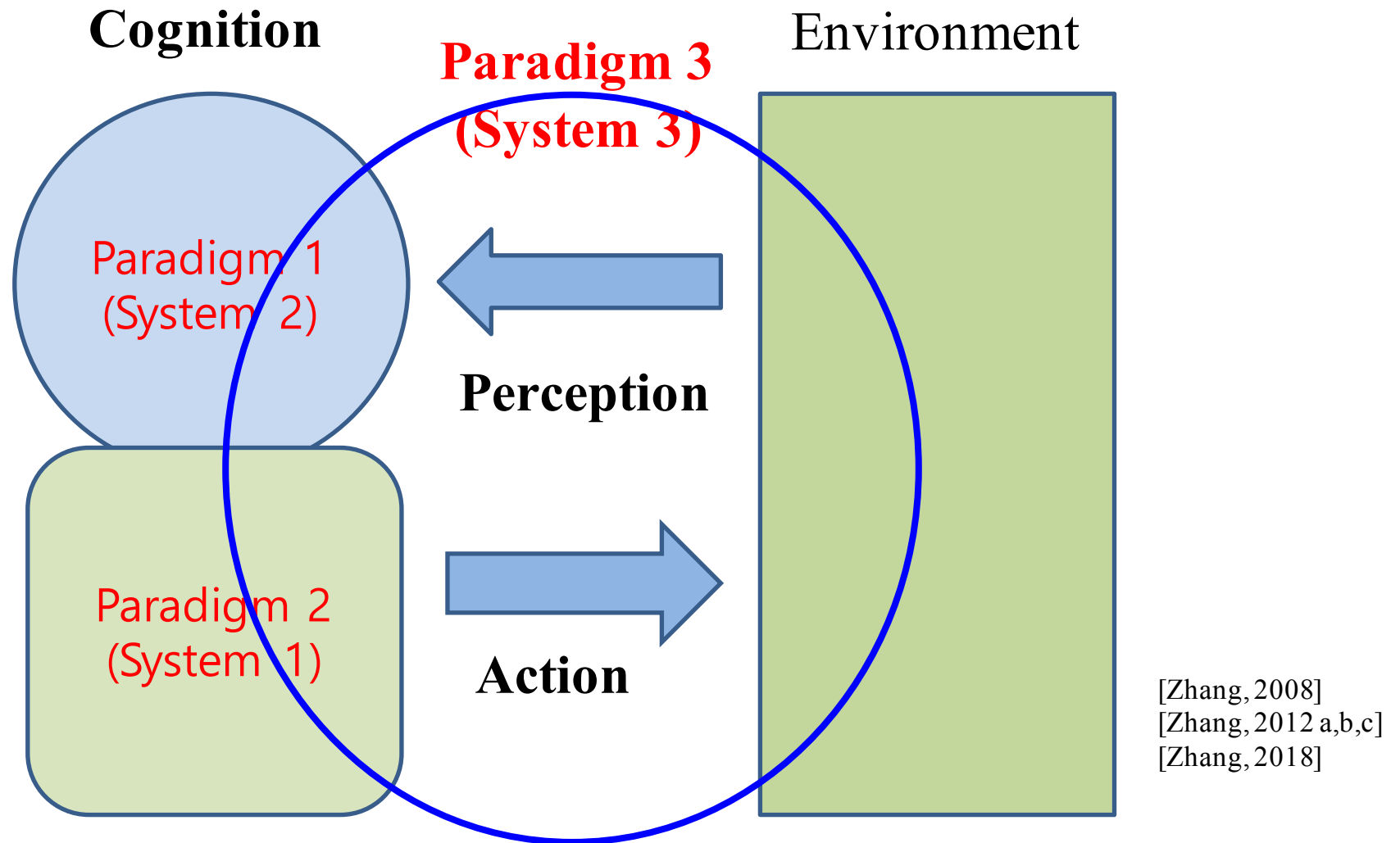
- Empirical/Inductive
- Probabilistic
- System 1 (Kahneman)
- Iconic/Visual
- Perception/Bottom-up
- Data-Driven
- **Learning Systems (Networks)**

❑ Cognitive AI (3G)

- Constructivistic/Dynamic
- Temporal
- System 3
- Enactive/Grounded
- Action/Interactive
- Reward-Based
- **Cognitive Systems (Agents/Robots)**

[Zhang, 2018] Human Intelligence and Machine Intelligence: Cognitive AI, *Communications of KIISE*, 36(1): 27-36, 2018.

New Paradigm: AI as Cognitive Systems



- Cognition grounded by dynamic perception-action cycle
- Knowledge construction by interaction with the world

Toward Human-Level Artificial Intelligence



3R: Real-Time Learning in Real-World and Real-Life



**Dynamic
Non-stationary**

**Multimodal
Heterogeneous**

High-dimensional

Big Data

Hyperscale

**Brain-Like Cognitive
Computation**

**Human-Level
Machine Learning**

Embodied Cognitive Agents

Human-Level Machine Learning

[Zhang, AAI SSS, 2009]

- Incremental learning
- Online learning
- Fast update
- One-shot learning
- Predictive learning
- Memory capacity
- Selective attention
- Active learning
- Context-awareness
- Lifelong learning
- Persistency
- Concept drift
- Multisensory integration



Teaching an agent by playing a multimodal memory game: challenges for machine learners and human teachers, B.-T. Zhang, *AAAI 2009 Spring Symposium: Agents that Learn from Human Teachers*, pp. 144-149, 2009. [\[PDF\]](#)

Mind Cloning

Mind Cloning

HUMAN

MACHINE



“Exbodied” Human Cognition

“Embodied” Machine Cognition

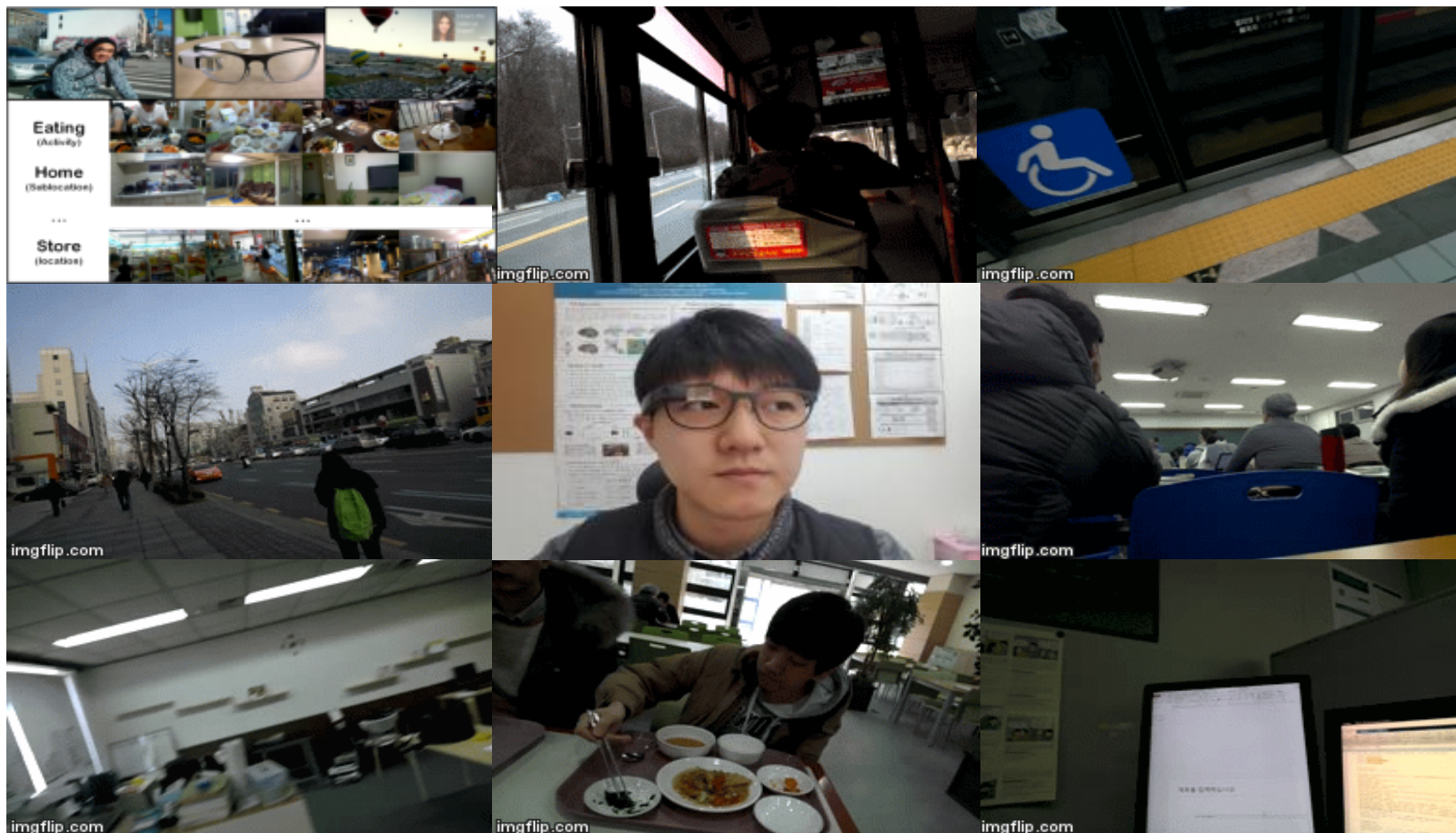
2. Human-Level ML Projects

- Project 1: Wearable Cognitive Agents
- Project 2: Visual Storytelling Agents
- Project 3: Robotic Cognitive Agents

Project 1: Wearable Agents for Everyday Life

- Real-world lifelogs collected by the Google Glass and Narrative Clip
 - 84 days (2,000,000 seconds), 3 subjects

[Lee et al., NIPS-2017]



Lifeome - Google Glasses for Lifelong Learning



- 3 persons during 14 days for their daily life
- Tools: Google glass, smartphone and a logging application
- Sensors: Camera, MIC, IMU, GPS (A-GPS)
- Logical Information: location (4-Square API), activity (logger app)
- Data size: 537 GB (video) + 2.7 GB (IMU) + 20 MB (GPS) + 70 KB (activity & location)

Category: 장소(Home, Office)나 활동 범주(Hobby, Sports)

Label: 활동 내용(reading a book, having a lunch, having a hair cut, looking for t-shirts, etc.)

