고등과학원
초학제 연구프로그램
올해의 주제 2019년도 연구
인공지능과 포스트휴머니즘

제3회 워크숍

인공지능, 뇌 그리고 학습

◆ 일시: 2019년 5월 31일(금) 15:00 ~ 17:40
◆ 장소: 고등과학원 1호관 1층 국제회의실 (1114호)
◆ 주관: 인공지능과 포스트휴머니즘 연구단
◆ 주최: 고등과학원 초학제 연구프로그램



고등과학원 초학제연구단
인공지능과 포스트휴머니즘

고등과학원

초학제 연구프로그램

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초 대 장

고등과학원에서 운영하는 **<초학제 연구프로그램>**의 '올해의 주제' 2019년도 연구를 진행하고 있는 **<인공지능과 포스트휴머니즘>** 연구단입니다. 오늘날 인공지능로봇 기술이 급속도로 발전하면서 사회관계 및 생활세계의 변화뿐 아니라, 그에 수반하는 윤리적·법적인 쟁점들의 부상과 더불어, 휴머니즘과 인간 정체성에서도 많은 변화가 예견되고 있습니다.

본 연구단은 이러한 시대적 조망에서 먼저 인공지능로봇 기술의 발전 배경과 현황 및 전망을 구체적으로 살펴보고, 인류 사회에 던지는 사회적 함의를 탐색하고자 합니다. 나아가 인간-인공지능 사이에 새로운 방식의 상호작용과 인류 사회의 변화, 이에 수반하는 윤리적·법적·사회적 쟁점들, 그리고 인공지능의 존재적 본질과 인간 정체성에 대한 이해의 변화와 같은 인간학적 주제들도 함께 논의해 보고자 합니다. 이를 바탕으로 궁극적으로 인간과 인공지능이 함께 공존하면서 발전할 수 있도록 하는 적합한 담론으로서의 포스트-휴머니즘을 모색해 보고자 합니다.

이를 위해 인공지능 분야의 핵심기술을 중심으로 해당 분야의 발전 배경과 현황 및 전망, 그리고 사회적·인간학적 함의 등을 주제로, 관련 전문가들을 모시고 학제 간 학문적 교류 및 소통을 위한 학술 워크숍을 개최하려 합니다. 본 연구단의 학술 워크숍에 많은 관심과 참여를 바랍니다.

<인공지능과 포스트휴머니즘> 연구단
연구책임자 이중원



제3회 워크숍

인공지능, 뇌 그리고 학습

알파고 등장 이래로 왓슨, 로스, 알파제로 등 인공지능 프로그램들이 두뇌의 신경그물 모형에 기반을 둔 기계학습machine learning을 통해 진화를 거듭하고 있습니다. 이제는 지도학습을 넘어 비지도 학습이 일반화되고 있고, 언젠가 인간처럼 개념학습을 통한 범주적 사고가 가능할지도 모릅니다. 두뇌에서 학습이 어떻게 이루어지는지, 이와 비교해서 기계학습 기술의 현황과 전망은 어떠한지, 스스로 학습하는 인공지능의 등장이 인간과 사회에 어떤 영향을 미칠지에 대해 열린 마음으로 진지한 대화를 나누고 학제 간 소통을 활성화 하고자 합니다.

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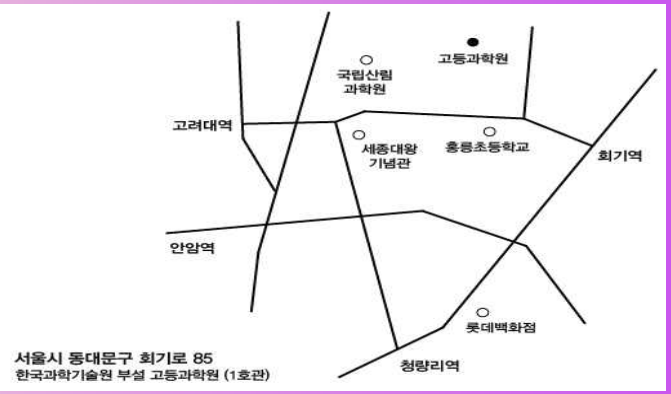
◆ 프로그램

시 간	발표자	제 목
15:00~15:10	이중원(서울시립대학교)	개 회 사
발 표		사회: 최인령(고등과학원)
15:10~15:50	이경민(서울대학교)	기억의 뇌 기전과 인간의 지능
15:50~16:30	이영준(한국교원대학교)	인공지능 시대의 학습과 교육
질의응답 및 토론		사회: 이중원(서울시립대학교)
16:50~17:10	이청호(세종대학교)	종합논평
17:10~17:40	질의응답 및 토론	

이 경 민	이 영 준
MIT 신경과학 박사, Cornell 대학병원 신경과 전공의 수련 후, 행동신경학과 인지신경과학을 전공하신 이경민 교수님은 현재 서울대학교 의학과 신경과학교실 교수이시자 대학원 협동과정 인지과학전공 겸임교수입니다. 또한 한국인지과학회장(2014), 게임이용자보호센터장(2016-8)을 역임하였고, 현재 Journal of Clinical Neurology 편집장, 게임과학포럼 상임대표를 맡고 있습니다. 기초 뇌과학 및 임상 신경학 분야의 다양한 주제들은 물론, 포스트휴머니즘 시대의 종교와 과학, 비디오게임을 통한 인지발달과 뇌 건강 증진 등의 주제에 대해 활발히 연구하고 있습니다.	미국 univ. of Minnesota에서 기계학습 및 지식처리 전공으로 박사학위를 받으신 이영준 교수님은 현재 한국교원대학교 컴퓨터교육과 교수로 재직하시면서 인공지능의 기계학습 및 지식처리, 그리고 정보통신시템 및 응용에 대한 연구를 진행하고 있습니다. 또한 현재 한국정보과학교육연합회 공동대표, 한국컴퓨터교육학회 회장, 한국정보기술학술단체총연합회 부회장이시고 기계학습뿐만 아니라 교육자로의 인간 학습에 대한 연구와 경험이 풍부합니다.

◆ 고등과학원 오시는 길



역에서
3번출구 방면, 도보 약 20분 소요

안암역에서
안암전철역 정류장 273번 버스(한국과학기술원 하차)

청량리역에서
현대코아 정류장 201번 버스(한국과학기술원 하차)

회기역에서
시조사삼거리 정류장 201번 버스(한국과학기술원 하차)

기억의 뇌 기전과 인간의 지능

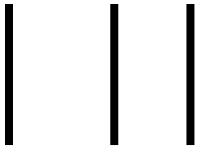
서울대학교 의과대학 신경과
대학원 인지과학 협동과정
이경민

Topics in this talk

- Brain and mind in time
  - Perception of onsets
    - Temporal order judgement and the brain
    - cf) Libet's experiments & the problem of introspection
  - End of perception, and the beginning of memory
    - Iconic memory
    - Working memory
  - Evolution of human brain and memory
    - On-line action and off-line memory
    - Exteriorized memory and extended cognition

From physical events to mental experiences

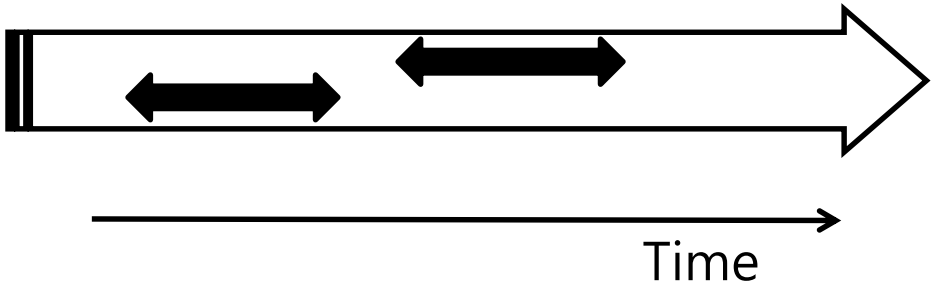
- **Physical** events: changes in space-time
  (a sequence of happenings)



- **Neural** processes: electrochemical patterns
  (low-pass filters,
  contrast enhancement,
  saturation, habituation, …)



- **Mental** experiences:
  protention-perception-retention
  (schema, stories,
  narratives linked by meaning)

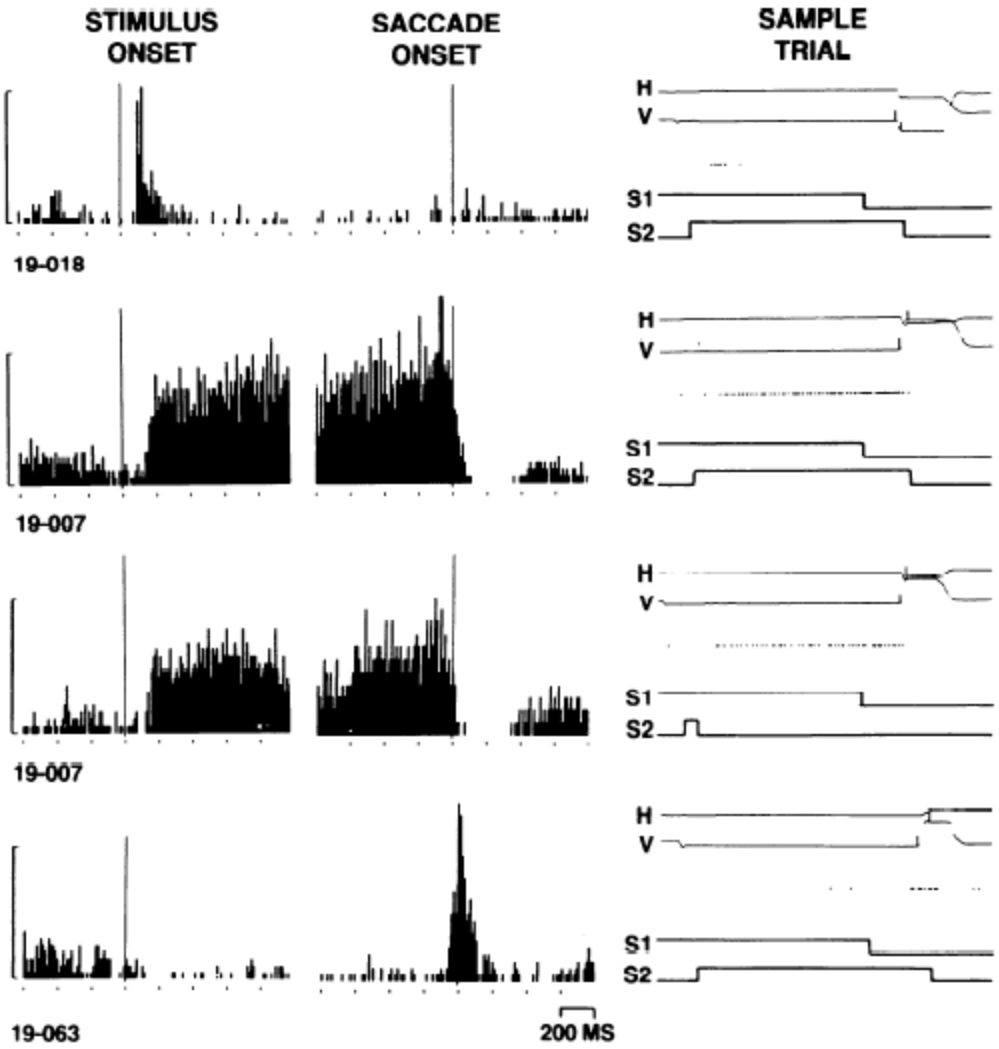


Phasic visual activity

Tonic visual activity
in stable saccade task
= delayed saccade

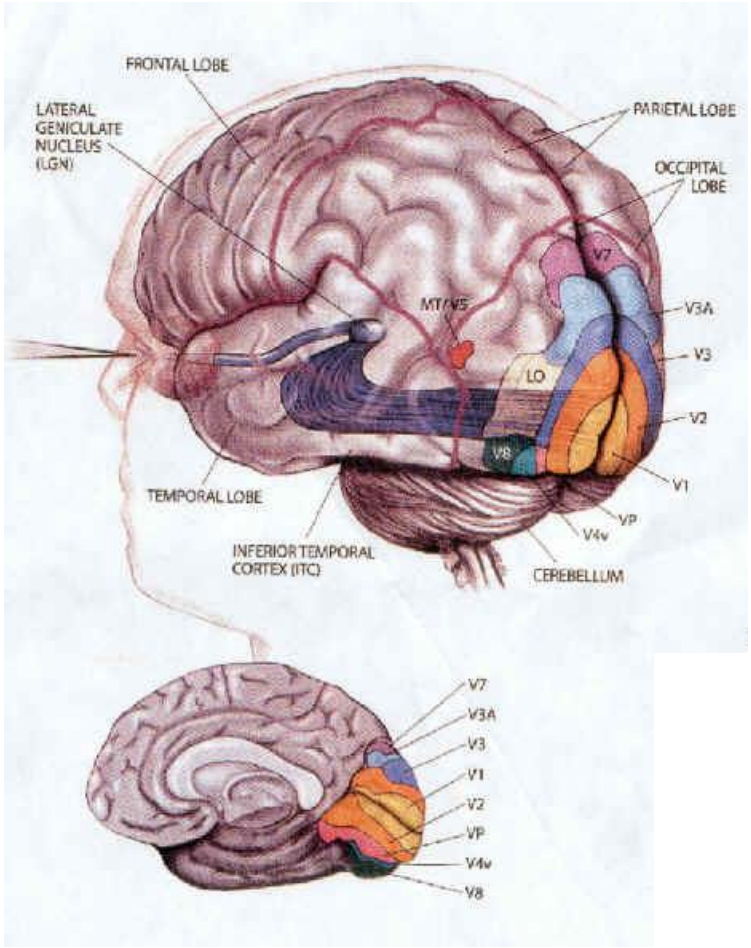
Tonic visual activity
in learned saccade task
= memory saccade

Movement activity

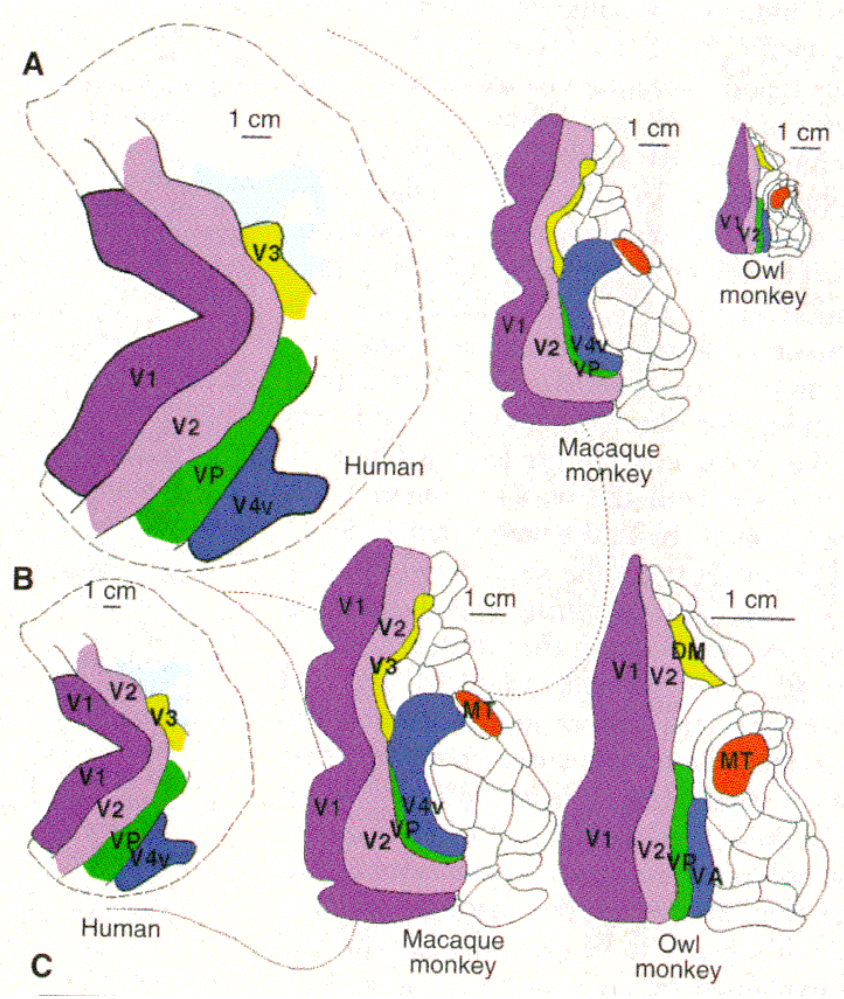


Bruce and Goldberg, 1985

Multiple visual areas in the brain



Logothetis et al., 2004



Tooltell et al., 1995

Brain and Cognition 69 (2009) 337–343

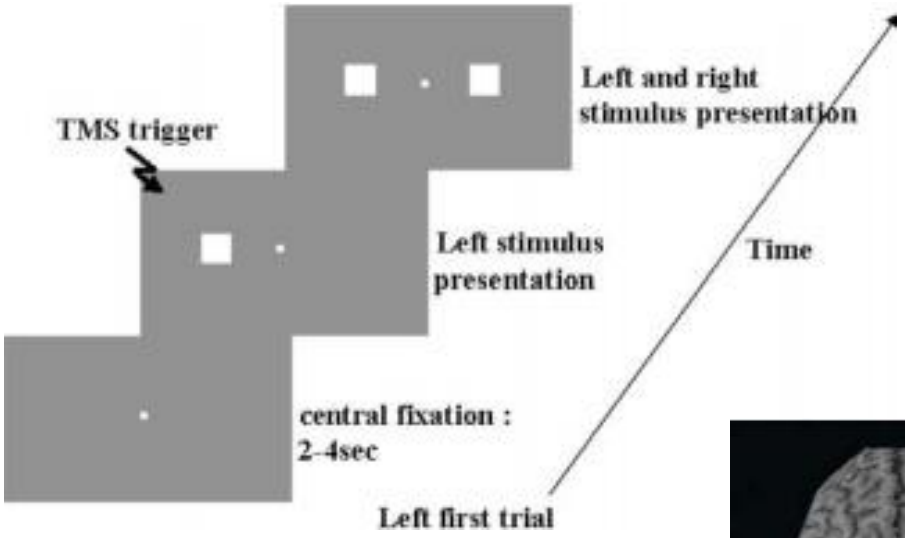
Contents lists available at ScienceDirect