날짜/시간 임의로 조정했을 경우 다시 현재 시간으로 동기화

실수로 레이블링 못 했을 경우 날짜/시간을 조정해서 추가할 수 있음

사용자가 Category 추가

사용자가 Label 추가



Lifeome - Embodied Cognition of the World

[Lee et al., Neural Networks, 2017] Lee et al. (2015)

● Event Recognition

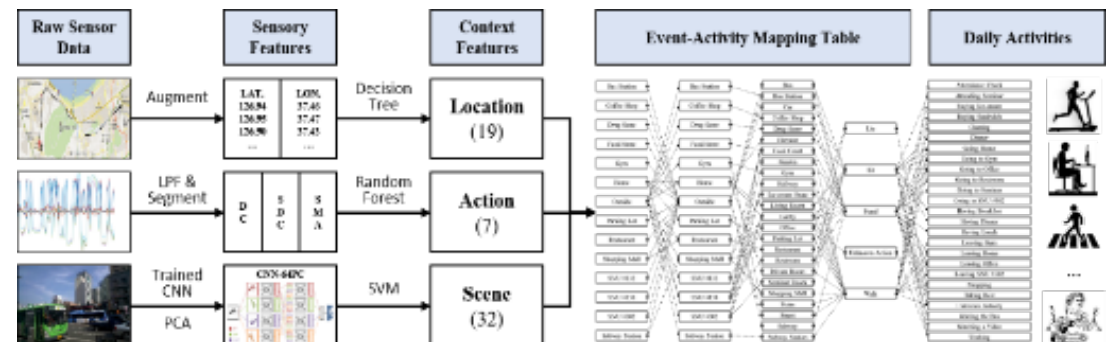
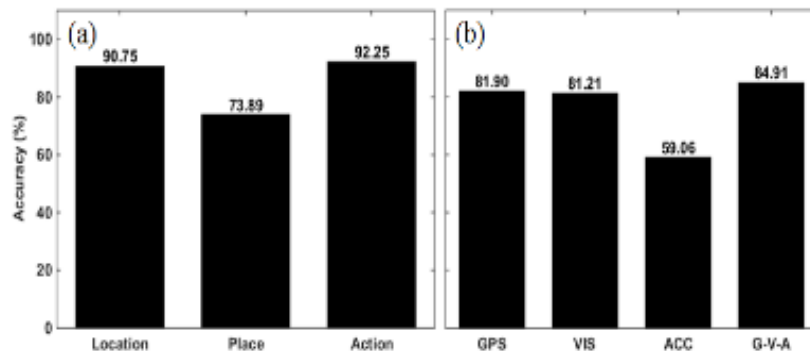
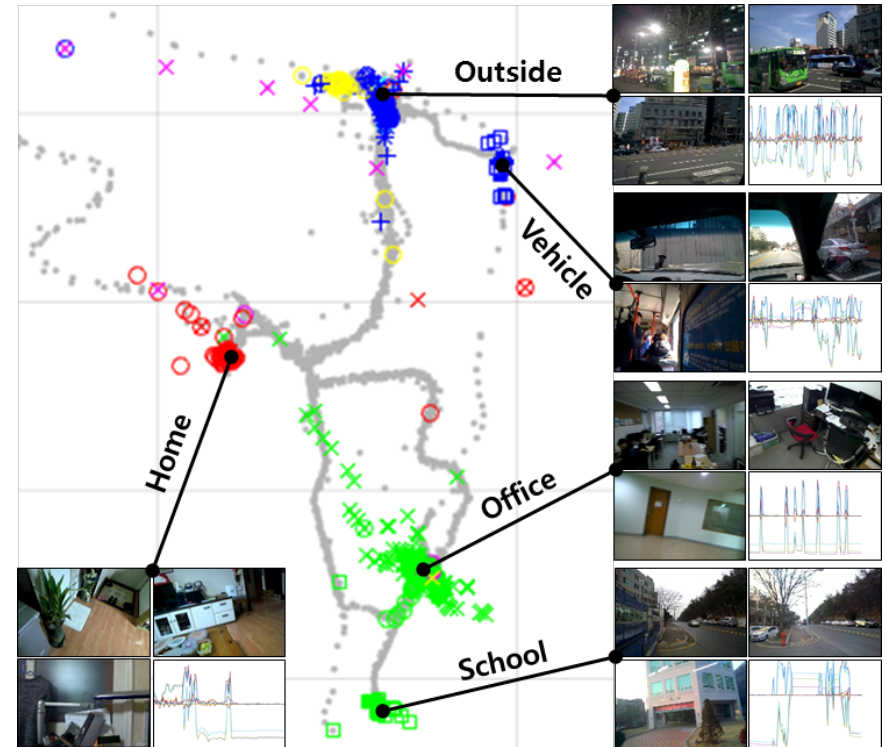
(Train instances: 207654, Test: 106974)

- Location (GPS): 90.75%
- Place (Vision): 73.89%
- Action (Accelerometer): 92.25%

● Activity Recognition

(Train instances: 207654, Test: 106974)

- GPS: 81.90%
- Vision: 81.21%
- Accelerometer: 59.06%
- **Integrated Symbolic Events: 84.91%**
(Previous location, current location, place, action)



Project 2: Visual Storytelling Agent

● Children's cartoon videos

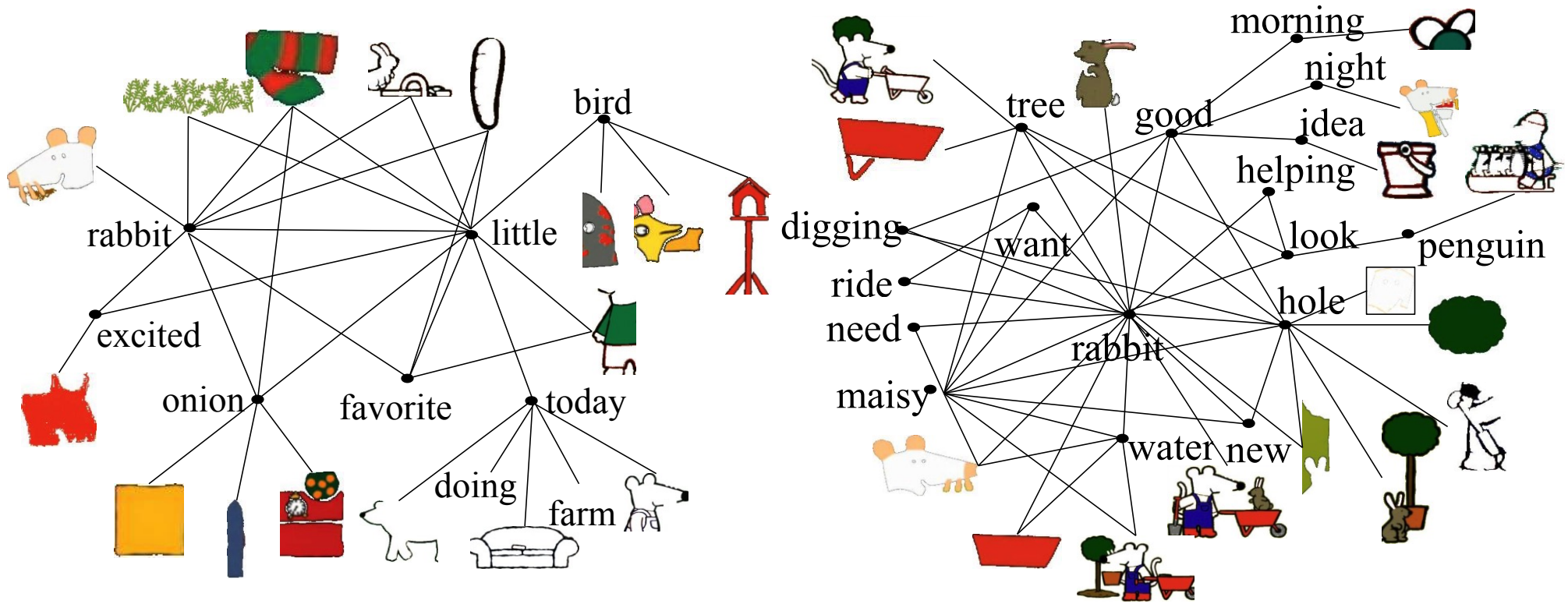
- Multimodal
- Vision + language
- Simple grammars
- Explicit story lines
- Image processing
- Pseudo-real
- Educational
- Cognitive



[Zhang et al., CogSci-2012]

[Ha et al., AAI-2015]

Constructive Learning by Deep Hypernets

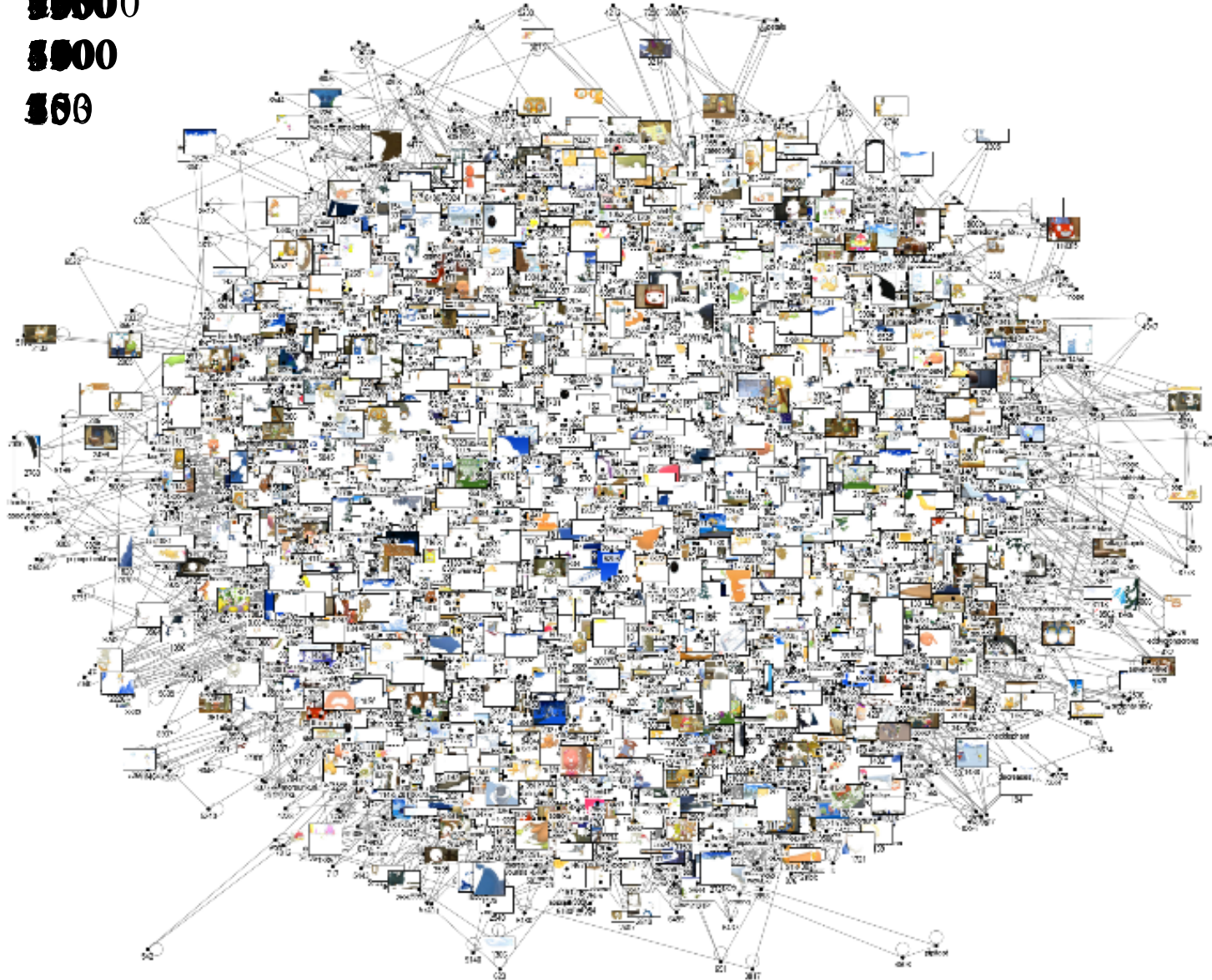


Episodes 1-4

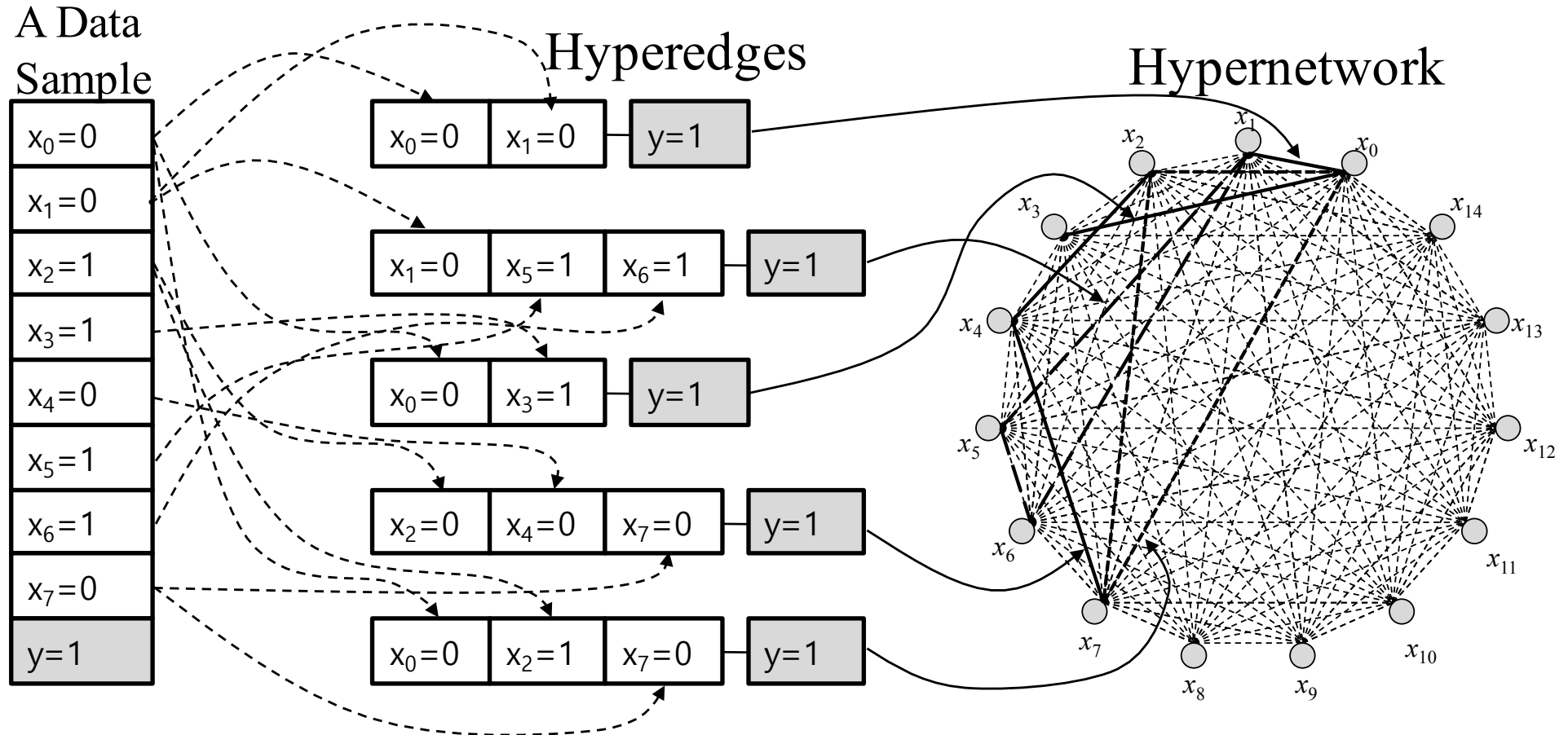
Episodes 1-6

Learning from Cartoon Videos

Image 개수 : **30000**
Word 개수 : **3000**
Episode 개수 : **300**



Evolving Hypernetworks: Hypernet as a Population of Hyperedges



Deep Hypernetworks

- Deep hypernetworks with hierarchical concept structure are used as knowledge base for Q&A

Hierarchical formulation

$$P(x) = \sum_{h_n} \cdots \sum_{h_1} P(h_n | h_{n-1}) \cdots P(h_2 | h_1) P(h_1 | x) P(x)$$