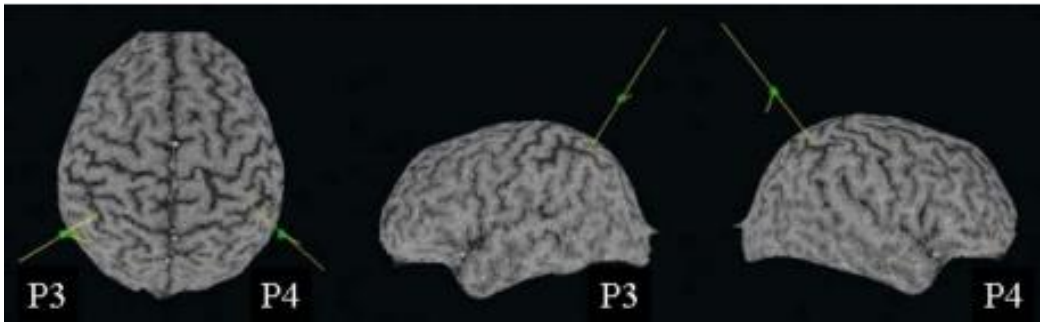
Brain and Cognition

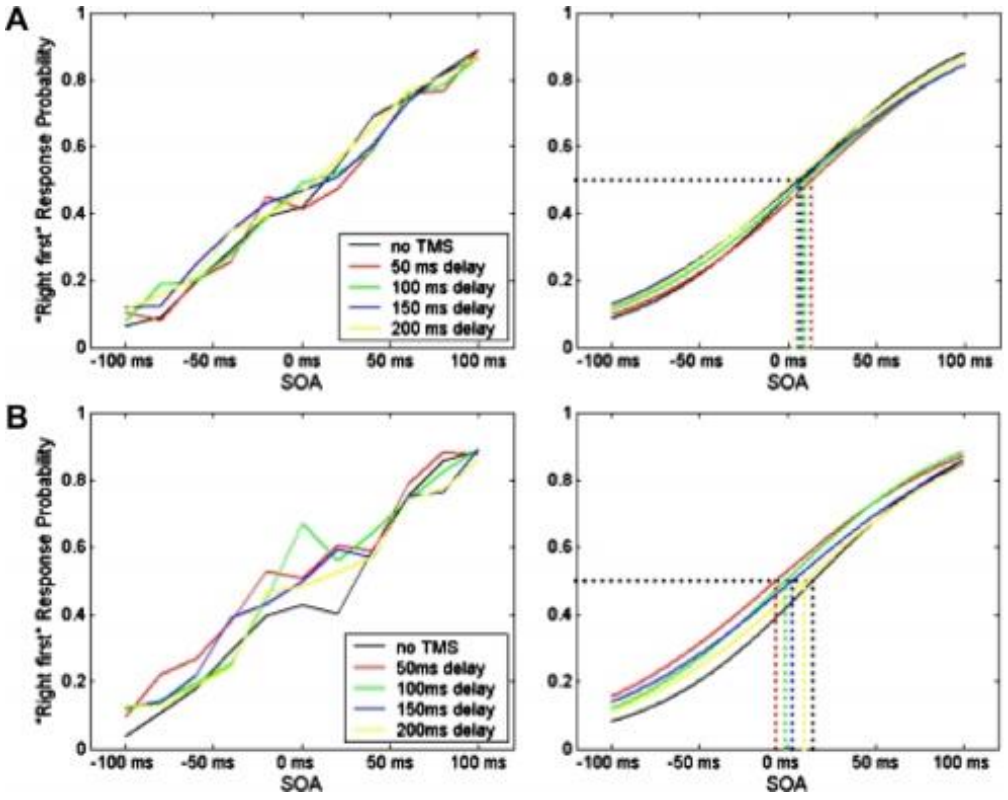
journal homepage: www.elsevier.com/locate/b&c

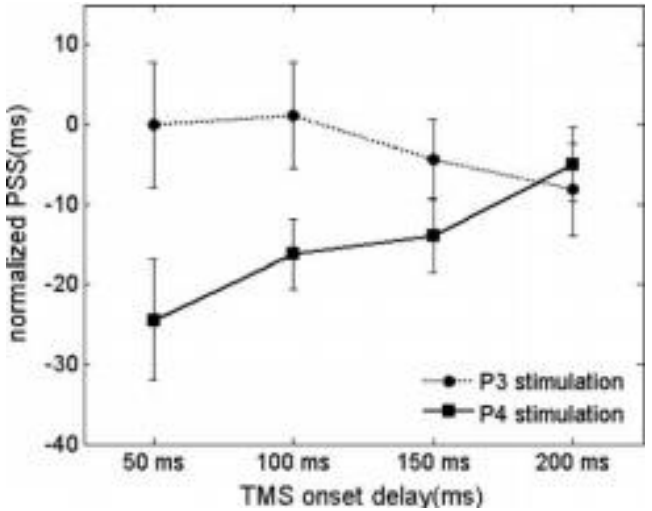
The role of the right posterior parietal cortex in temporal order judgment

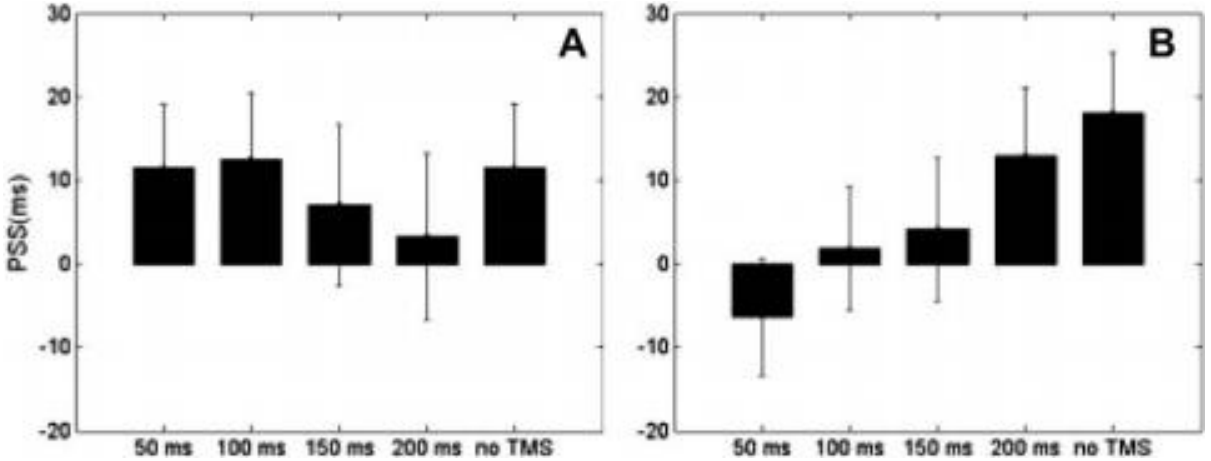
Sung-Ho Woo [a] , Ki-Hyun Kim [a,b] , Kyoung-Min Lee [a,c,*]





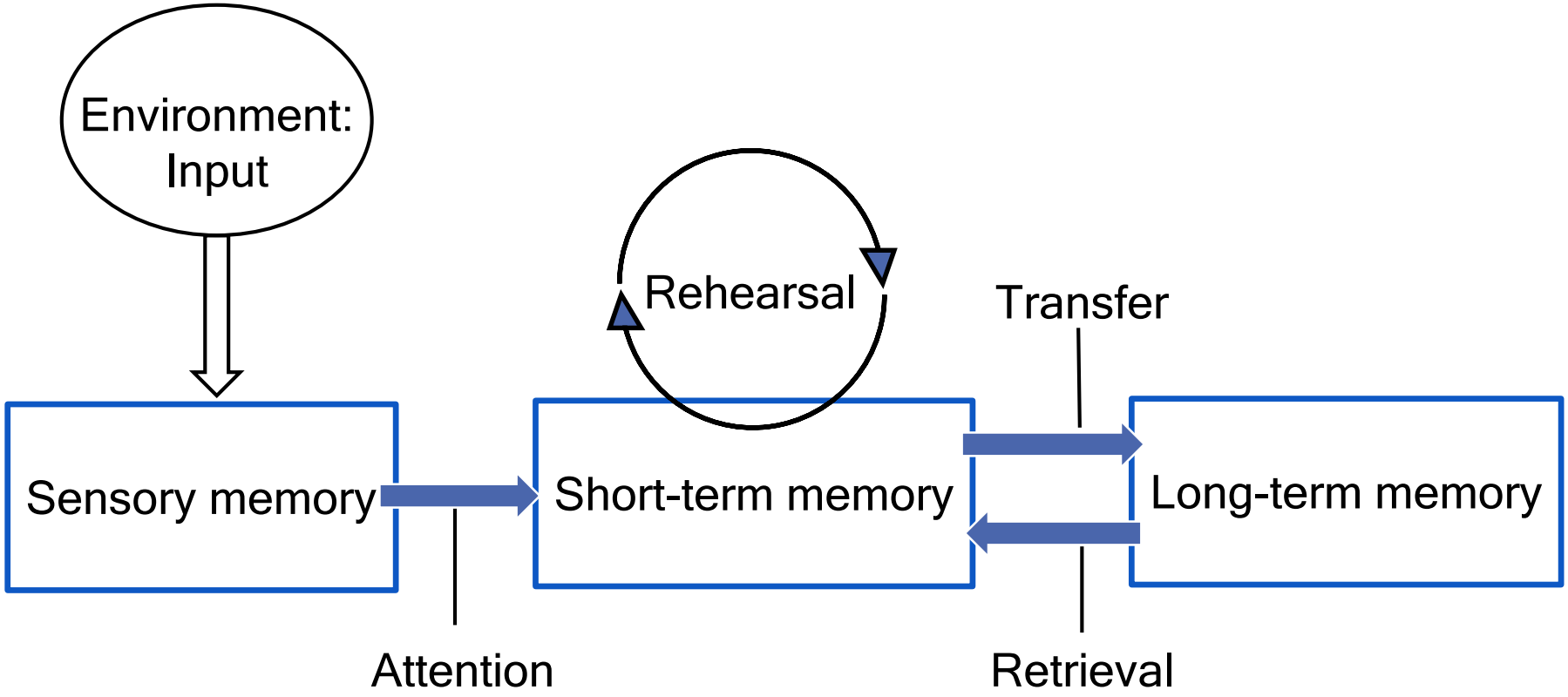

A
B
"Right first" Response Probability
SOA
-100 ms
-50 ms
0 ms
50 ms
100 ms
no TMS
50 ms delay
100 ms delay
150 ms delay
200 ms delay
50ms delay
100ms delay
150ms delay
200ms delay


normalized PSS(ms)
TMS onset delay(ms)
50 ms
100 ms
150 ms
200 ms
P3 stimulation
P4 stimulation


A
B
PSS(ms)
50 ms
100 ms
150 ms
200 ms
no TMS

Multiple memory systems (1/2)

- Classification by the maintenance time
  - Sensory memory: up to about 2 seconds
    - Iconic memory (visual)
    - Echoic memory (auditory)
  - Short-term memory: seconds to minutes
    - Visuospatial memory: up to 4 items
    - Verbal memory: the magic number 7 +/- 2
  - Long-term memory: unlimited time



Multi-store model of memory by Atkinson & Schiffrin (1968)

Fast decay of iconic memory in observers with mild cognitive impairments

Zhong-Lin Lu*†‡§¶, James Neuse†, Stephen Madigan†, and Barbara Anne Dosher‖

*Laboratory of Brain Processes (LOBES), Departments of †Psychology and ‡Biomedical Engineering, and §Neuroscience Graduate Program, University of Southern California, Los Angeles, CA 90089-1061; and ‖Memory, Attention, and Perception (MAP) Laboratory, Department of Cognitive Sciences and Institute of Mathematical Behavioral Sciences, University of California, Irvine, CA 92697-5100

Communicated by Richard F. Thompson, University of Southern California, Los Angeles, CA, November 15, 2004 (received for review April 28, 2004)

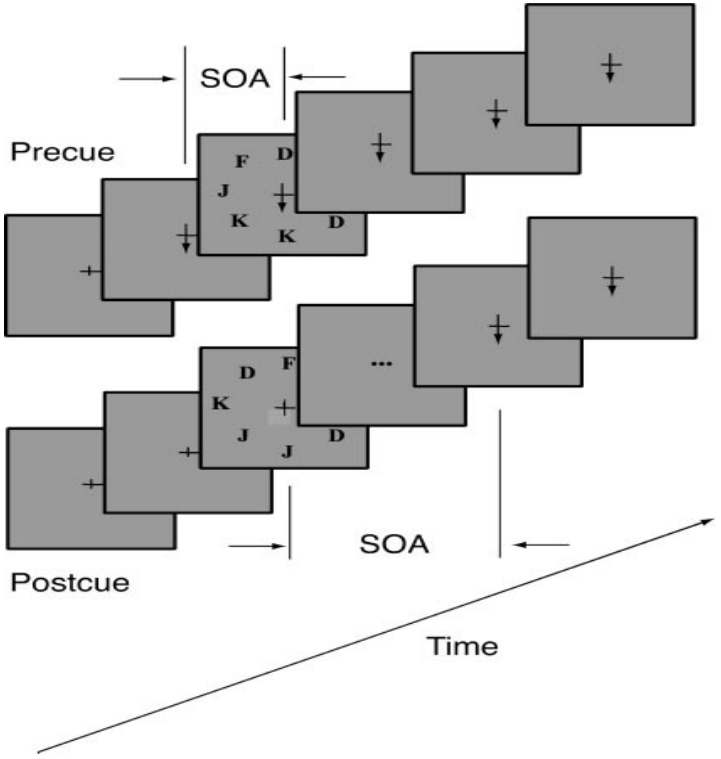
In a previous clinical report, unusually fast decay of iconic memory was obtained from a subject who later developed Alzheimer's disease. By using the partial-report paradigm, iconic memory (a form of visual sensory memory) in a group of observers with mild cognitive impairments (MCI) was characterized and compared with that of young college-age adults and older controls. Relatively long stimulus exposures were used for all three groups to ensure that older observers could perceive the stimuli. A set of conventional neuropsychological tests assessed cognitive functions of the MCI and older control groups. We found that iconic memory decayed much faster for observers with MCI than for normal controls, old or young, although the two groups of older observers performed at equivalent levels in precue tests (assay of visibility) and tests cued at long delays (assay of short-term memory). The result suggests that fast decay of iconic memory might be a general characteristic of observers with MCI who are at much higher than average risk of developing Alzheimer's disease later in life.