Joint probability of hidden variables $h_i^{(s)}$ in the s^{th} layer

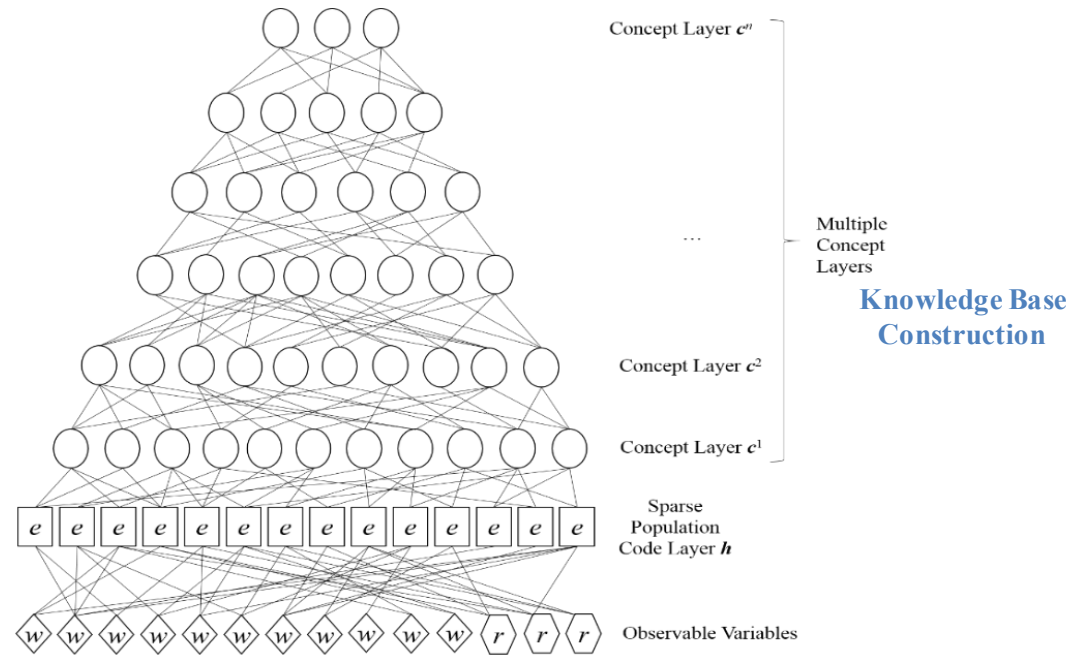
$$P(h_s) = \frac{\exp(-E(h_s))}{\sum_j \exp(-E(h_j))}$$

$$E(h_j) = h(s(h_j))$$

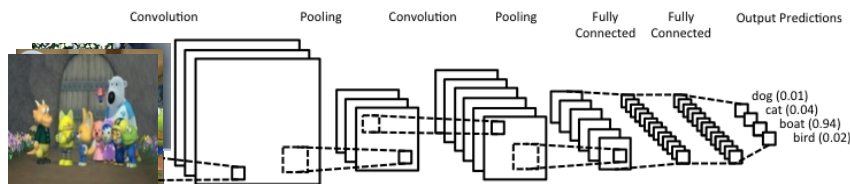
$$s(h_j) = \sum_{i_1} w_{i_1}^{(j)} h_{i_1}^{(j)} + \sum_{i_1, i_2} w_{i_1 i_2}^{(j)} h_{i_1}^{(j)} h_{i_2}^{(j)} + \dots + \sum_{i_1, i_2, \dots, i_k} w_{i_1 i_2 \dots i_k}^{(j)} h_{i_1}^{(j)} \dots h_{i_k}^{(j)}$$

Learning is done by adjusting $s(h_j)$ towards maximizing likelihood $P(x|W)$

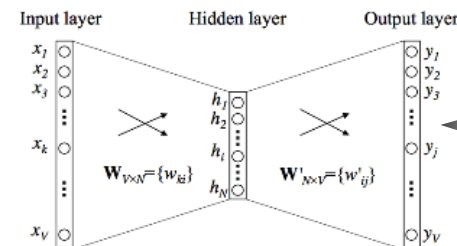
$$\frac{\nabla}{\nabla w_{i_1, i_2, \dots, i_k}^{(k)}} \ln \prod_{n=1}^N P(x^{(n)} | W) = N \left\{ \left[x_i, x_{i_2}, \dots, x_{i_k} \right]_{Data} - \left[x_i, x_{i_2}, \dots, x_{i_k} \right]_{P(x|W)} \right\}$$



Fc7 Feature of Convolutional Neural Networks



Neural Word Embedding Using Word2vec



Preprocessing

Hide-and-seek
MountainCloud
Chair
Swimming Play
Pororo House
DinnerCrong
Soccer Hi
What

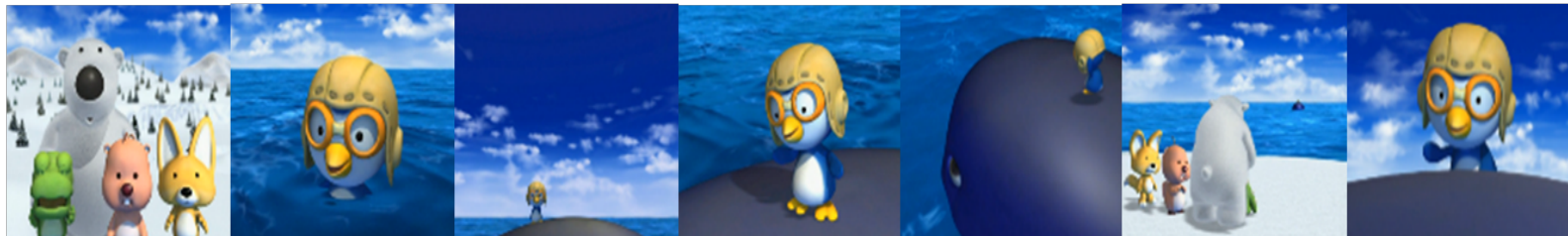
1. K.-M. Kim, C.-J. Nan, J.-W. Ha, Y.-J. Heo, and B.-T. Zhang, "Pororobot: A Deep Learning Robot That Plays Video Q&A Games", *AAAI 2015 Fall Symposium on AI for Human-Robot Interaction (AI-HRI 2015)*, 2015.
2. J.-W. Ha, K.-M. Kim, B.-T. Zhang, "Automated Visual-Linguistic Knowledge Construction via Concept Learning from Cartoon Videos," In *Proceedings of the Twenty-Ninth AAAI Conference on Artificial Intelligence (AAAI 2015)*, 2015.
3. B.-T. Zhang, J.-W. Ha, M. Kang, "Sparse Population Code Models of Word Learning in Concept Drift," In *Proceedings of Annual Meeting of the Cognitive Science Society (Cogsci)*, 2012.

Video QA

● Examples of Video QA using Cartoon Videos 'Pororo'

* S and L indicate short-term memory and long-term memory

Sequence of Images



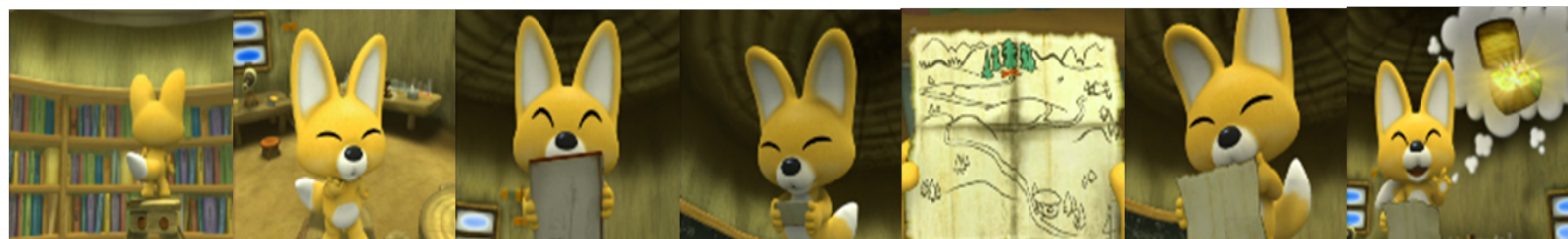
Questions

Can pororo swim out too far?
How can pororo swim well?

Answers (S/L)

Yes / Yes
Because they were so loud / His tall height and great strength

Sequence of Images



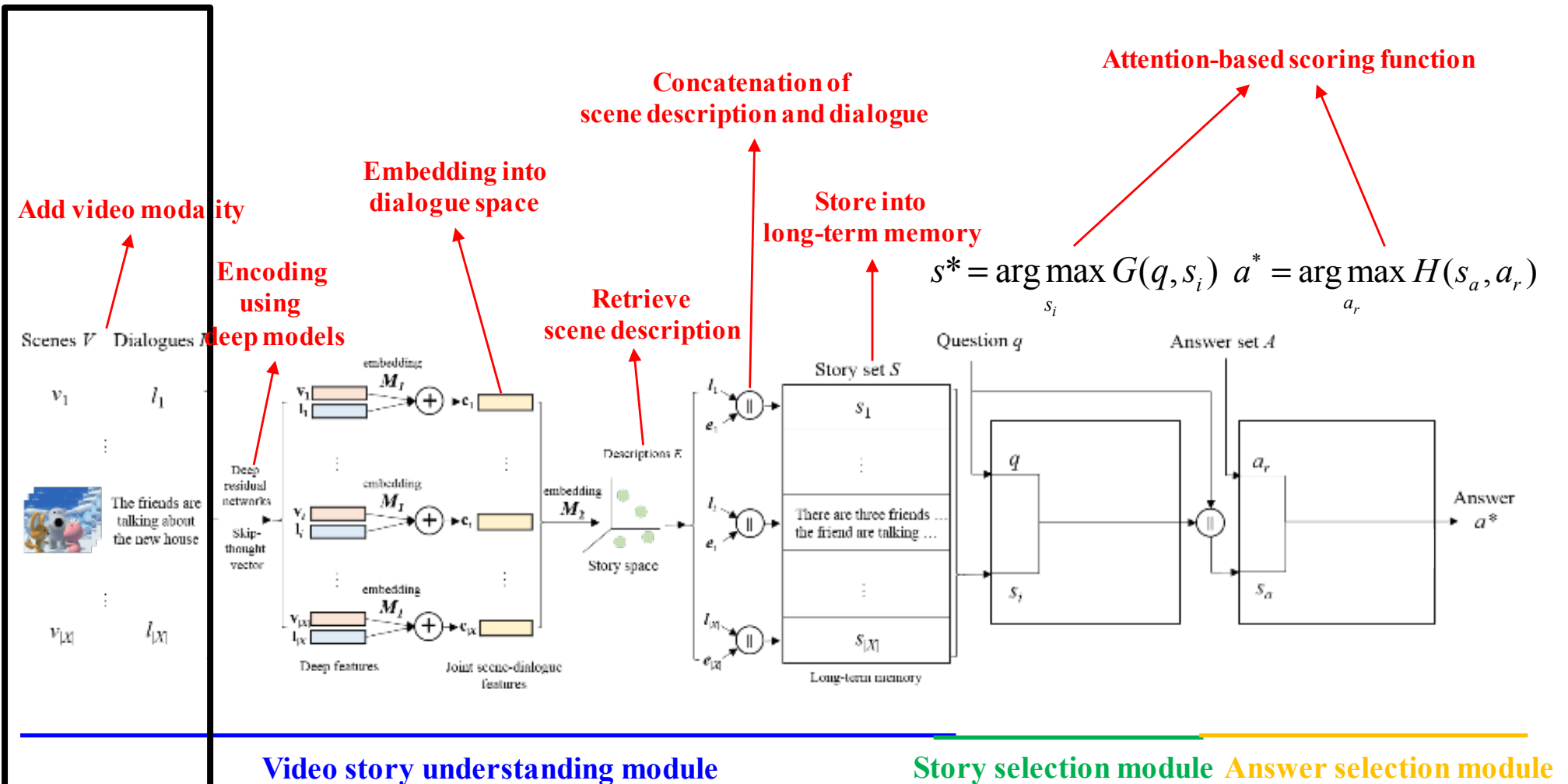
Questions

What did eddy trying to go to the playground all day?
What does eddy find in her sleep?