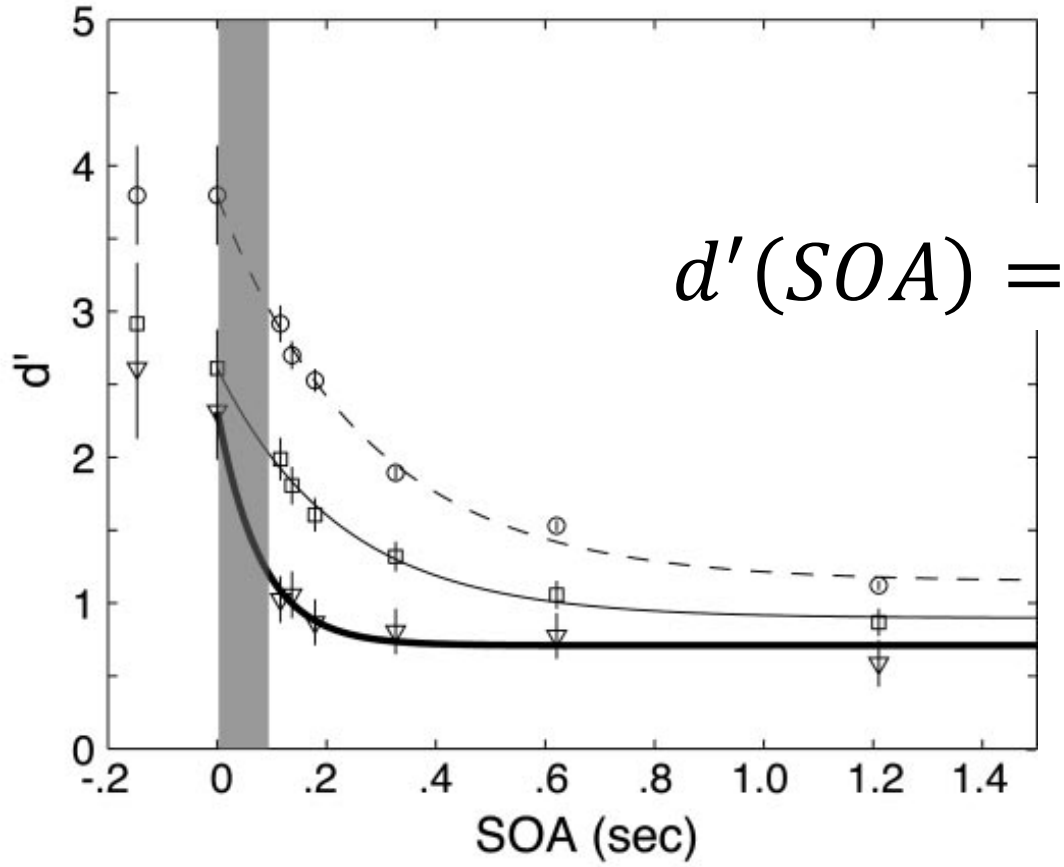
sensory memory duration | Alzheimer's disease | neuropsychological test

was able to identify the target item with 75% accuracy (chance, 25%) in partial-report displays with eight items when he was cued to the target location ≈200 ms before the display. The observer reported that he was able to see the stimulus but unable to remember the identity of the item at probe.

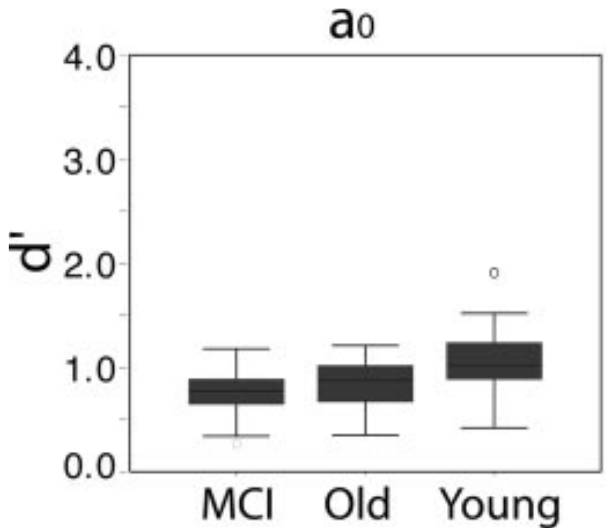
Yang's study was conducted in 1997. At the time when the study was conducted, Yang's unusual observer was a healthy 58-yr-old individual who appeared to be normal in every aspect and was performing a very high-profile job. Puzzled by the observation, Yang documented this unusual case in his dissertation without further investigation. We learned in the summer of 1999 that the unusual observer in Yang's study could no longer carry out his job duties because of poor memory functions. He was diagnosed subsequently with Alzheimer's disease (AD).

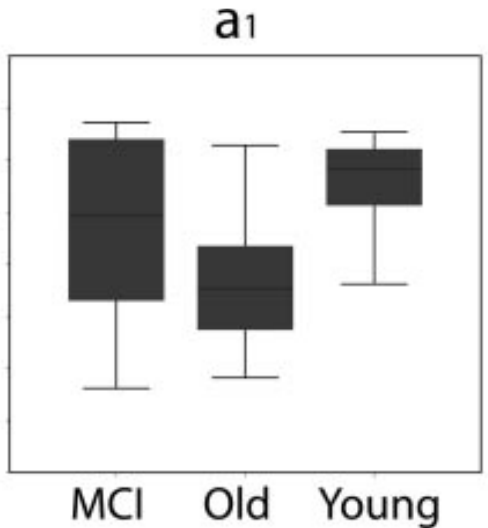
Although the clinical dementia rating (CDR) and measures of other cognitive abilities of the unusual observer in Yang's study are not available, descriptions in Yang's dissertation suggest that the observer might have had only mild cognitive impairments (MCI) at the time of the partial-report experiments. Was Yang's observation an accidental cooccurrence of restricted iconic-

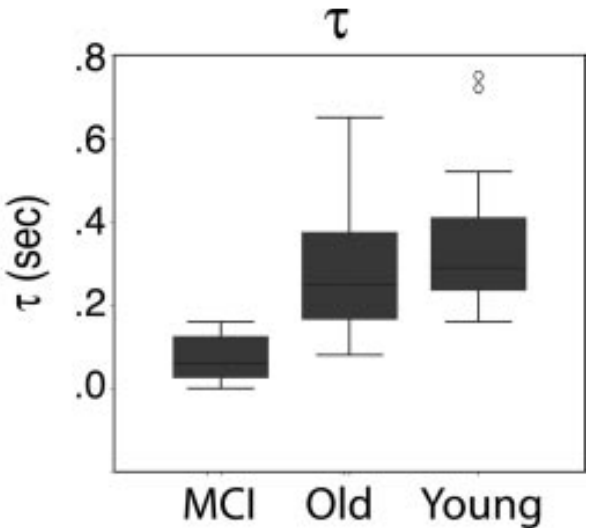




$$d'(SOA) = a_0 + a_1\, e^{-SOA/t}$$







VISUAL COGNITION, 2017
https://doi.org/10.1080/13506285.2017.1416007

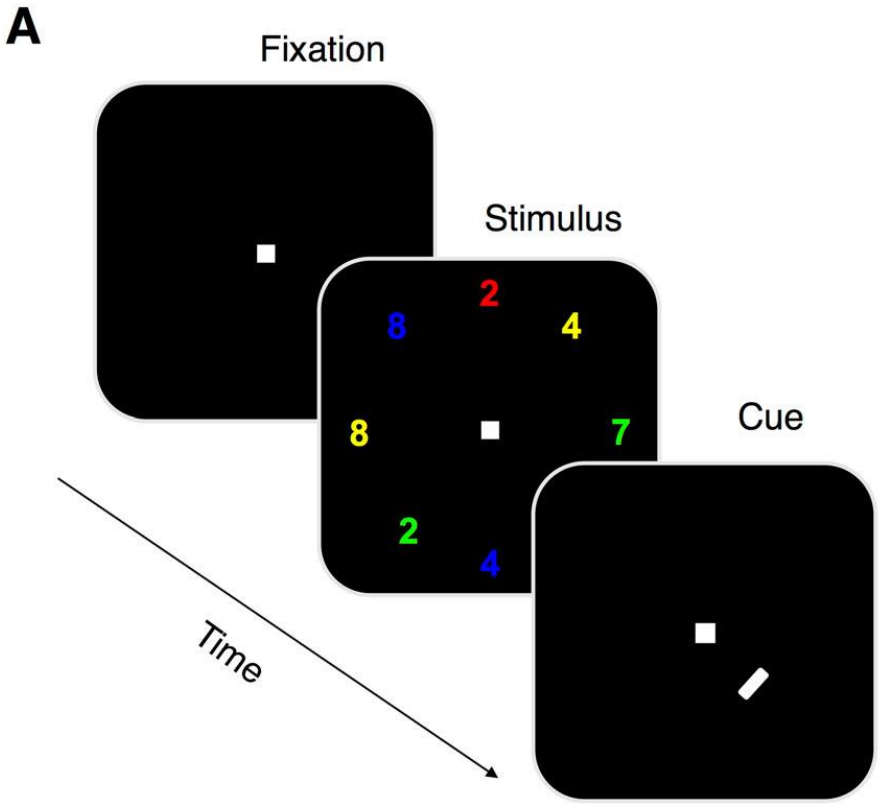
Routledge
Taylor & Francis Group

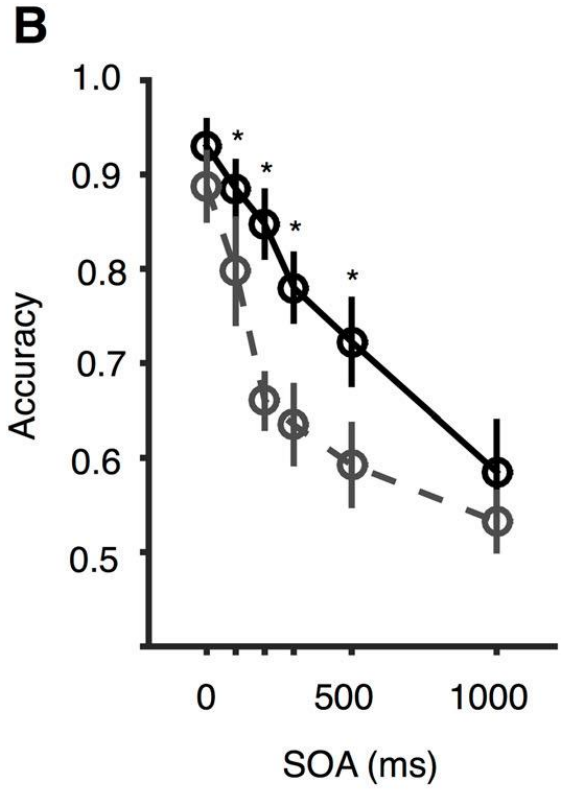
Check for updates

Visual attribute modulates the time course of iconic memory decay

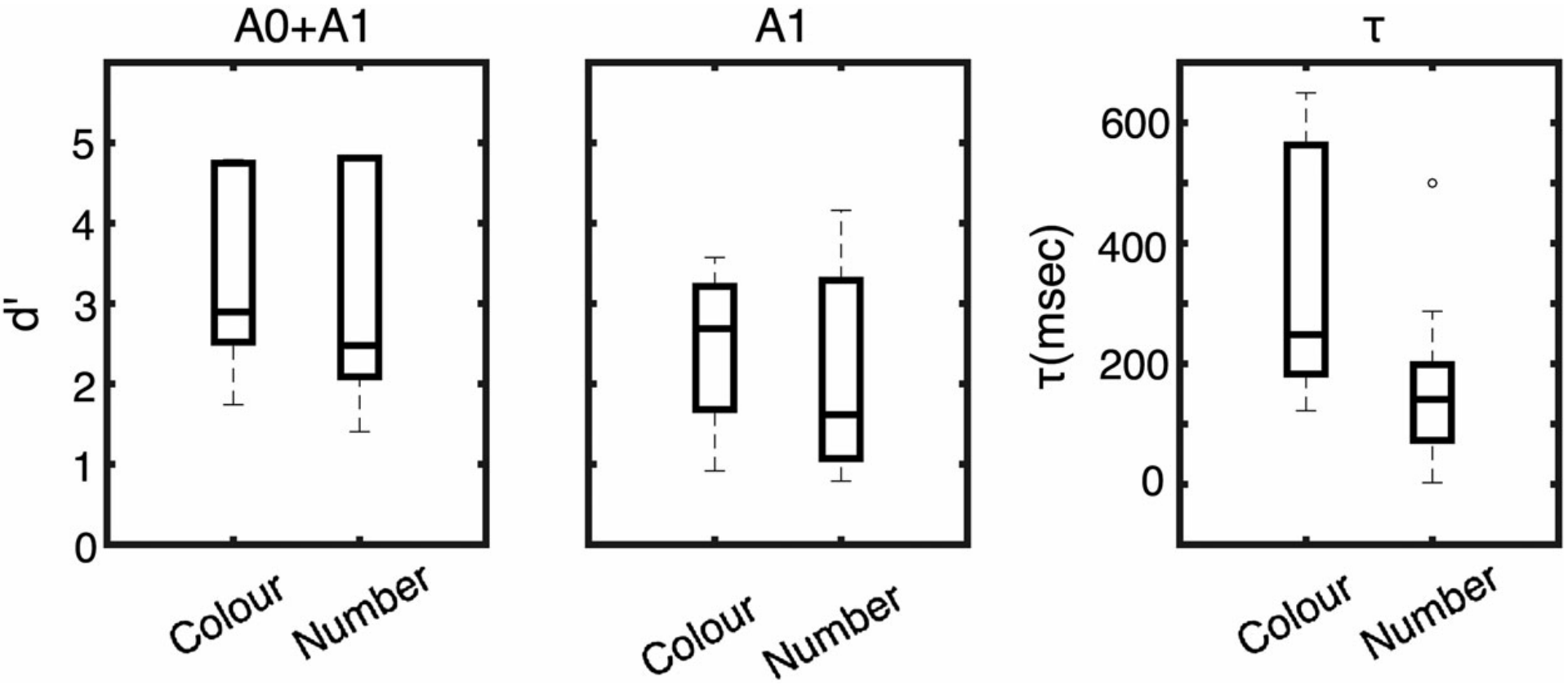
Woojong Yi[a], Min-Suk Kang[b,c] and Kyoung-Min Lee[a,d]

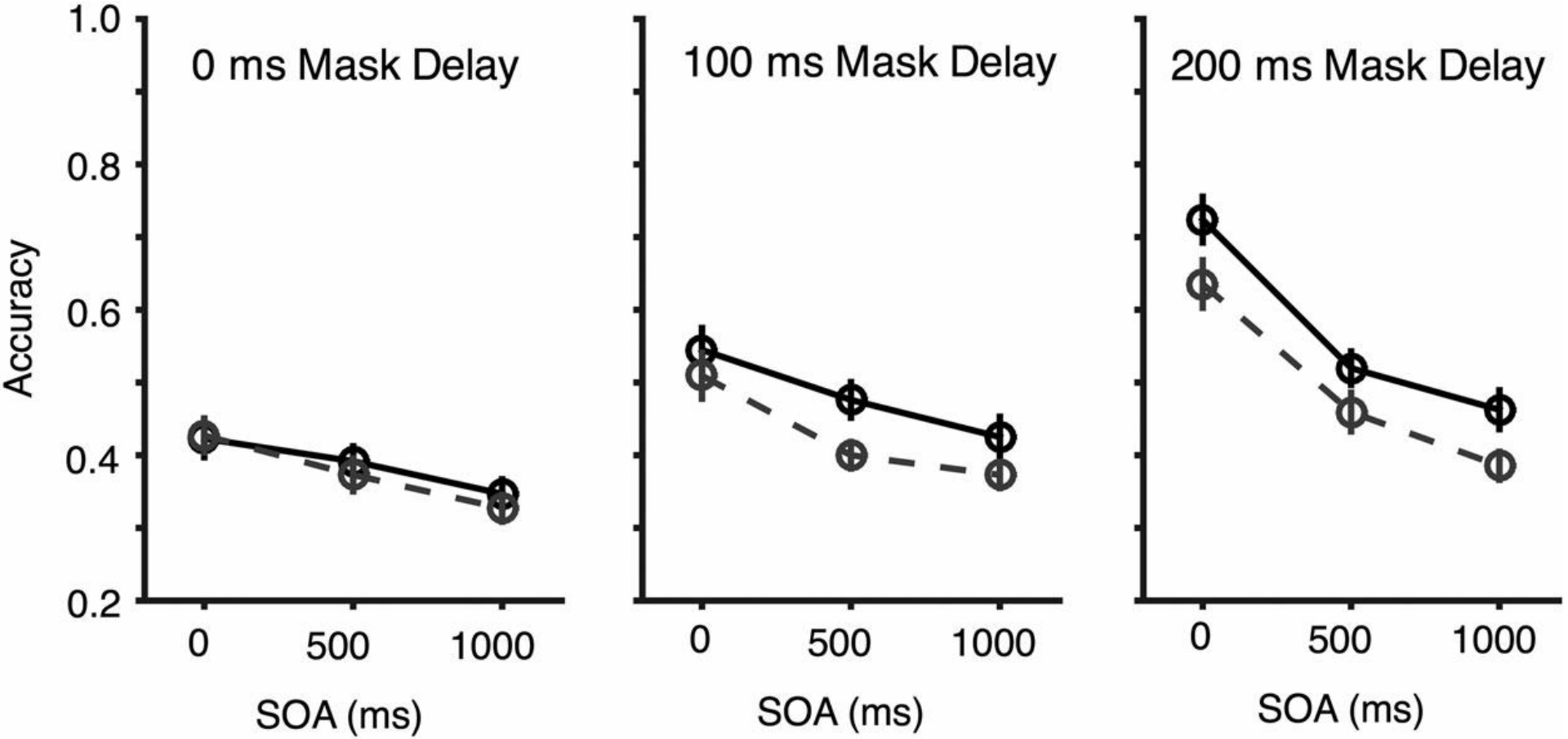
[a]Interdisciplinary Program of Cognitive Science, Seoul National University, Seoul, Republic of Korea; [b]Department of Psychology, Sungkyunkwan University, Seoul, Republic of Korea; [c]Center for Neuroscience Imaging Research (CNIR), Institute for Basic Science (IBS), Suwon, Republic of Korea; [d]Department of Neurology, Seoul National University Hospital, Seoul, Republic of Korea



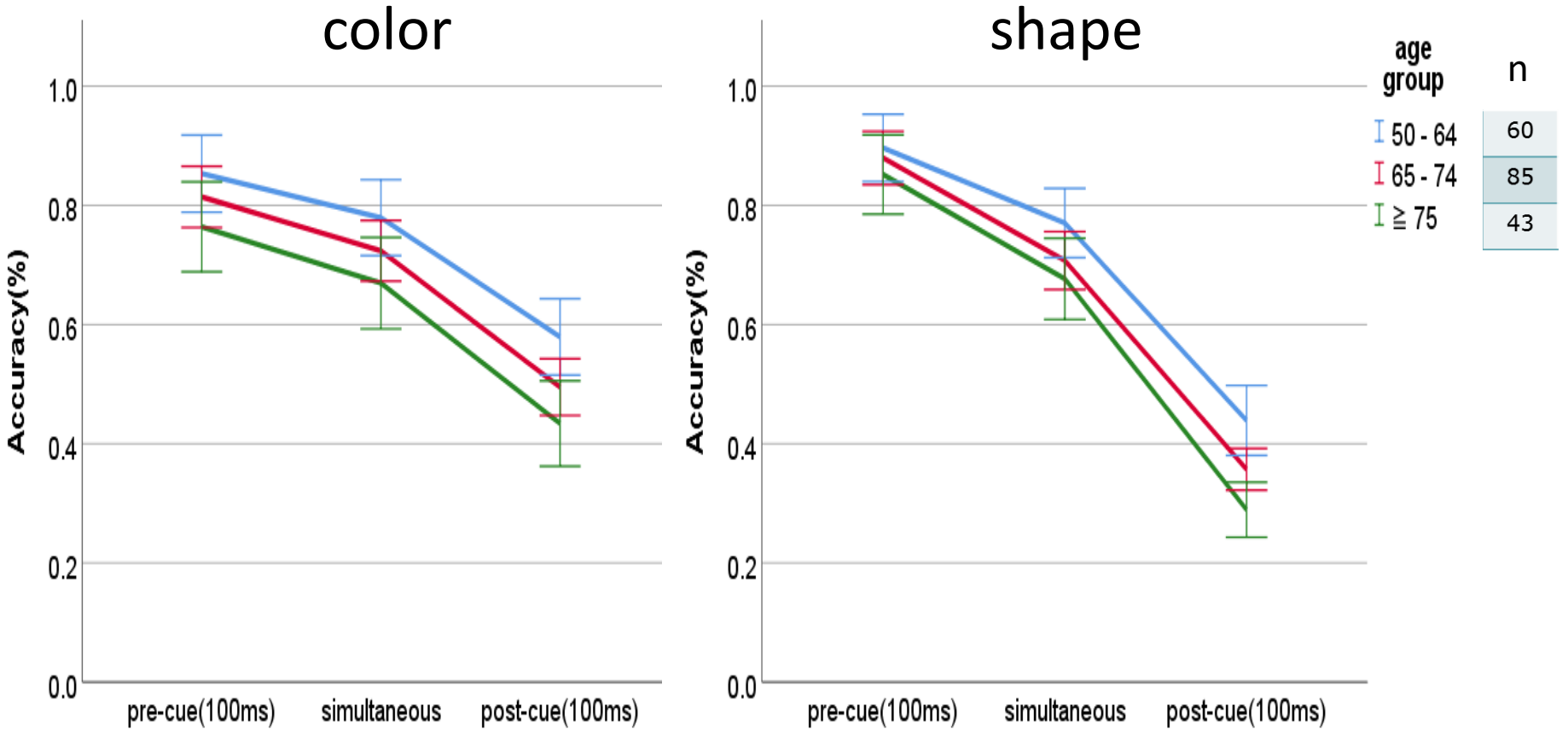


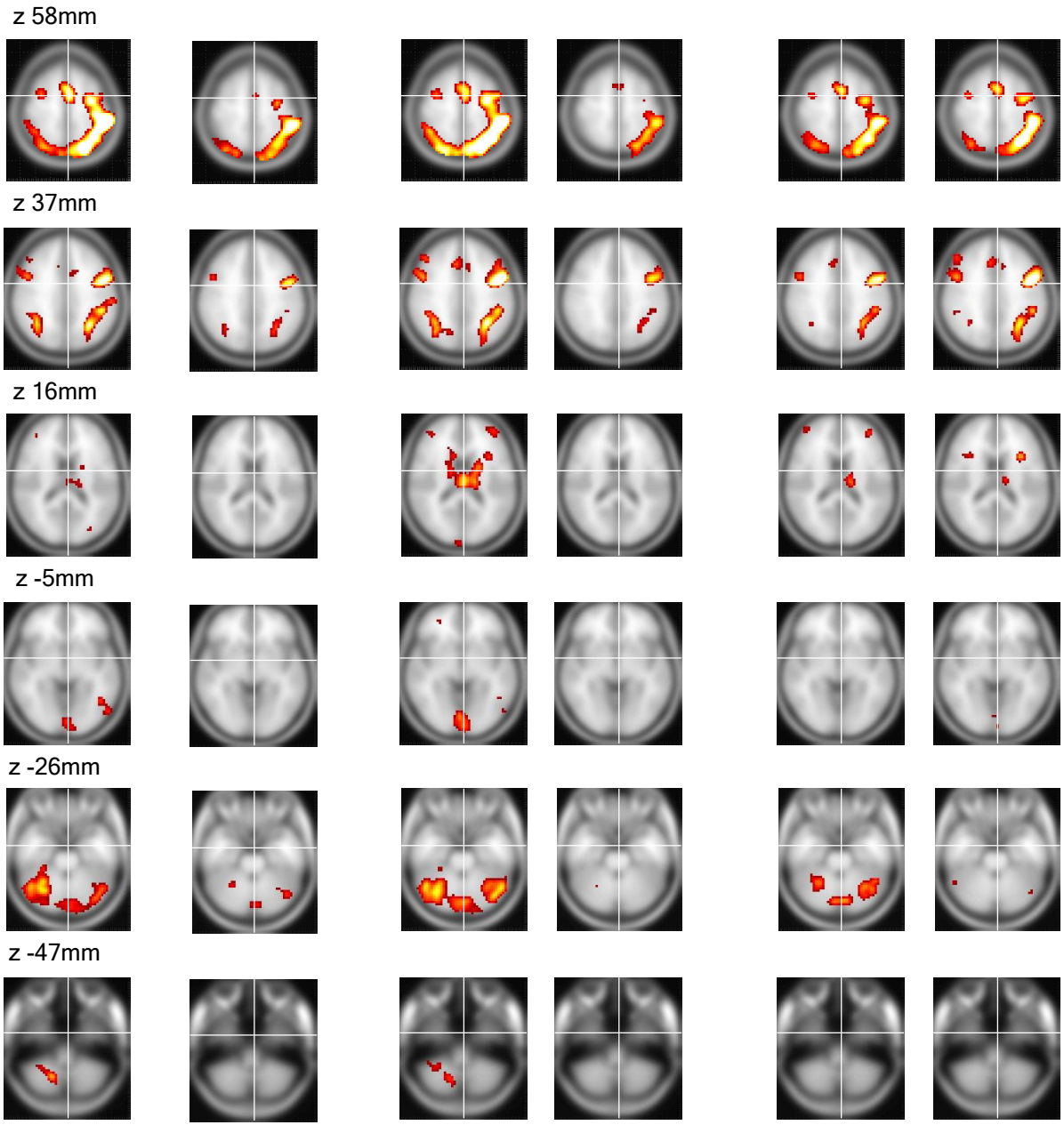
$$d'(SOA) = A0 + A1 * exp(-SOA/\tau)$$



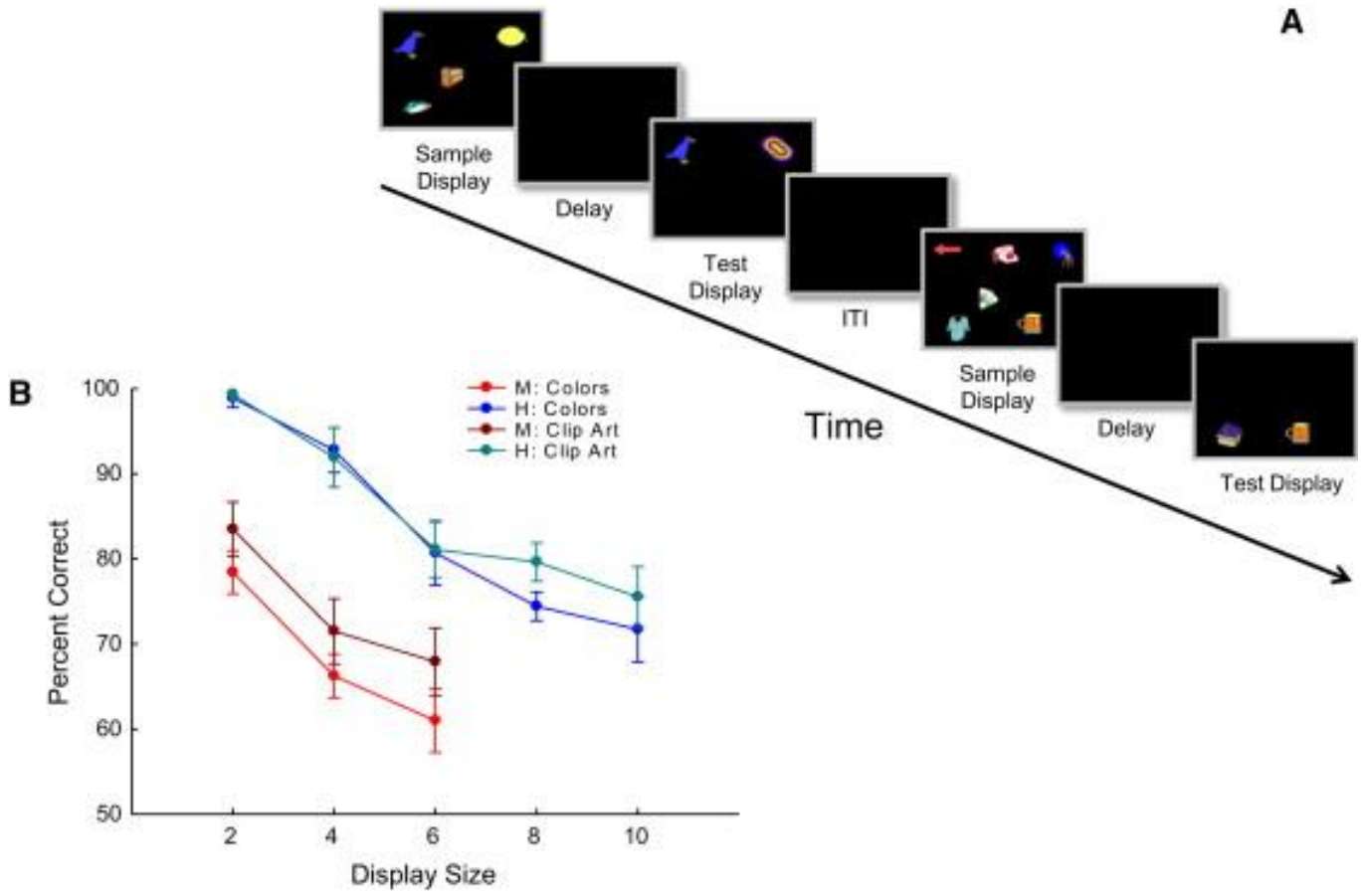

1.0
0.8
0.6
0.4
0.2
Accuracy
0 ms Mask Delay
100 ms Mask Delay
200 ms Mask Delay
0
500
1000
SOA (ms)

Aging effects on the iconic memory




C pre
N pre
C post
N post
z 58mm
z 37mm
z 16mm
z -5mm
z -26mm
z -47mm


9
6 7 4 8
3 5
20th Century Fox Research Library
01:05:44:07



Elmore et al. *Current Biology* 2011

Visual Short-Term Memory Compared in Rhesus Monkeys and Humans

OPEN ACCESS Freely available online

PLOS ONE

The Frontal Eye Fields Limit the Capacity of Visual Short-Term Memory in Rhesus Monkeys

Kyoung-Min Lee*, Kyung-Ha Ahn

Department of Neurology, Seoul National University Hospital, Seoul, Republic of Korea

Abstract

The frontal eye fields (FEF) in rhesus monkeys have been implicated in visual short-term memory (VSTM) as well as control of visual attention. Here we examined the importance of the area in the VSTM capacity and the relationship between VSTM and attention, using the chemical inactivation technique and multi-target saccade tasks with or without the need of target-location memory. During FEF inactivation, serial saccades to targets defined by color contrast were unaffected, but saccades relying on short-term memory were impaired when the target count was at the capacity limit of VSTM. The memory impairment was specific to the FEF-coded retinotopic locations, and subject to competition among targets distributed across visual fields. These results together suggest that the FEF plays a crucial role during the entry of information into VSTM, by enabling attention deployment on targets to be remembered. In this view, the memory capacity results from the limited availability of attentional resources provided by FEF: The FEF can concurrently maintain only a limited number of activations to register the targets into memory. When lesions render part of the area unavailable for activation, the number would decrease, further reducing the capacity of VSTM.

Citation: Lee K-M, Ahn K-H (2013) The Frontal Eye Fields Limit the Capacity of Visual Short-Term Memory in Rhesus Monkeys. PLoS ONE 8(3): e59606. doi:10.1371/journal.pone.0059606

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Competing Interests: The authors have declared that no competing interests exist.