Answers (S/L)

Baking / Making a new toy
Stars / Ball

Deep Embedded Memory Networks (DEMNN)



Video story understanding module

Story selection module Answer selection module

[Kim et al., IJCAI-2017]

[Kim et al., ECCV-2018]

VQA in RoboCup@Home (2017)

[Ha et al., AAI-2015]

[KimJ et al., NIPS-2016]

[KimK et al., IJCAI-2017]

[KimJ et al., ICLR-2017]

[Lee et al., NIPS-2018]



Pororobot (SNU)

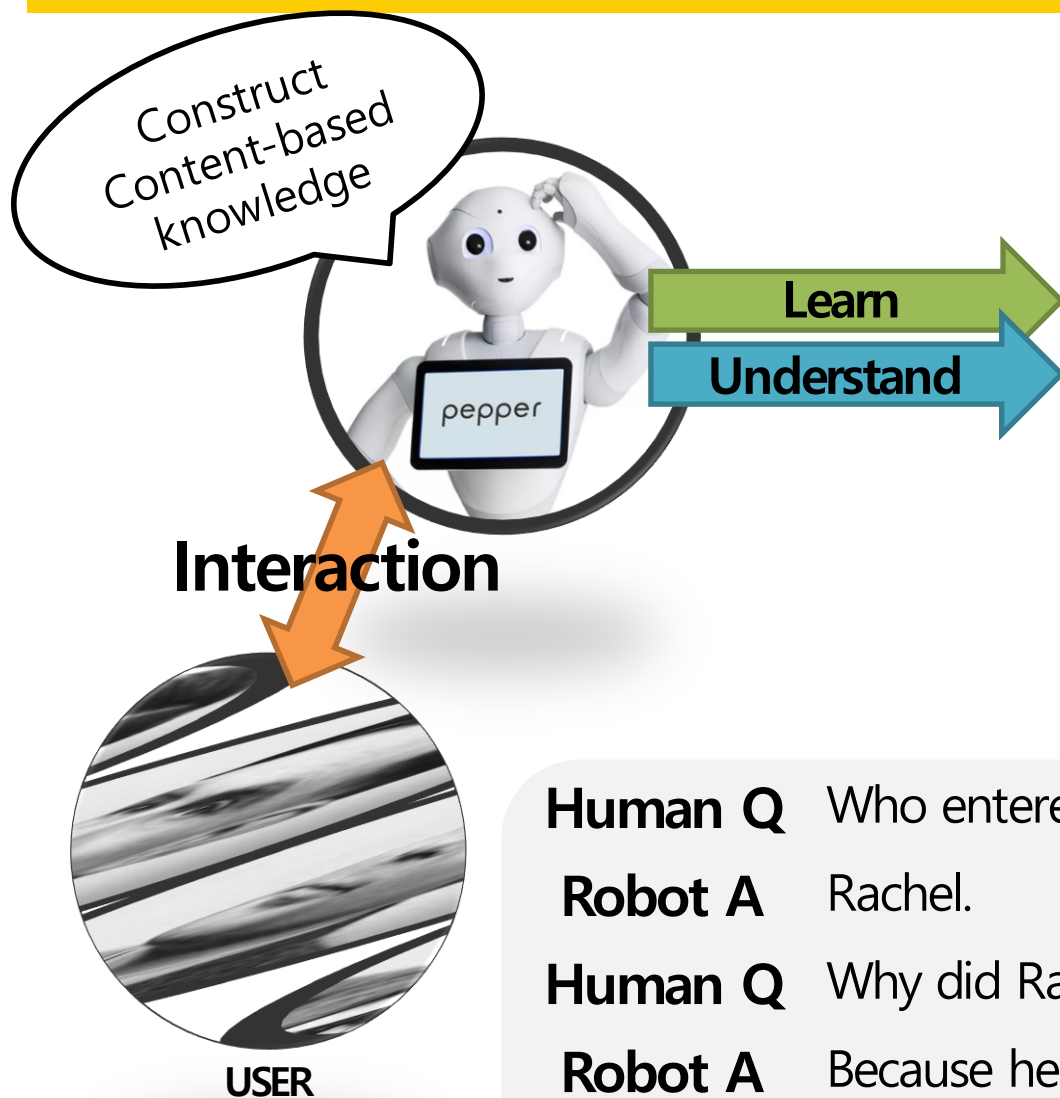
[Ha et al., AAAI-2015]

[Kim et al., IJCAI-2017]



<https://www.youtube.com/watch?v=OtkEkLpjs3s&t=1s>

Video Turing Test (VTT): Q&A Dialog on Video Stories



Video as a testbed of real environment

Human Q Who entered the café wearing a bridal dress?

Robot A Rachel.

Human Q Why did Rachel try to leave her fiancé?

Robot A Because he betrayed her.

... Multi-turn Q&A dialogue about video story

VTT Challenge

Humans and machines watch the same videos and answer the questions.
Audience evaluates who are the humans and who are the machines.

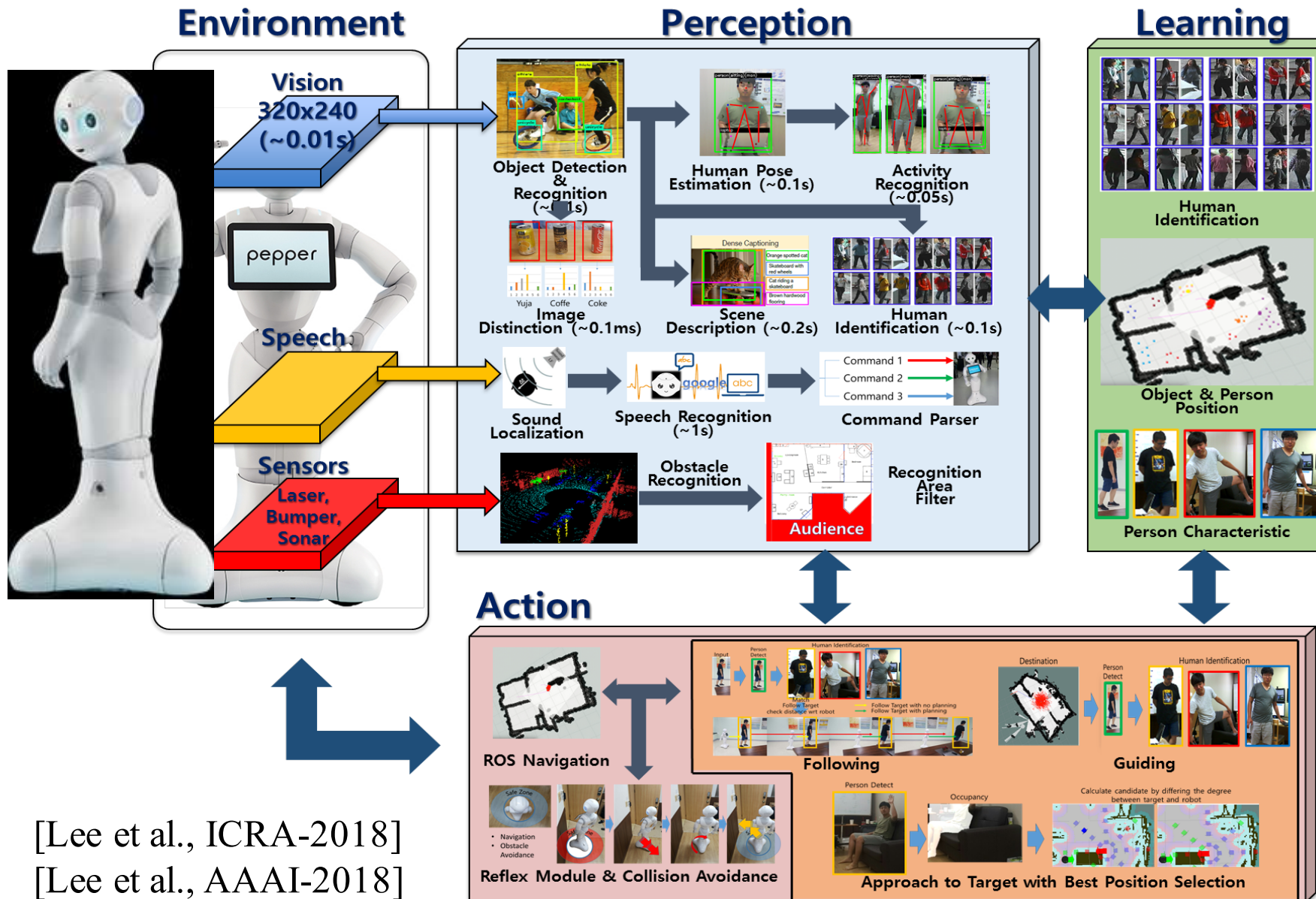


No. 3 is a human!