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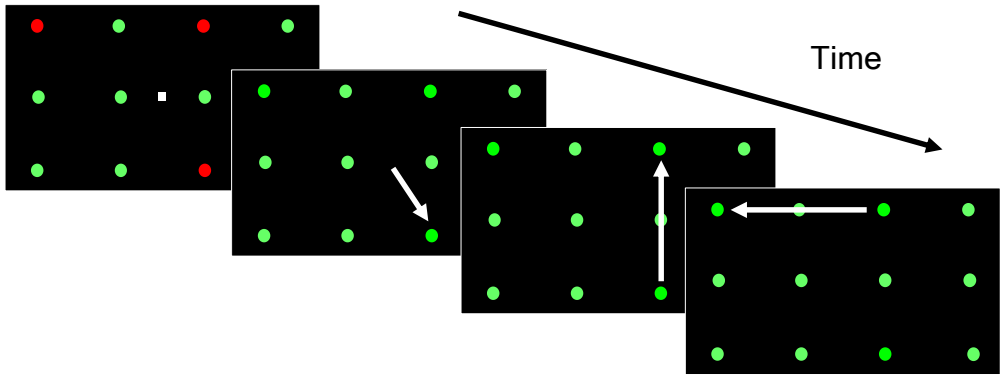
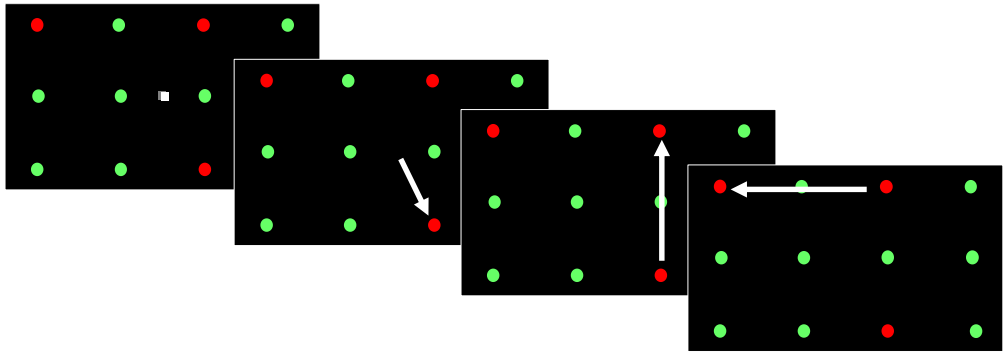
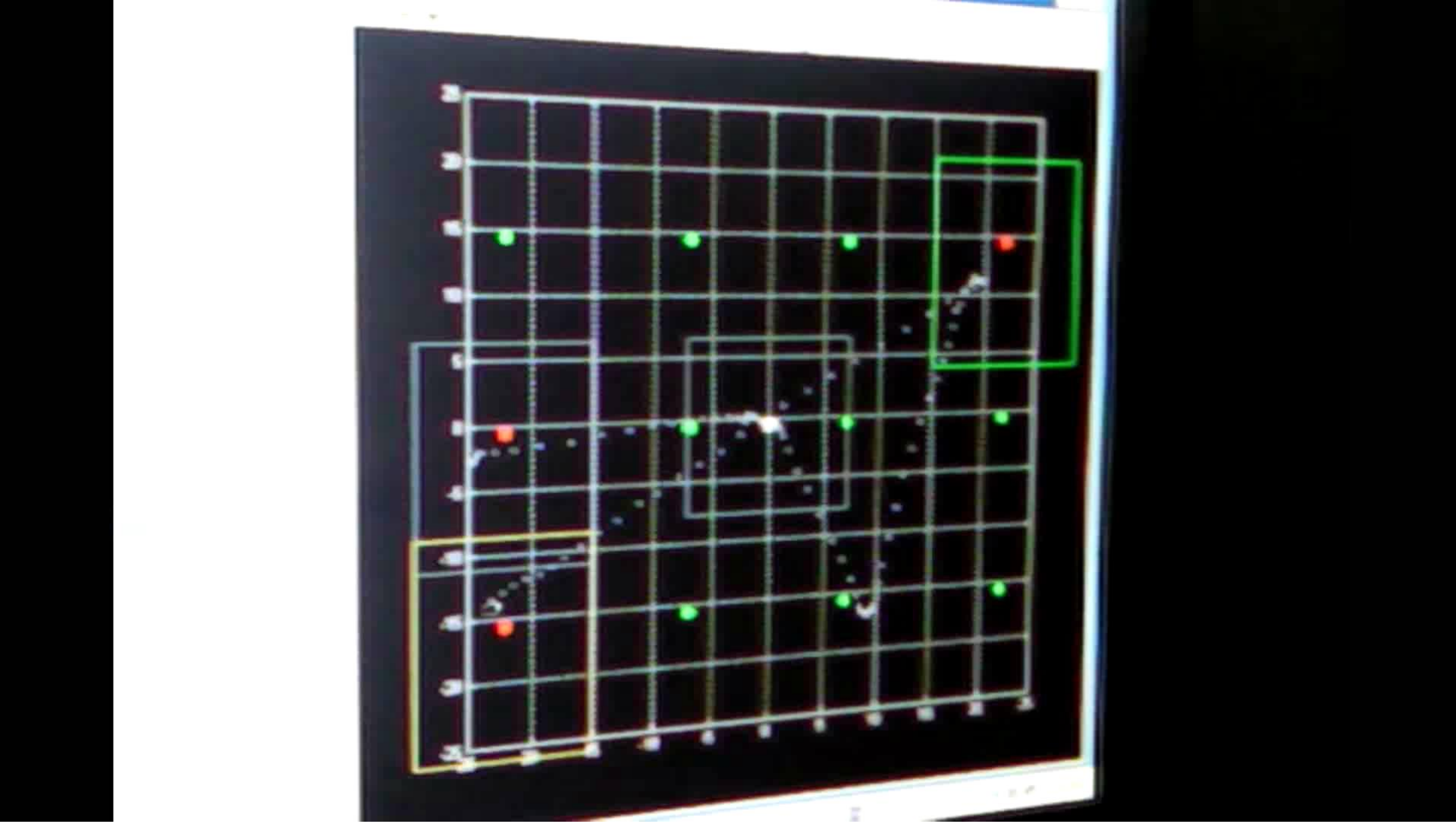
Multi-target memory-guided saccade task (MEM)

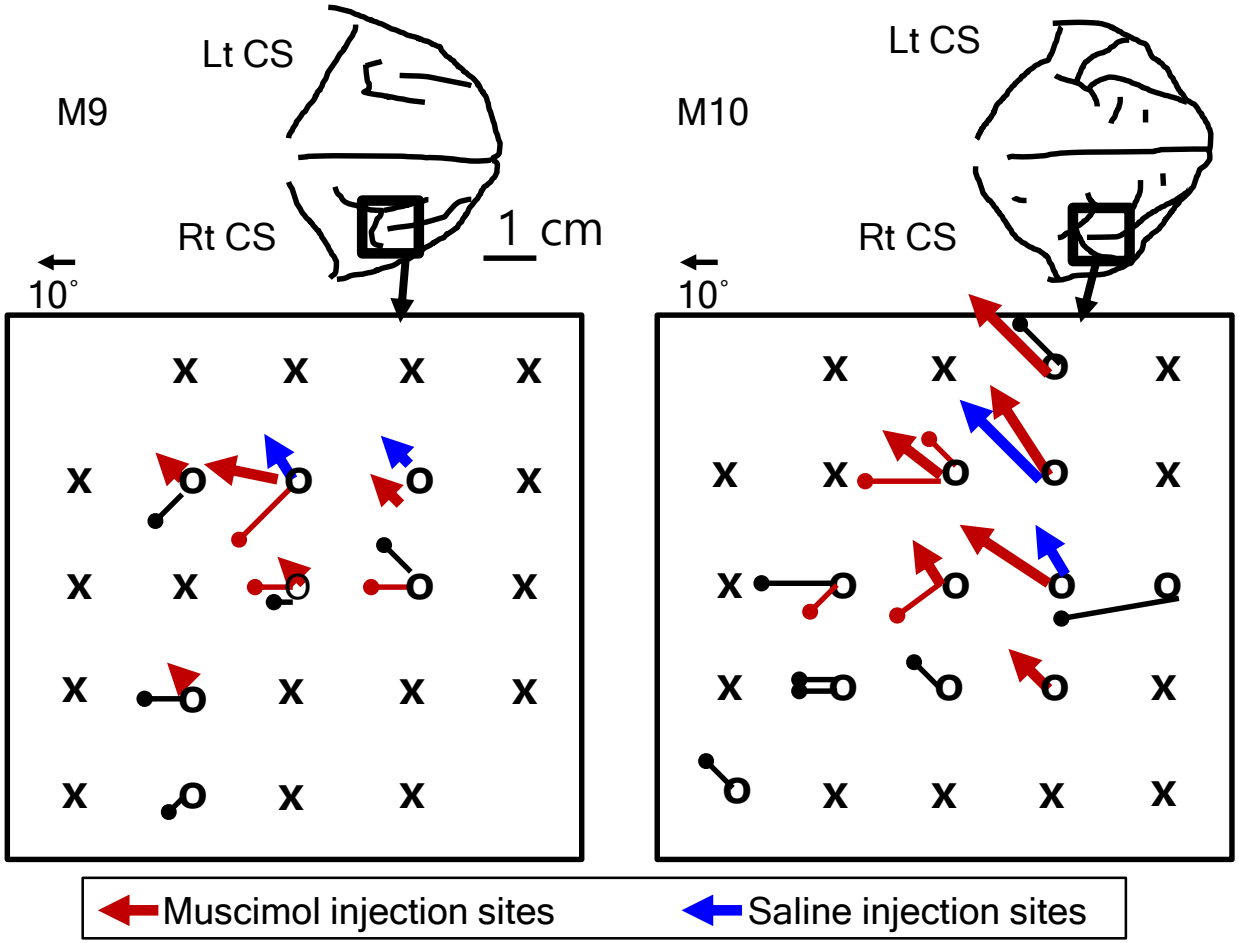


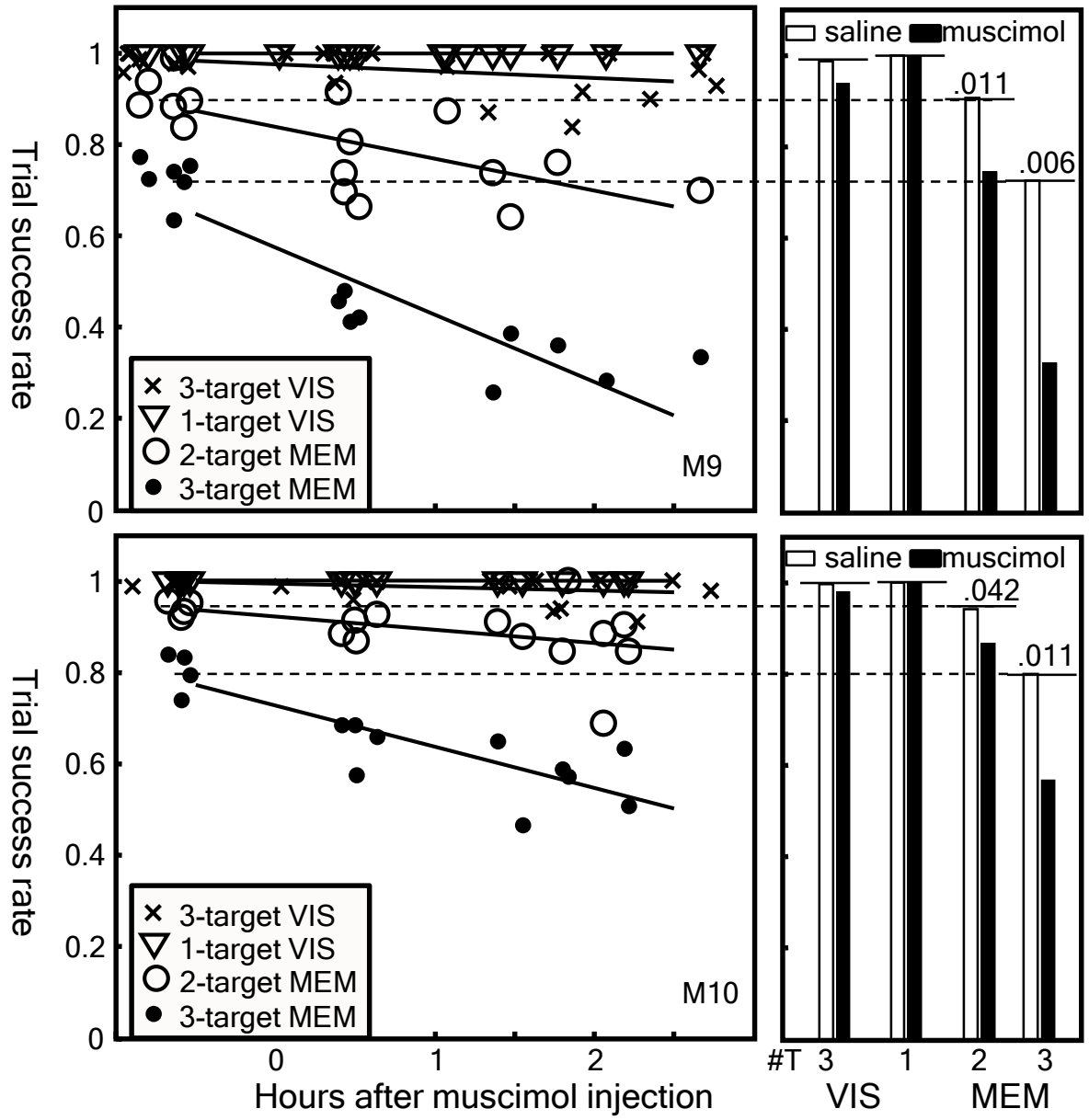
Multi-target visually-guided saccade task (VIS)

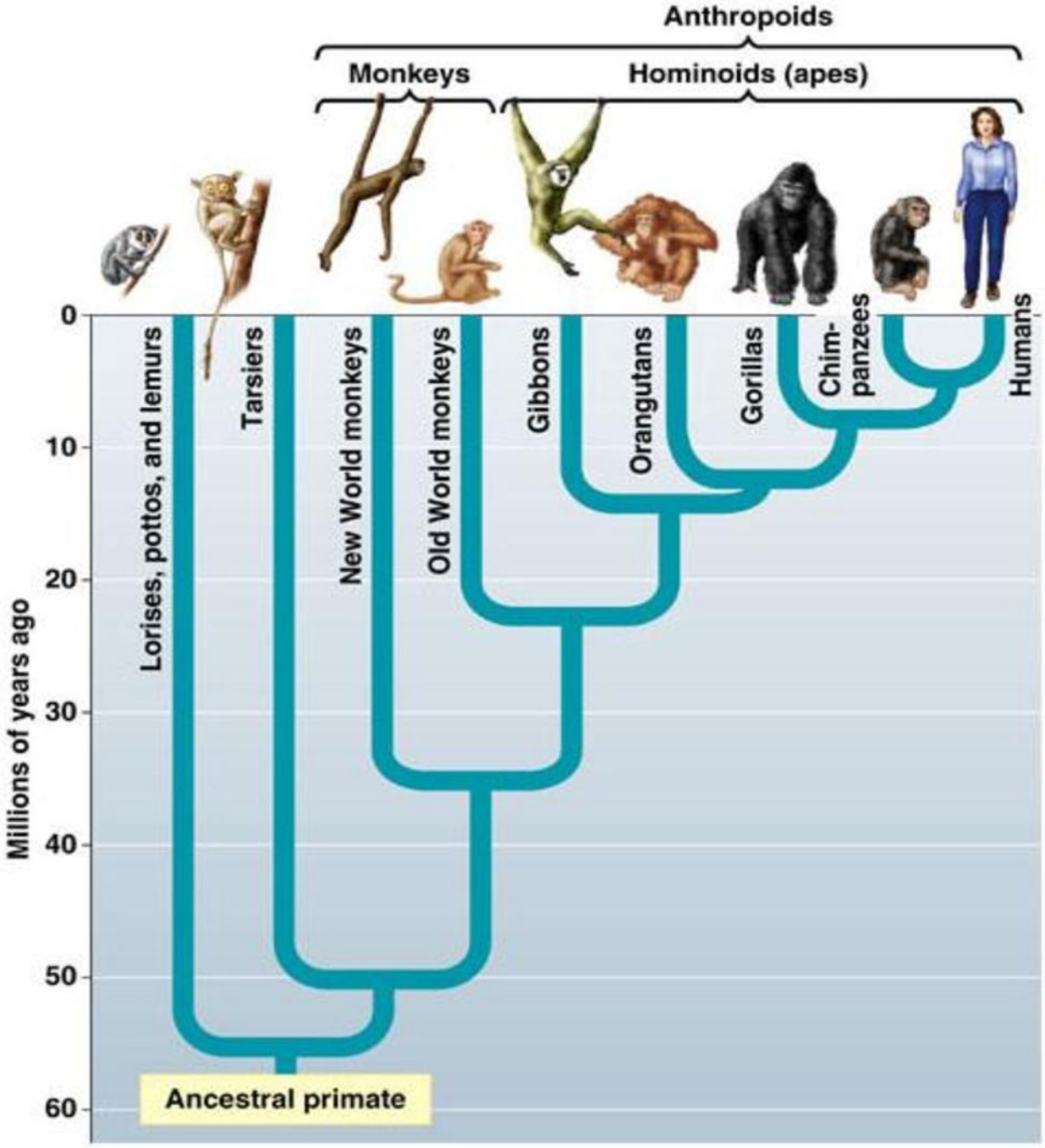






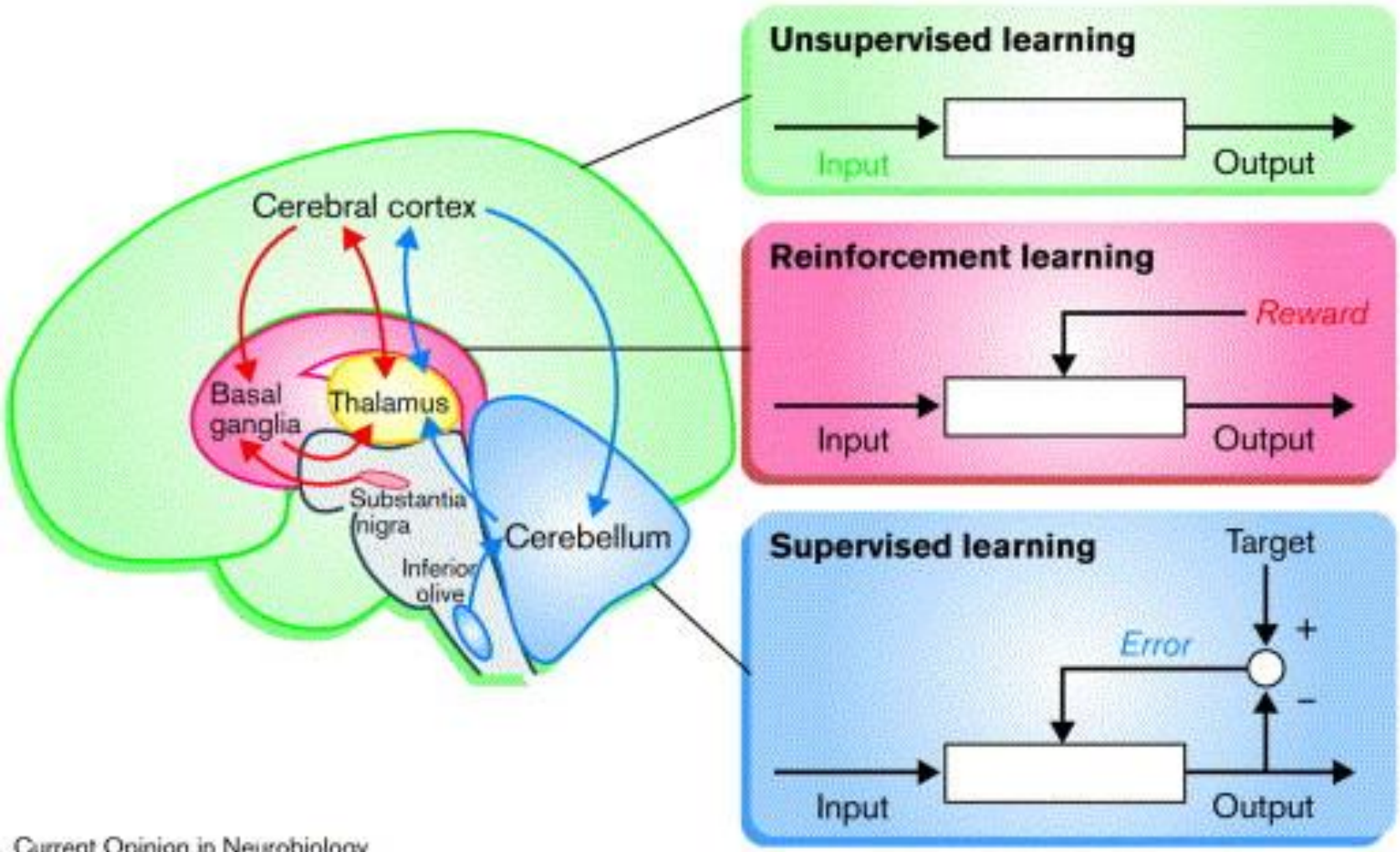

M9
Lt CS
Rt CS
1 cm
10°
M10
Lt CS
Rt CS
10°
Muscimol injection sites
Saline injection sites


Trial success rate
1
0.8
0.6
0.4
0.2
0
3-target VIS
1-target VIS
2-target MEM
3-target MEM
M9
saline
muscimol
.011
.006
M10
.042
.011
0
1
2
Hours after muscimol injection
#T 3 1 2 3
VIS
MEM


Anthropoids
Monkeys
Hominoids (apes)
Millions of years ago
0
10
20
30
40
50
60
Lorises, pottos, and lemurs
Tarsiers
New World monkeys
Old World monkeys
Gibbons
Orangutans
Gorillas
Chim-
panzees
Humans
Ancestral primate

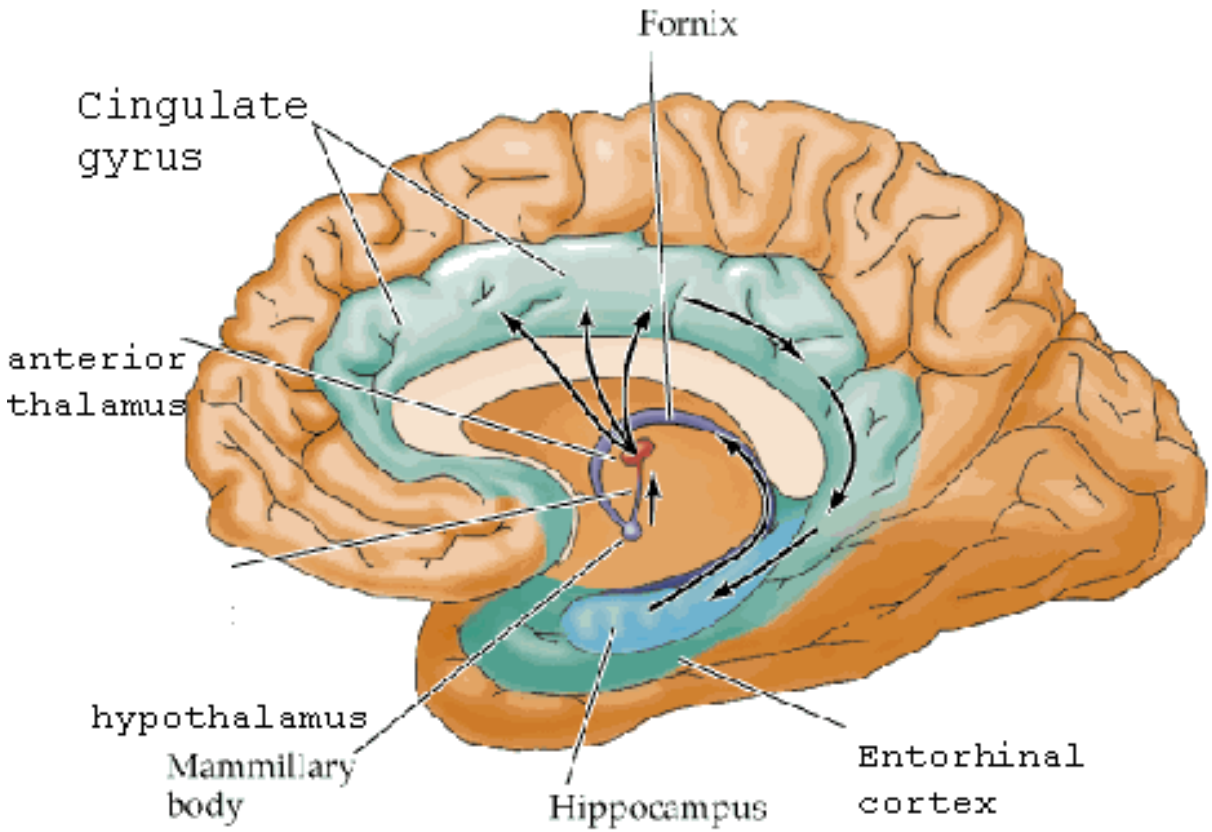
Multiple memory systems (2/2)

- Classification by learning algorithms
  - Reinforcement learning by reward prediction error at the basal ganglia
  - Supervised learning by target error at the cerebellum
  - Unsupervised learning by competitive association at the cerebral cortex
- Classification by the information contents
  - Hippocampus: “representational”
  - Striatum: “associative”
    - sequences of own actions/responses: motor and non-motor
    - stimulus-response associations
- Classification by awareness of memory content
  - Implicit / procedural memory: habit, skill, priming
  - Explicit / declarative memory: episodic m., semantic m.

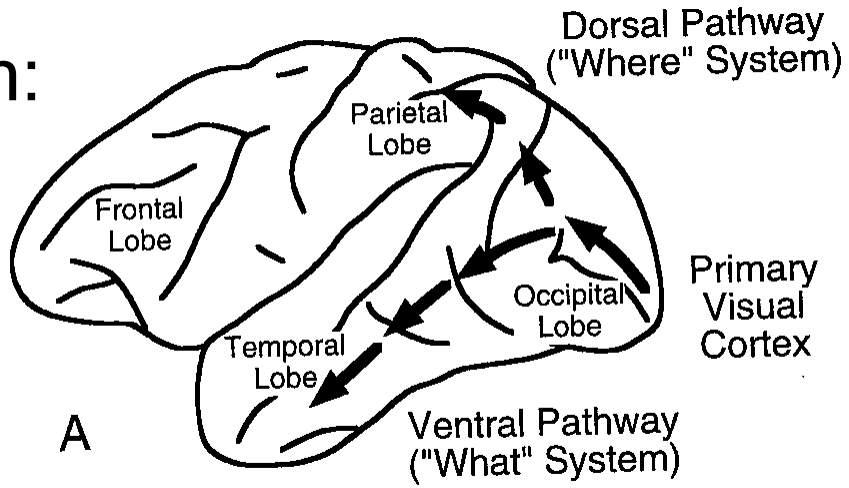


Current Opinion in Neurobiology

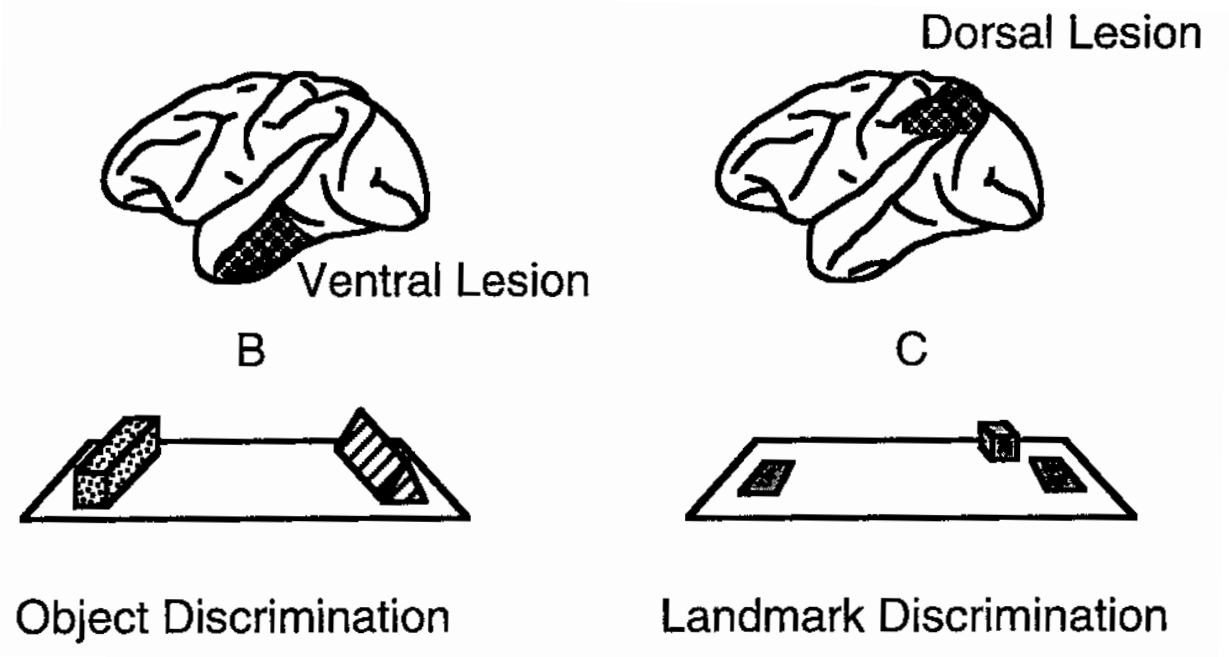
Limbic system (the Papez circuit) for long-term declarative memory



Dual pathways in the brain:



According to Ungerleider and Mishkin, …

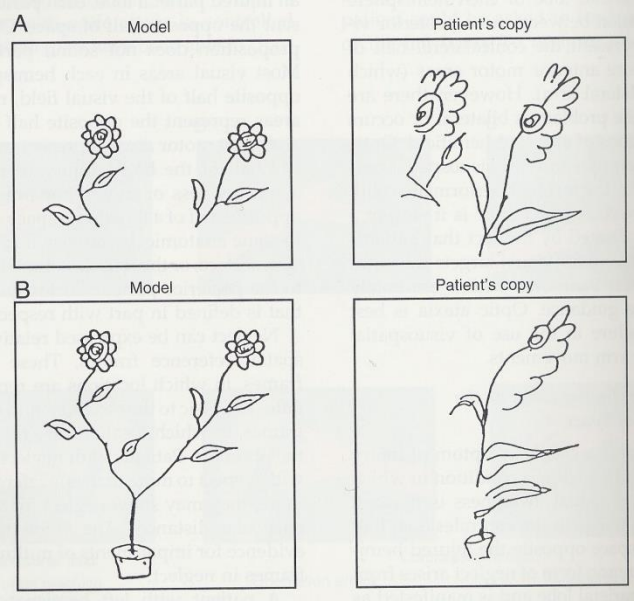


According to Goodale and Milner, …

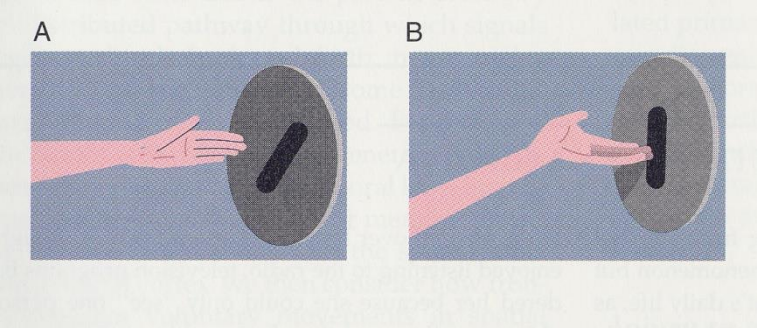
Dorsal lesions cause visuo-motor incoordination (= optic ataxia).

Ventral lesions cause perceptual unconsciousness (= visual agnosia).

Conscious perception



Visuomotor action



What is intelligence?