No. 3 is an AI. No. 5 is a human.



Project 3: Robotic Cognitive Agents for Home Service



[Lee et al., ICRA-2018]
 [Lee et al., AAI-2018]

AUPAIR Robot

AUPAIR Team (SNU & Surromind Robotics)
*Winning the **RoboCup@Home 2017***



<https://www.youtube.com/watch?v=a2ZJTpbMWsQ>

<http://mnews.joins.com/article/21823070#home>

Tidyboy: A Home Service Robot (SNU)

Tidyboy

Seoul National University and Pusan National University (Joint Team)



パートナーロボットチャレンジ リアルスペース / Partner Robot Challenge Real Space

Task-1

お願い、部屋を片付けて
Tidy Up Here

00:10:44



<https://youtu.be/--TqhXOFun0>

3. Challenge: Self-reflective Learning

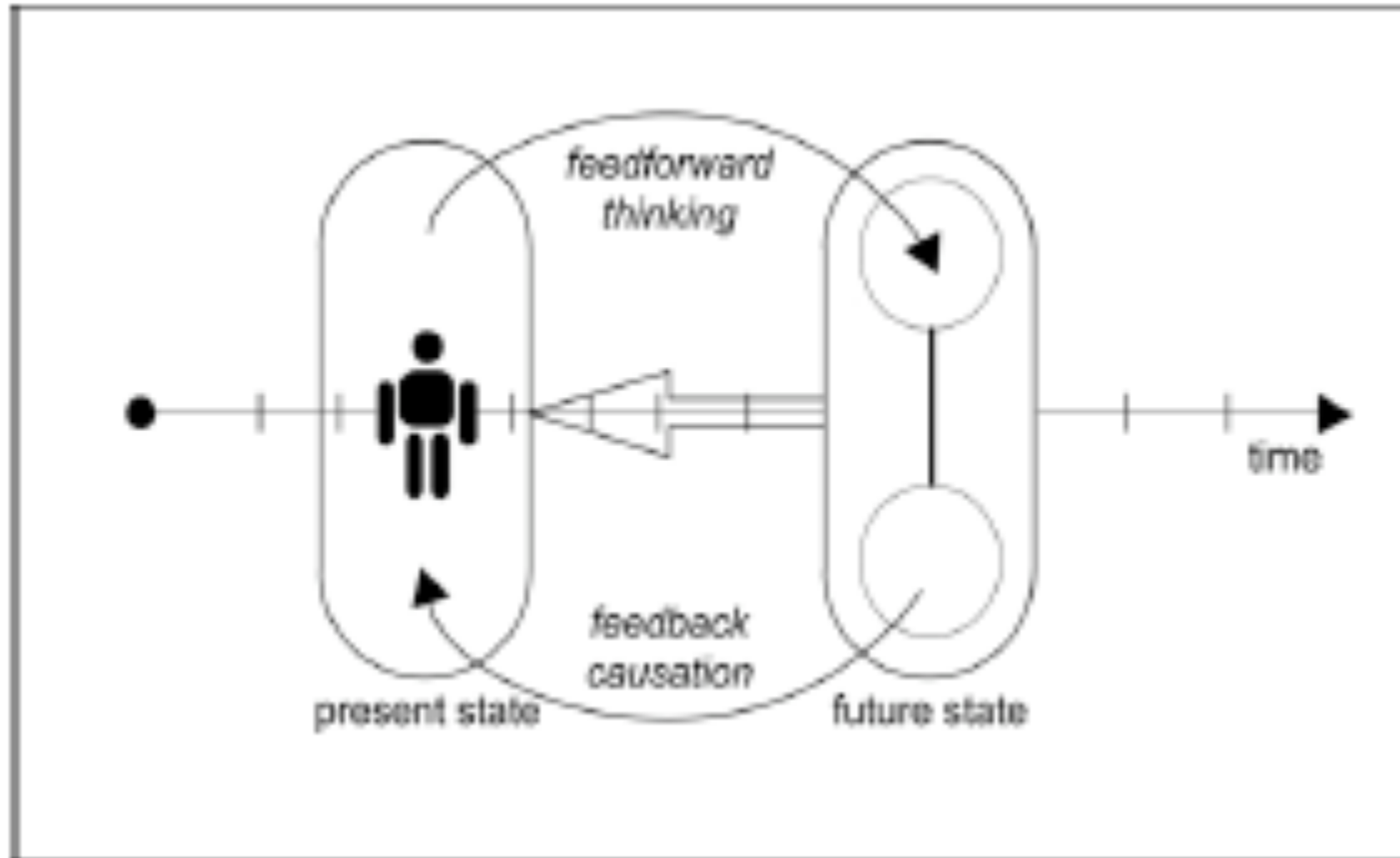
Question

Can machines learn 24/7 continually without human intervention?

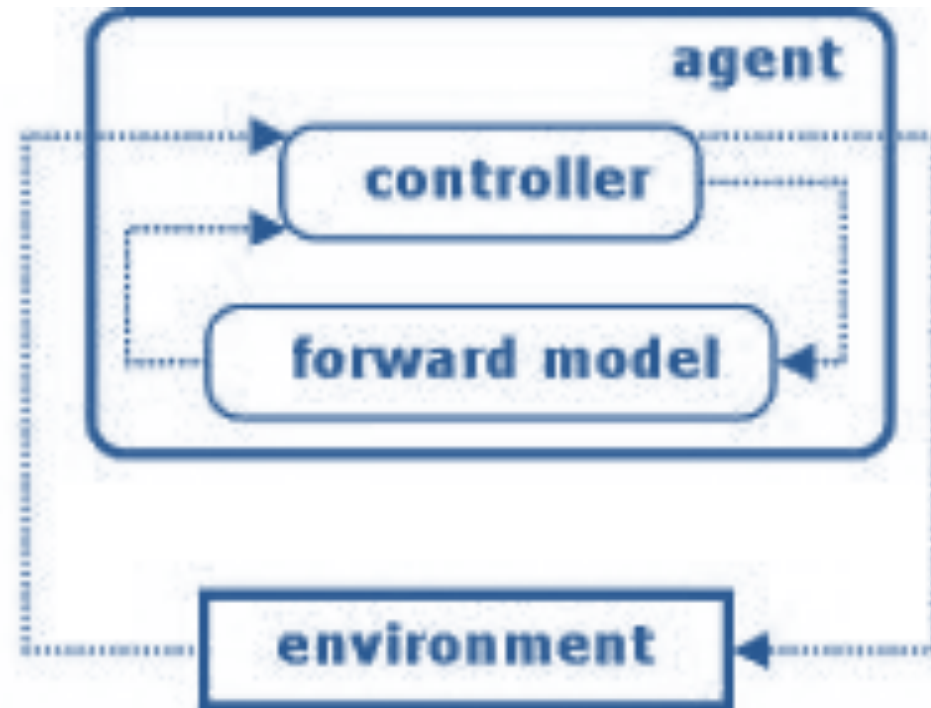
Example



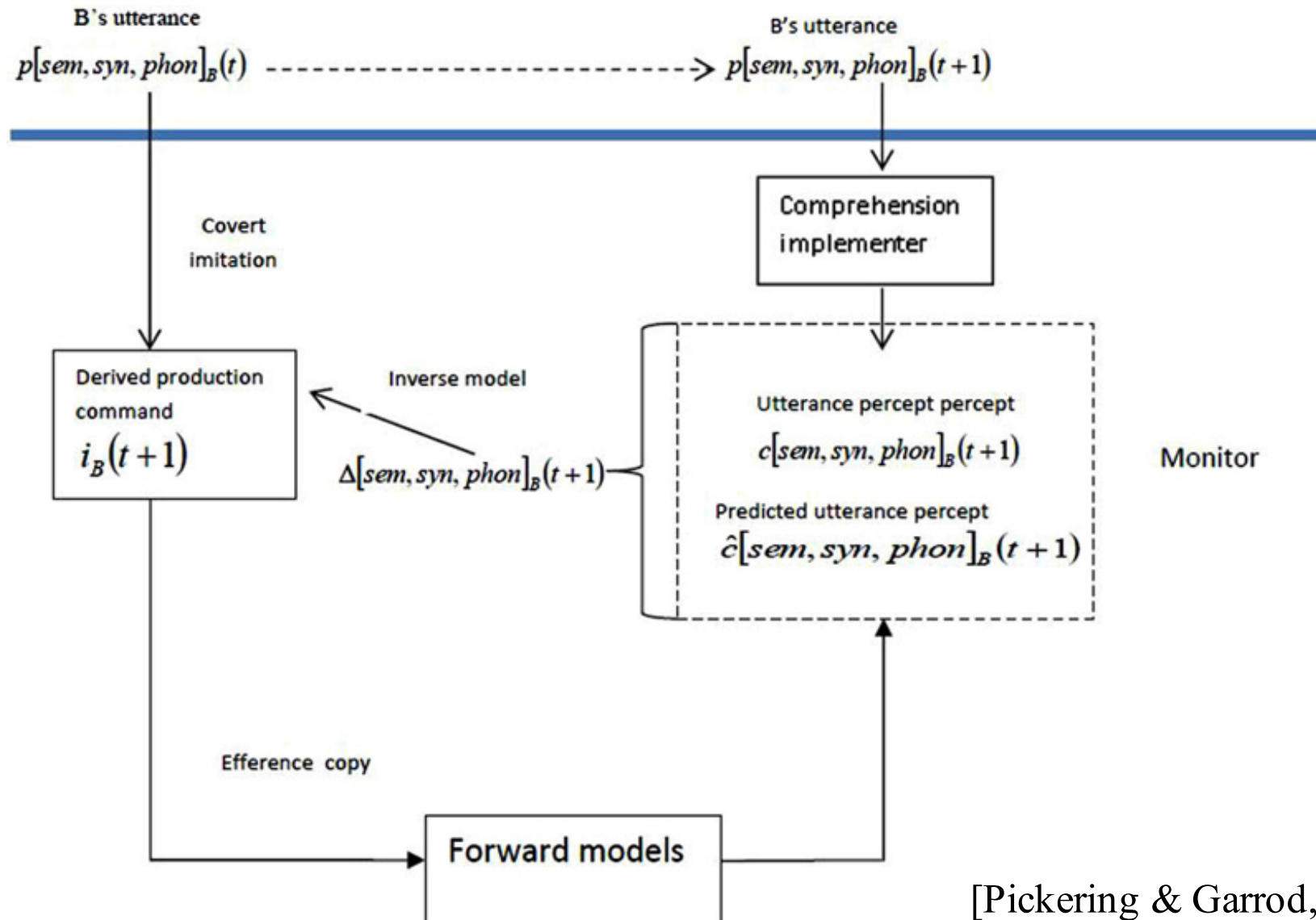
Feedback Causation



Forward Model

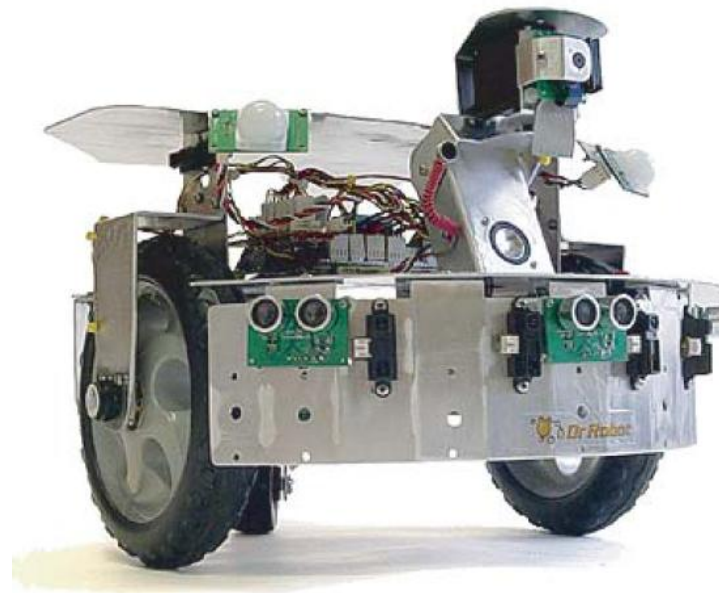
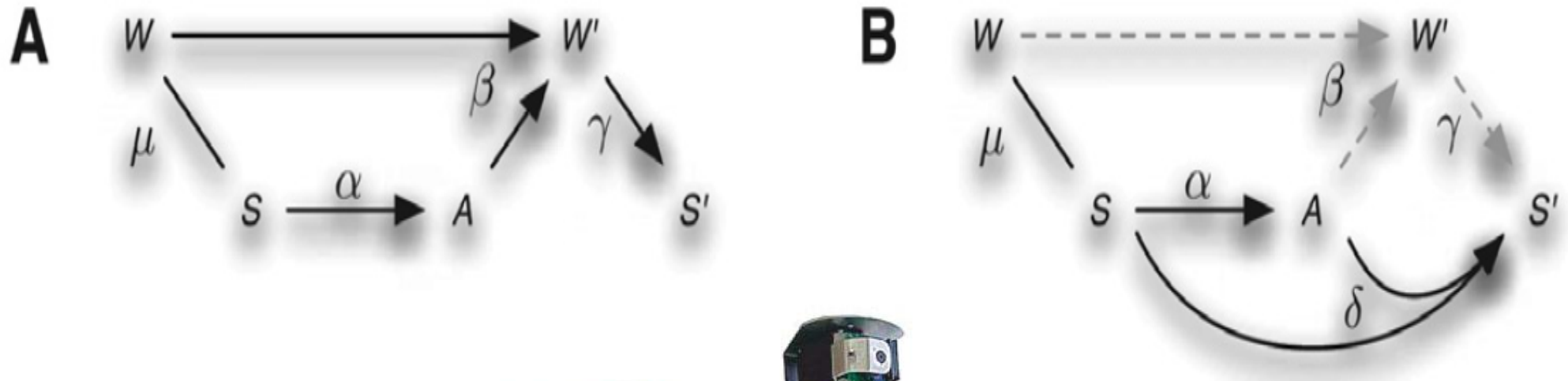


Interactive Alignment Model of Conversation



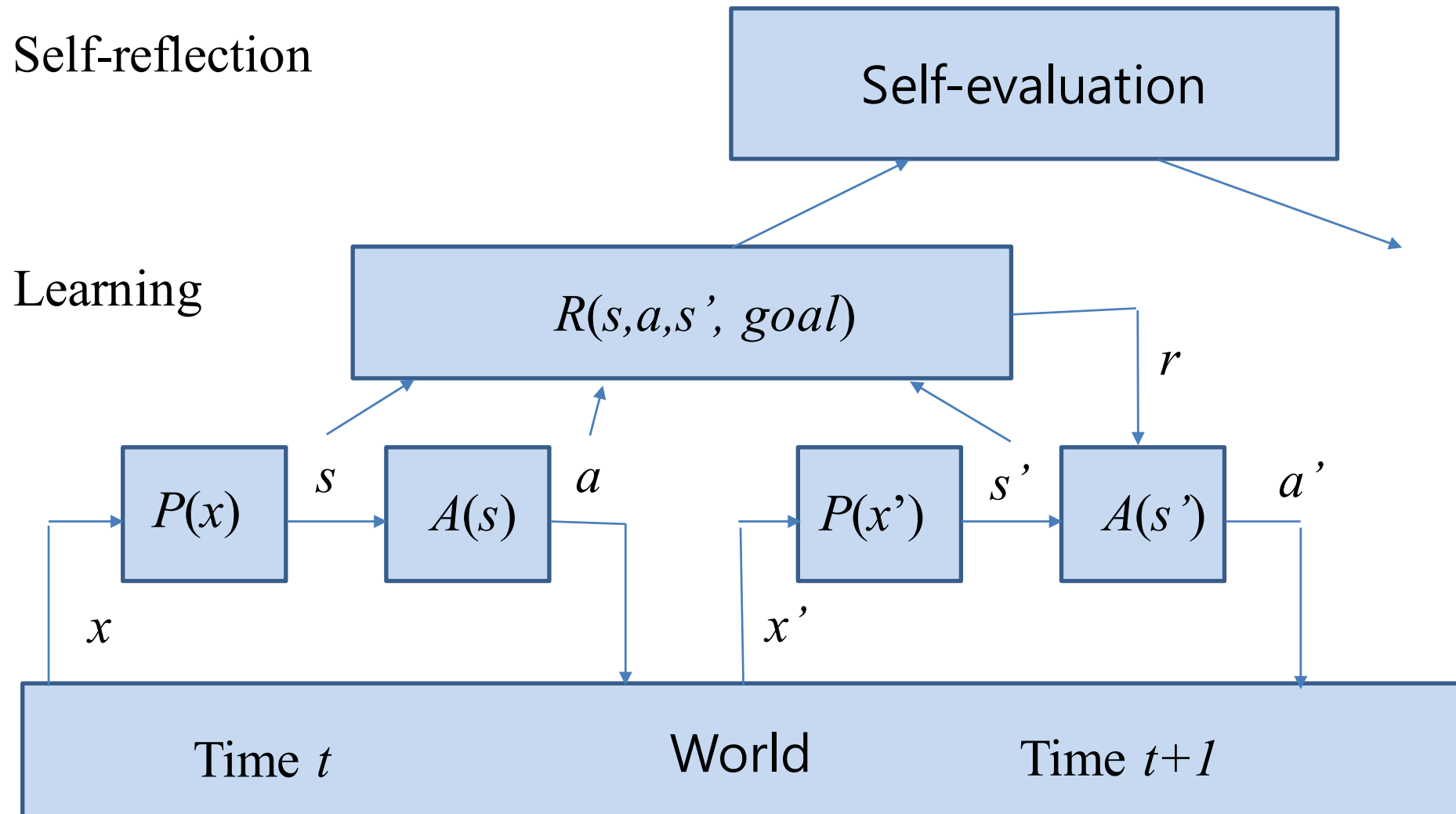
[Pickering & Garrod, 2013]