- Knowledge (episteme) = representational
  - Storage of facts and events
  - Encyclopedia, dictionary, corpus, big data
- Skill (techne) = computational
  - Problem-solving abilities
  - Formulas, algorithms, schemas
- Adaptive production (poiesis) with environments
  - Embedded, embodied, extended, situated
  - Involves the brain, body, society, & the universe
  - Plastic: the Flynn effect, Vygotsky and Luria
  - Experiential processes as the unit of intelligence

Mnemonic views of human intelligence

- Knowledge (episteme) **= explicit memory**
  - Storage of facts and events
  - Encyclopedia, dictionary, corpus, big data
- Skill (techne) **= implicit memory**
  - Problem-solving abilities
  - Formulas, algorithms, schemas
- Adaptive self-production (autopoiesis) = **memory exteriorized on the brain, society, & environment**
  - Embedded, embodied, extended, situated
  - Plasticity of cognitive styles:
    the Flynn effect, Vygotsky and Luria

인간지능 진화의 추세와 변이

- 진화 = 개체간 변이와 반복을 통한 종의 변화
- 추세: Homo sapiens의 특질
  - 지속적 표상을 이용한 정보 처리 과정
  - 사회적 조직화: 언어, 교육
  - 다층적 인지 체계
- 변이: 개체간 변이
  - 다양한 거주 환경이 제공하는 affordances
  - 사회적 압력: the Flynn effect, Vygotsky & Luria

인지의 구체성(具體性, embodiedness)

- 인지 구체성의 두 측면
  - 물리적 특이성에 기반한 감각세계
    sensory modalities ➔ Umwelt, affordance
    피동적 체화

  - 가소적 연결성에 기반한 학습과 적응
    plastic connectivity ➔ learning
    능동적 체화

인지적 변이와 가소성의 뇌 기반

- 뇌 정보처리의 복합적 층위 구조
  - 감각 정보 처리 = 지각과 운동
    → 척수, 뇌간, 대뇌피질
  - 정보 처리 기제의 변조 = 학습
    → 소뇌, 기저핵, 변연계
  - 정보 처리와 학습의 통제 =인지 제어
    → 전전두엽

지능 체계에 대한 물리적 제약

- 가능한 정보 체계들의 집합에서 선택
- 정보 체계의 실현에서 물질성 = 물리적 제한성
  개체의 물리적 재생산을 통한 정보 체계의 지속
  - 제한1: 최소 에너지 법칙 (에너지 효율성)
  - 제한2: 정보 처리의 정확성과 신속성의 양립:
    추상적 표상 ⇐⇒ 구체적 실재
  - 제한3: 종의 적응성과 효율성의 최적화:
    개체의 변이와 반복 (exploration-exploitation)
    - 진화의 기전은 적자 생존이 아니라 적자 산출
      = 변화의 필연성에 대항하는 다양성의 확보가 필수

요약: 뇌 발달과 지능의 진화

- 뇌의 이중성: 생체 조직이면서 정보 처리 체계
  - 전기화학적 회로: 에너지 대사, 뇌 혈류 조절
  - 정보처리 체계: representation + computation
- 물질적 존재와 정보처리 과정의 상호 작용
  - 가소성 신경망에 의한 개체의 경험 축적
  - 개체의 재생산과 변이 축적을 통한 종의 진화
- 인간 지능 이해의 확장
  - 구성의 확대: embedded, embodied, extended
    ➔ Ecological intelligence
  - 내용의 확장: rational reasoning, cognitive nonconscious, intelligent processes
    ➔ Posthuman intelligence

인공지능 시대의 학습과 교육

이 영 준
한국교원대학교

2019. 5. 31.

목 차

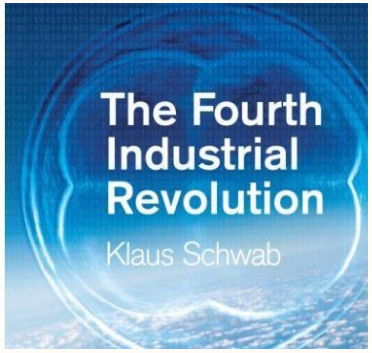
- **지능정보시대**
- 인공지능의 발달과 학습
- 인간의 학습과 기계 학습
- 맺는말

WSIS Forum 2019

- **ITU WSIS AI FOR GOOD BRIEFING**
- **Life plus Enterprise in 2019 to 2022 – 4th Industrial Revolution to the 5th Machine Age: Investments, Challenges, Opportunities and Frontier Innovations**

- Stephen Ibaraki

4th Industrial Revolution to 5 MUX

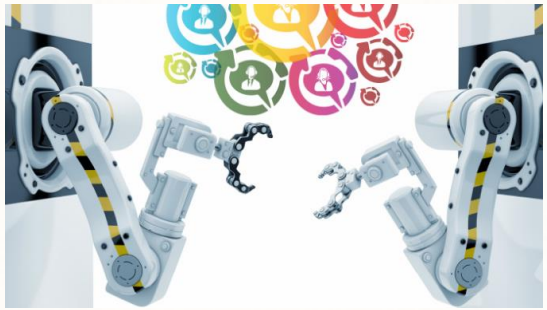




The Fourth Industrial Revolution now: Society 5.0 &
5th Machine-age Unlimited X-revolution (5 MUX)

Three clusters: Physical (4D printing, IoT, …), Digital (transformation), Biological (CRISPR, Cloning, Synthetic life)

EXTREME automation, connectivity



Cyber-physical systems driven by AI and robots



Ex. 2019: MIT Scientists engineer new CRISPR/Cas12b platform for DNA targeting

http://news.mit.edu/2019/scientists-engineer-crispr-cas12b-dna-targeting-0122

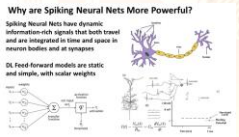
Slide credit: S. Ibaraki

5 MUX : Life

CASAL: Four forms of life (Classic, Augmented, Synthetic, Artificial: Life) existing in 2019



CASAL are four forms of life:
(1) Classic, the **modern form of our species** existing for tens of thousands of years an represented by all of here today
(2) Augmented, those of us, who are already augmented by **technology wearables and implants**—I am augmented and a founding member of a think tank created by VW/Audi where augmented humans participate. Kindred and Neurolink are examples of startups working in this area already
(3) Synthetic, early **fully synthetic genomes**, which are appearing in labs this year with humans appearing in under ten years; **Clones** are possible now with China cloning primates and **embryo genetic editing** in Dec 2018
(4) Artificial, **early AI children evidenced by Sophia**, as a hint of what is to come—sharing/accelerating their development and knowledge through a Mind Cloud. Mind.ai , Orbai.ai examples; Gates' creates company worth 10x Microsoft.

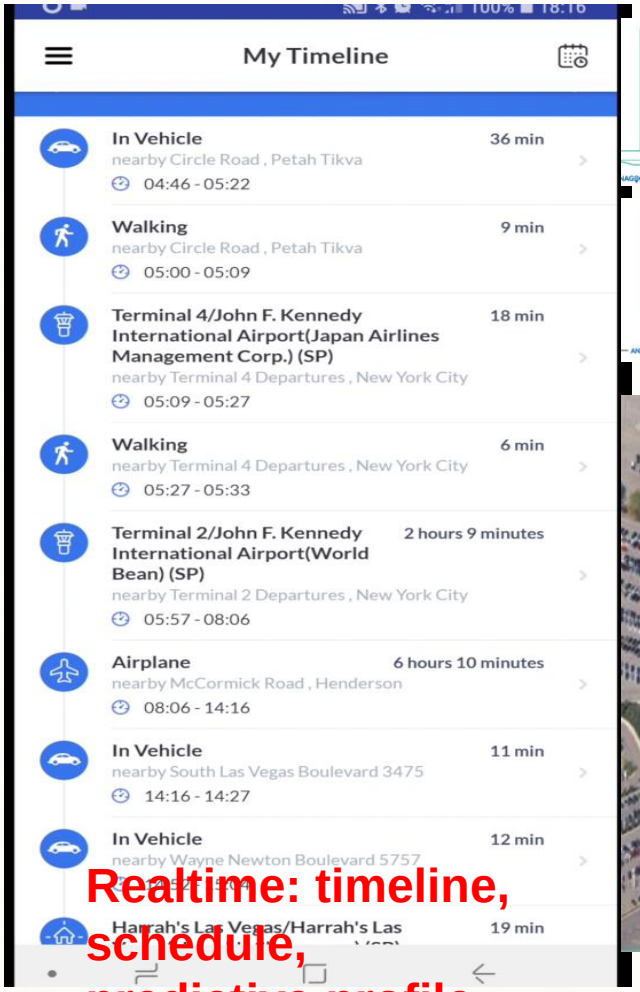




Slide credit: S. Ibaraki

5 MUX today – AI on the Edge—no Personally Identifiable Information shared

Automotive & Mobility: Map all behavior and provide instant recommendations
Banking: Map customer activities providing precise real-time services matching lifestyle
Insurance: Provide personalized services from predictive and prescriptive analytics
Retail: Track purchases inside and outside of retail locations to provide precise services
Adtech: accurate location based advertising personalized to behaviors
Telecom: provide targeted services from tracking data



Realtime: timeline, schedule, predictive profile

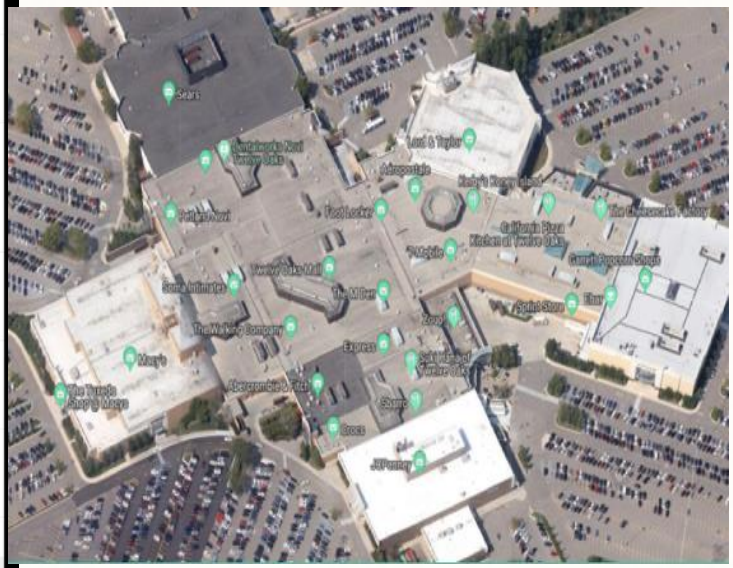








Anagog use case videos



Slide credit: S. Ibaraki

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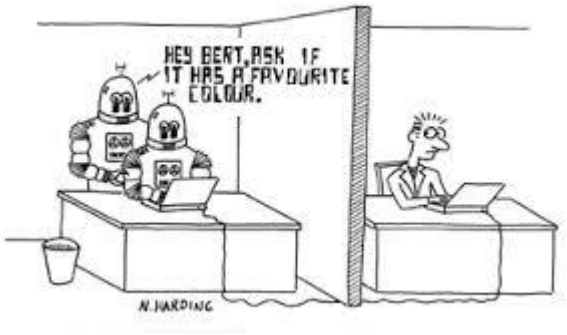
- **인공지능의 발달과 학습**
- 인간의 학습과 기계학습
- 맺는말

인공지능 연구의 역사

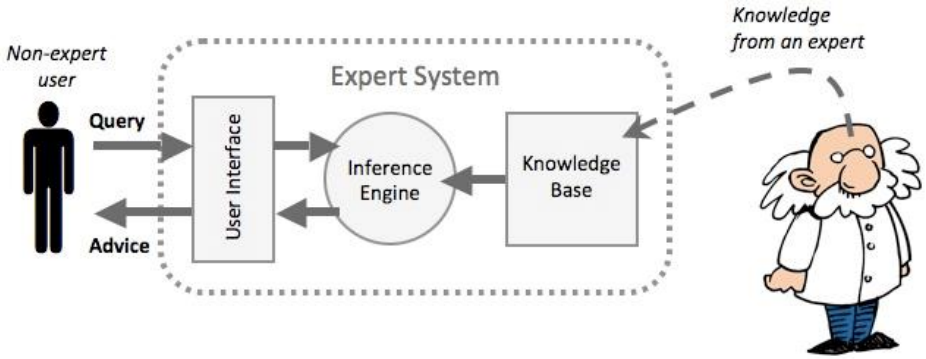
1950~70년대: 1차 황금기



1980년대 초: 2차 황금기

"Divide and Conquer"

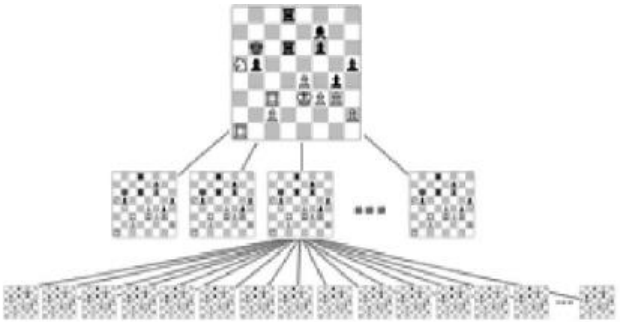
"Expert Systems"



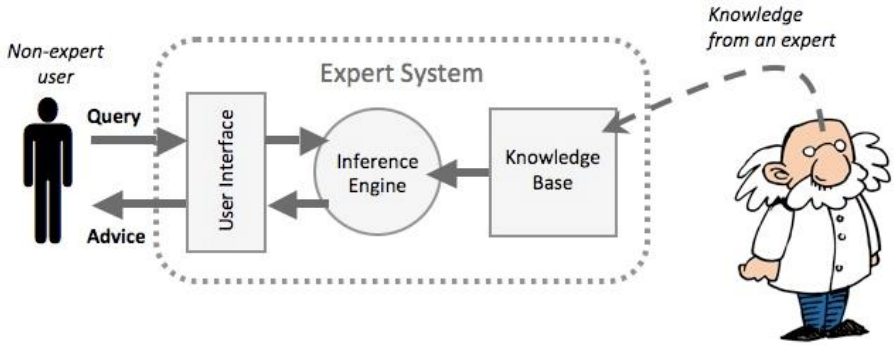
오늘: 3차 황금기



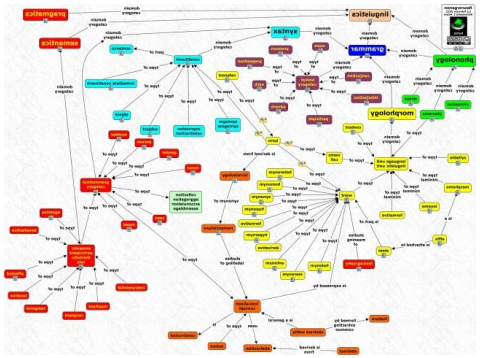
과거의 인공 지능



다양한 경우의 수를 파악하여 최적화



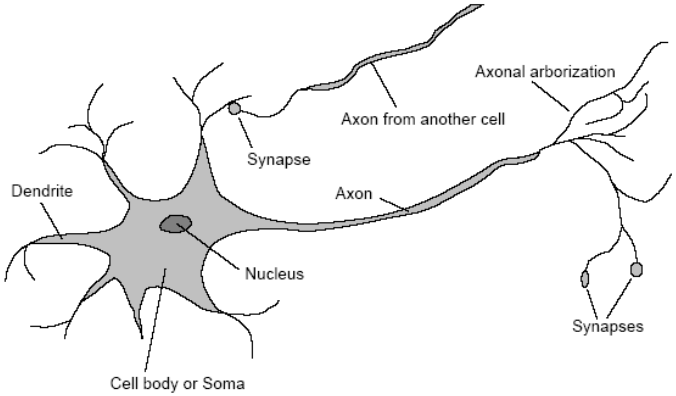
방대한 DB에서 간단한 추론 규칙을 통한 질의 응답



구문 분석을 통한 문장 구조화

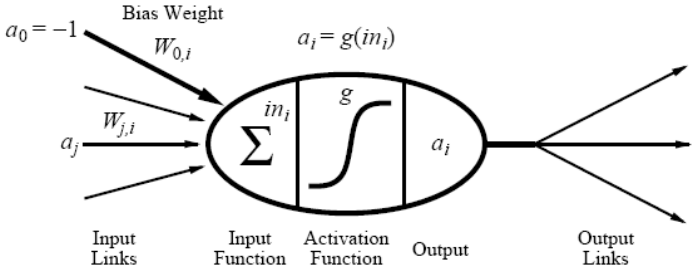
(Artificial) Neural Networks

- Motivation: human brain
  - massively parallel (*10^{11} neurons, ~20 types*)
  - small computational units with simple low-bandwidth communication (*10^{14} synapses, 1-10ms cycle time*)