Prediction in the Perception-Action Cycle

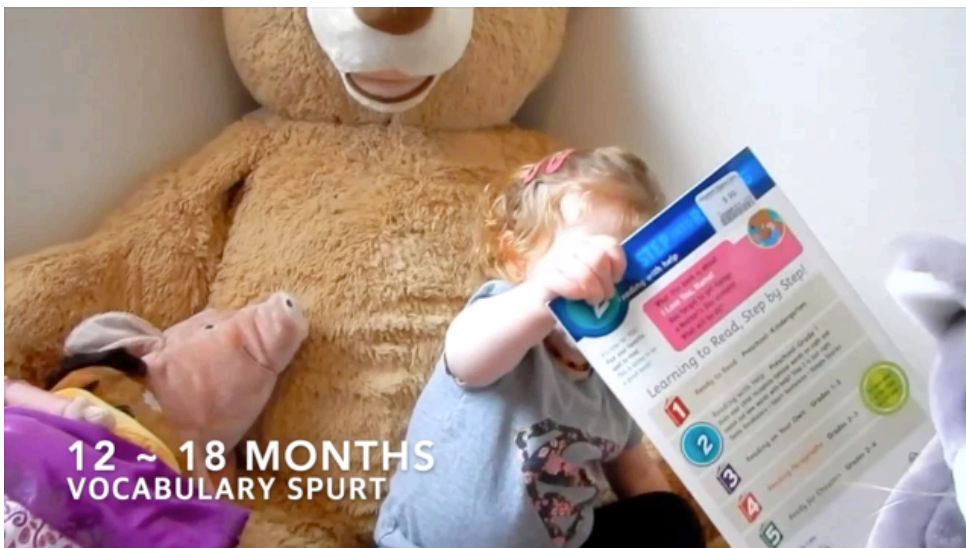


[Zahedi *et al.*, *Adaptive Behavior*, 2009]

Self-reflective Learning

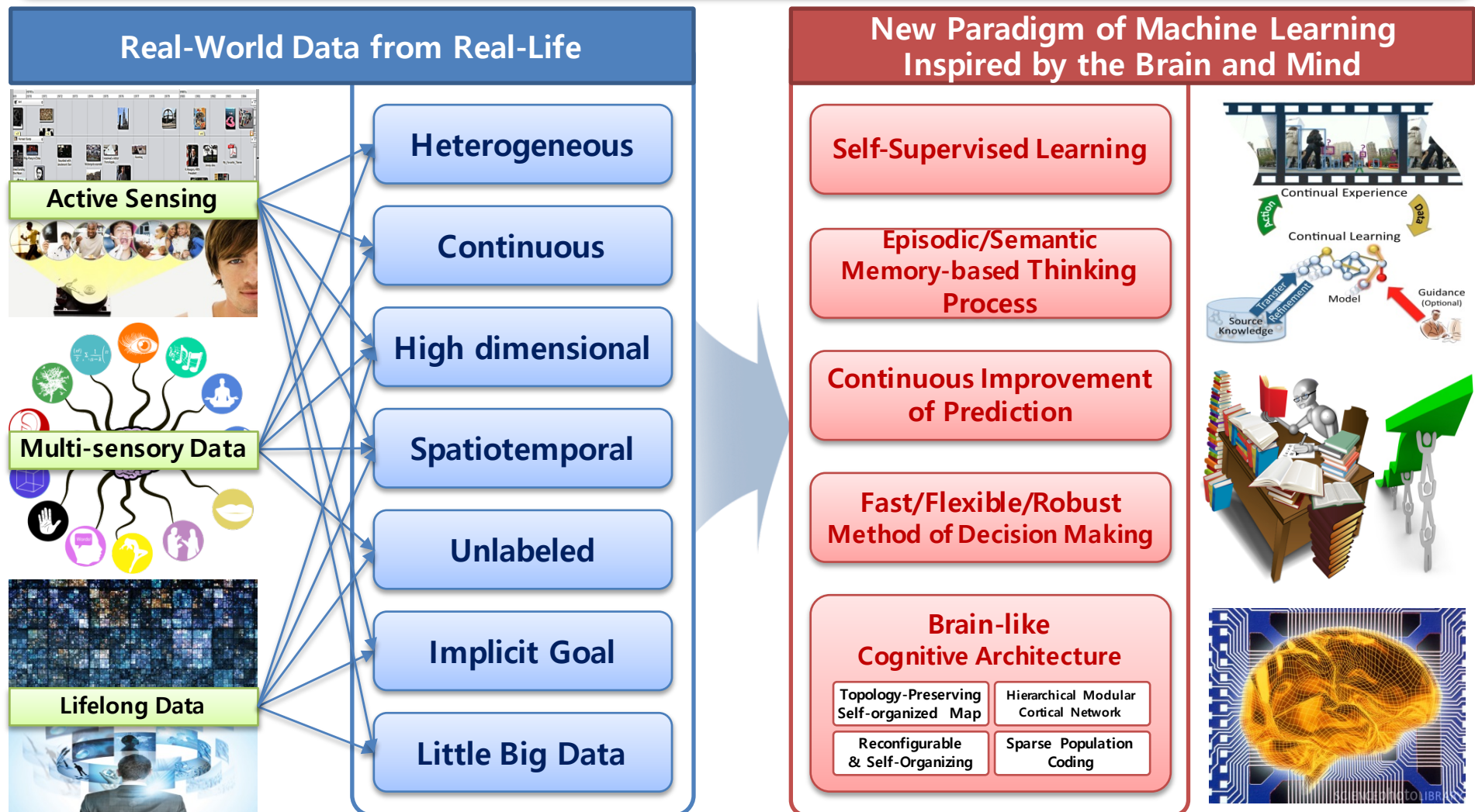


BabyMind



BabyMind

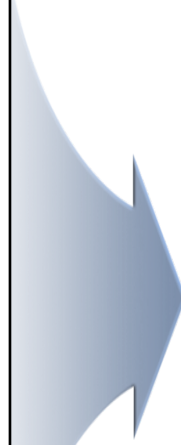
Improving Skills and Knowledge by Continual Learning through Interaction with the Real World



BabyMind

Traditional AI

- **Passive**
- **Static**
- **Closed System**
- **Supervised Learning**
- **Deep Networks**
- **Text-Based Data**
- **Knowledge-Centric**
- **Learning from Examples**
- **Short-term Decision**

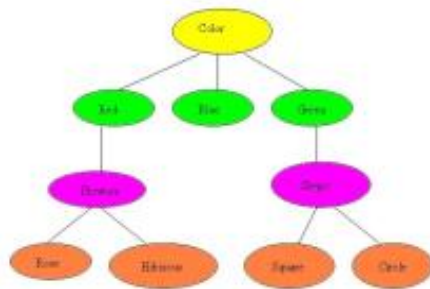
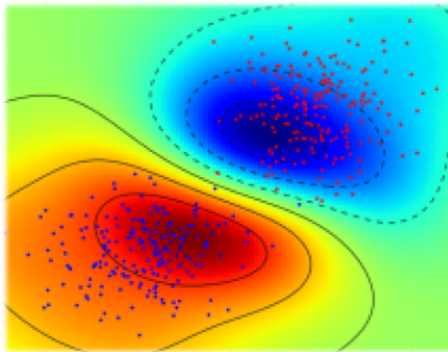


Cognitive AI

- **Active**
- **Dynamic**
- **Open System**
- **Autonomous Learning**
- **Self-developing Networks**
- **Sensor-Based Data**
- **Action-Centric**
- **Learning by Experiment**
- **Long-term Mission**

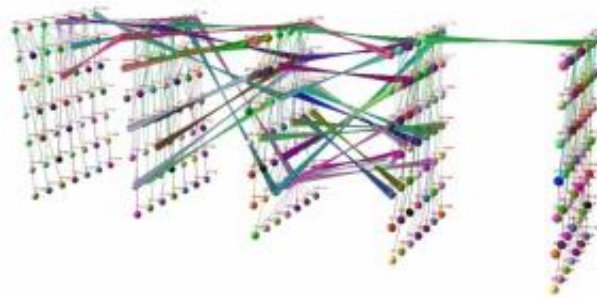
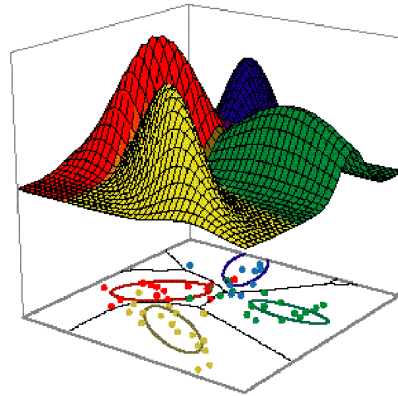
The Next Generation: **Autonomous Learning**

1G: Supervised Learning (1985~2000)



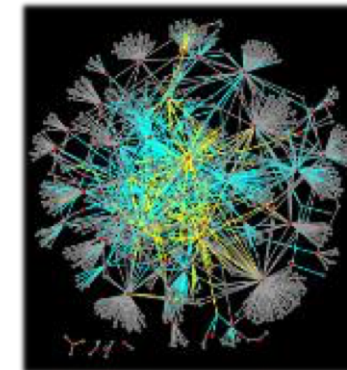
- **Decision Trees**
- **Kernel Methods**
- **Multilayer Perceptrons**

2G: Unsupervised Learning (2000~2015)



- **Deep Networks**
- **Markov Networks**
- **Bayesian Networks**

3G: Autonomous Learning (Next Generation)



- **Learning by Experiment**
- **Perception-Action Cycle**
- **Self-reflective Learning**

4. Prospect

Autonomous Cognitive Machines



Future of AI