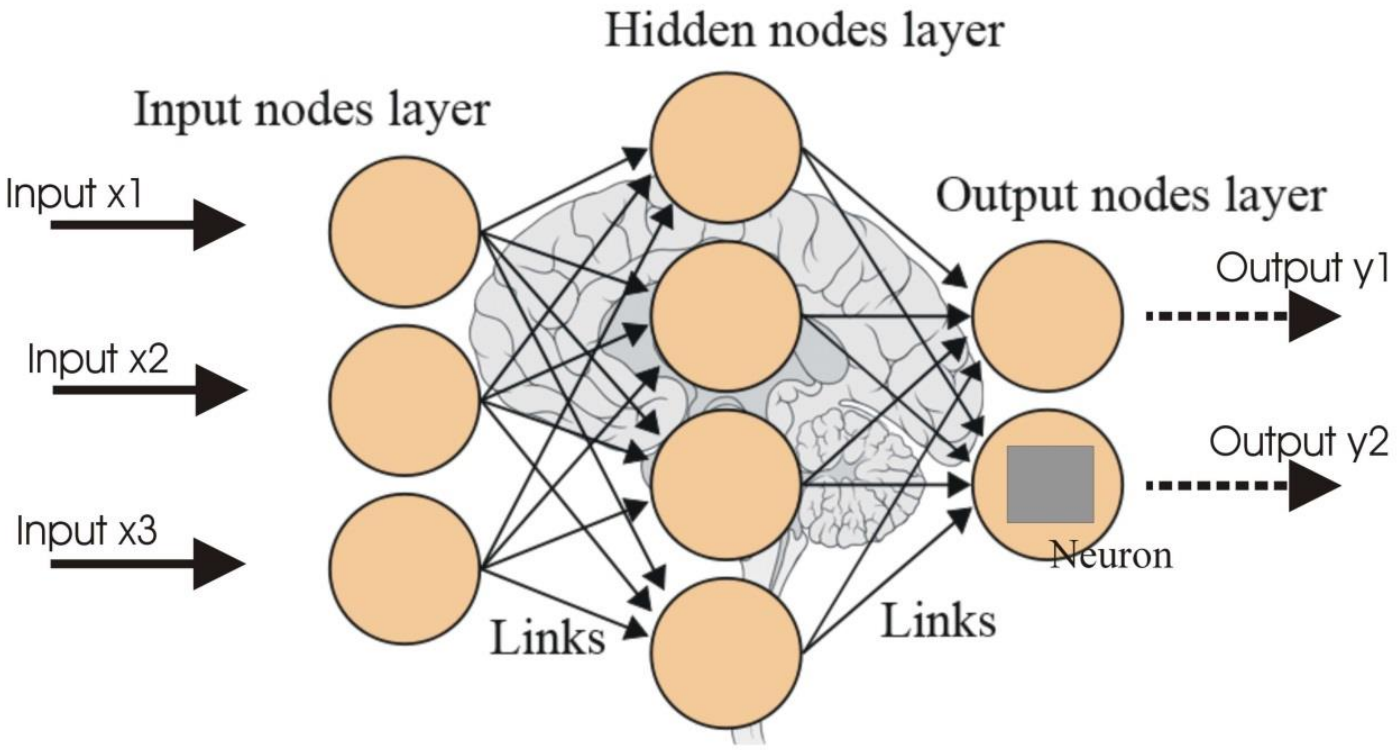


- Realization: neural network
  - *units* (≈ neurons) connected by *directed weighted links*
  - *activation function* from inputs to output

$$a_i \leftarrow g(in_i) = g\left(\sum_j W_{j,i} a_j\right)$$



인공 신경망


Hidden nodes layer
Input nodes layer
Output nodes layer
Input x1
Input x2
Input x3
Output y1
Output y2
Neuron
Links
Links

분류

- 주어진 이미지 분류하기

f() = “apple”

f() = “tomato”

f() = “cow”

이런 함수는 어떻게 만들 수 있을까?

input =

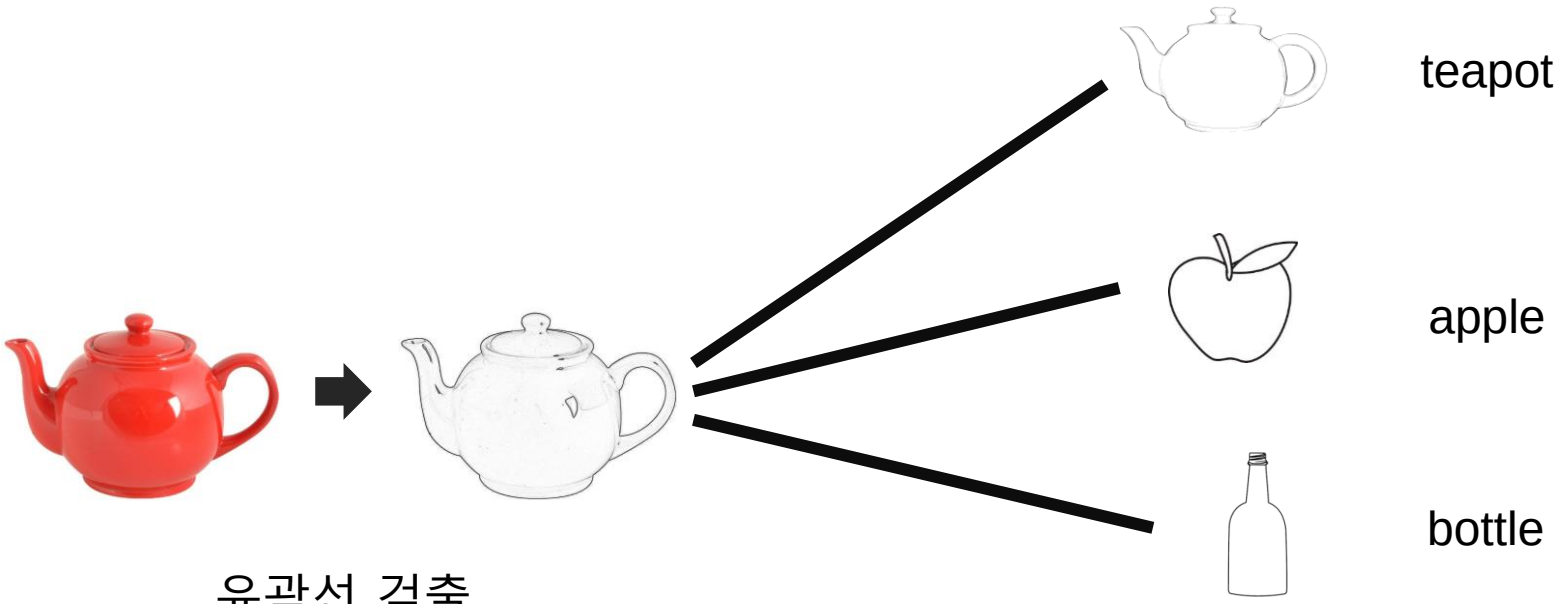


```
public static string WhatIsIt ( Bitmap input ) {

  // ? ? ? ?

  return nameOfIt;
}
```

비트맵 이미지를 입력 받아 무엇인지 출력하는 함수

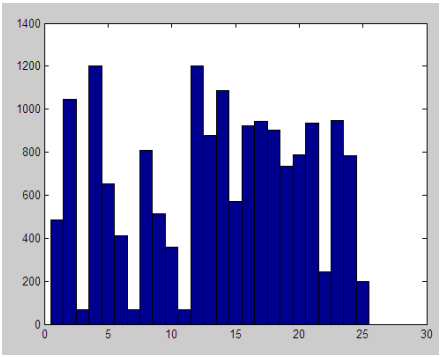


윤곽선 템플릿을 겹쳐보았을 때 얼마나 잘 겹치는지를 비교하여 제일 잘 겹친 것을 선택!

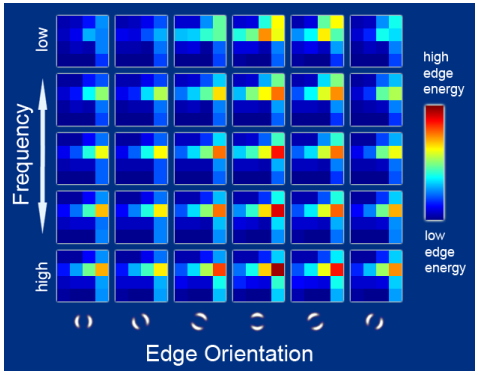
Features

- Raw pixels
- Histograms
- Feature descriptors









성능 올리기가 쉽지 않다



반대로 돌아간 teapot은?



무늬가 있는 teapot은?



특이하게 생긴 teapot은?



배경과 섞여 있는 특이한 teapot은?



사람은?

다른 분야도 제각기 다양한 알고리즘 시도

음성 인식

- 음성 검출, 퓨리에 변환
- 각종 음향학적 필터
- 음소 추출
- 은닉 마르코프 모델 (HMM)

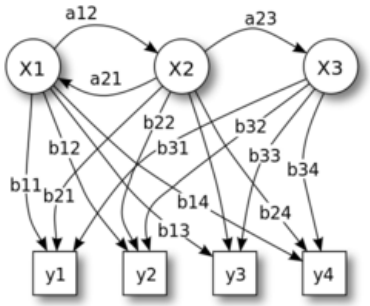
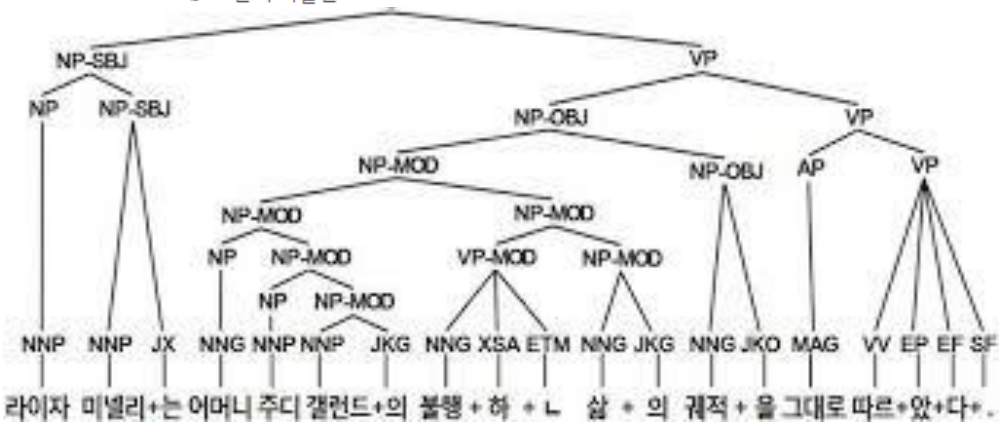


그림 1. 은닉 마르코프 모델의 확률 모수들 (예시)
X — 상태들
y — 얻을 수 있는 관측값들
a — 상태 전이 확률들
b — 출력 확률들

자연어 처리

- 형태소 분석
- 구문 트리
- 기계 번역
- 키워드 추출

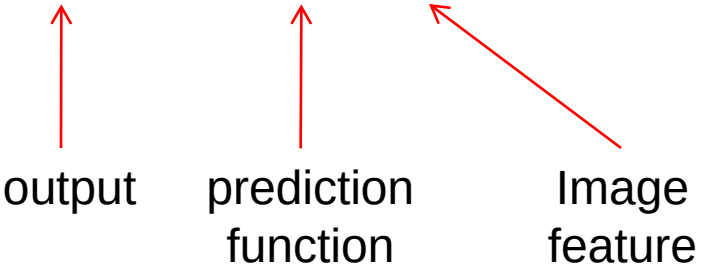


사람처럼 할 수 없을까?

- 배우면서 점점 잘하게 되는 만능 알고리즘?
  - 프로그램하지 않아도
  - 수 많은 데이터들을 통해
  - 내부 동작을 스스로 구성해가며
  - 기존에 고안했던 방법론 이상의 성능을 내었으면...

The machine learning for classification

$$y = f(\mathbf{x})$$



- **Training:** given a *training set* of labeled examples $\{(\mathbf{x}_1, y_1), \ldots, (\mathbf{x}_N, y_N)\}$, estimate the prediction function f by minimizing the prediction error on the training set
- **Testing:** apply f to a never before seen *test example* **x** and output the predicted value y = f(**x**)

Procedure Steps

Training

Training Images



Training Labels

Image Features

Training

Learned model

Testing



Test Image

Image Features

Learned model

Prediction

목 차

- 지능정보시대
- 인공지능의 발달과 학습
- **인간의 학습과 기계학습**
- 맺는말

Learning is…

- To acquire knowledge of a subject or a skill through education or experience,
- To gain information about somebody or something, or
- To memorize something, for example facts, a poem, or music.
- ……

What is Learning?

- *"Learning denotes changes in a system that ... enable a system to do the same task … more efficiently the next time."* - Herbert Simon
- *"Learning is constructing or modifying representations of what is being experienced."* - Ryszard Michalski
- *"Learning is making useful changes in our minds."* - Marvin Minsky

So, how do people learn?

- We don’t know for sure.

So, how do people learn?

- We have multiple theories that provide glimpses of an answer from many different perspectives. These stem from psychologists, philosophers, sociologists, anthropologists, evolutionary biologists, linguists, neuroscientists…

General learning theories

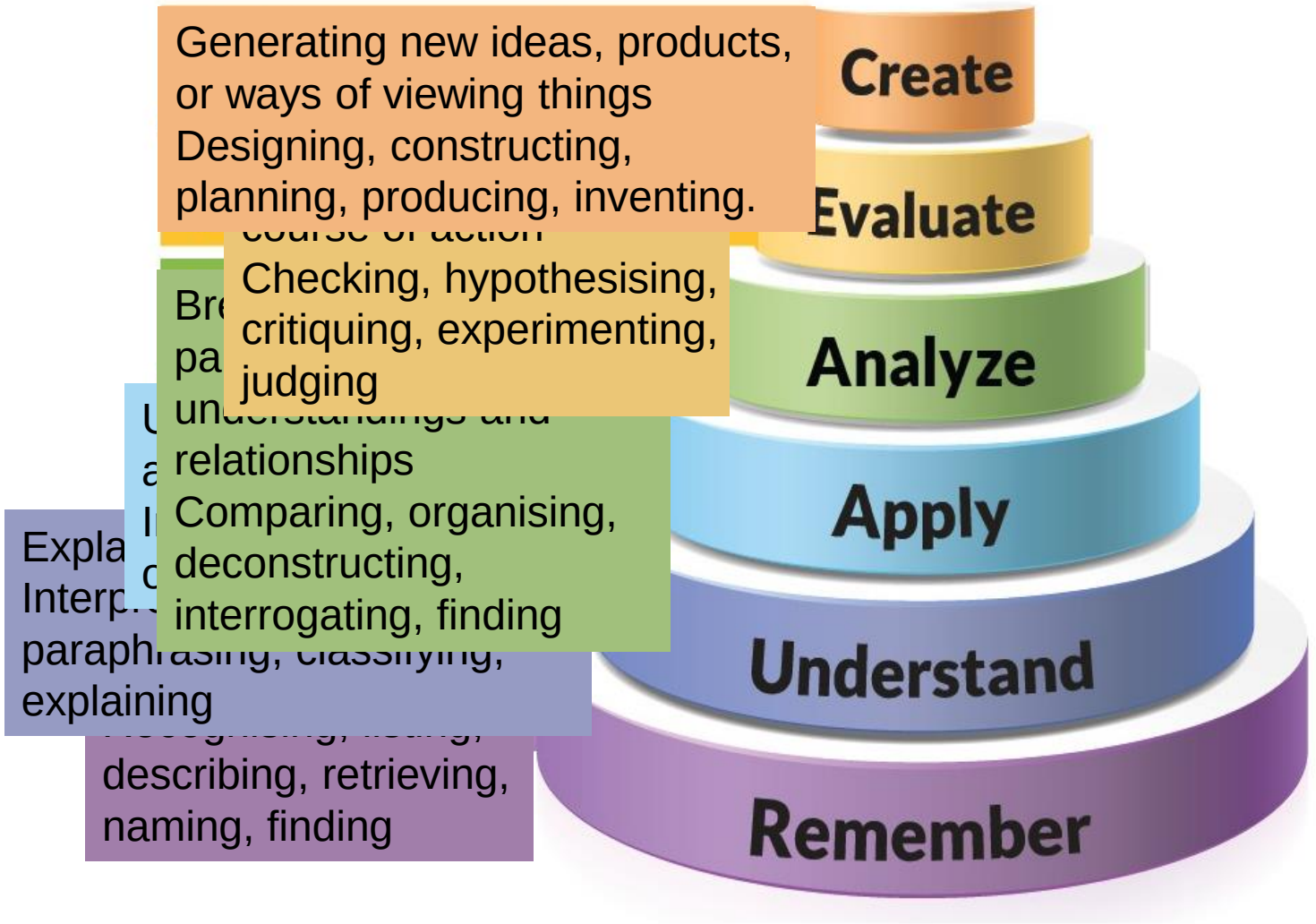
- Behaviorism
- Cognitivism
- Constructivism

Representations of the Learning Process

- Behaviorism
  - Stimulus-Response
  - Reinforced Behavior
  - Antecedent Behavior Consequence
  - Sequenced knowledge and skills presented in logical limited steps
- Cognitivism
  - Cognitivist Learning Perspective
  - Information Processing
  - Schema
  - Mental Models
- Constructivism
  - Inquiry-based
  - Discovery learning

Characteristics of Human Learning

Higher-order thinking



BLOOM'S REVISED TAXONOMY

What is Machine Learning ?

- A core objective of a learner is to generalize(predict) from its experience

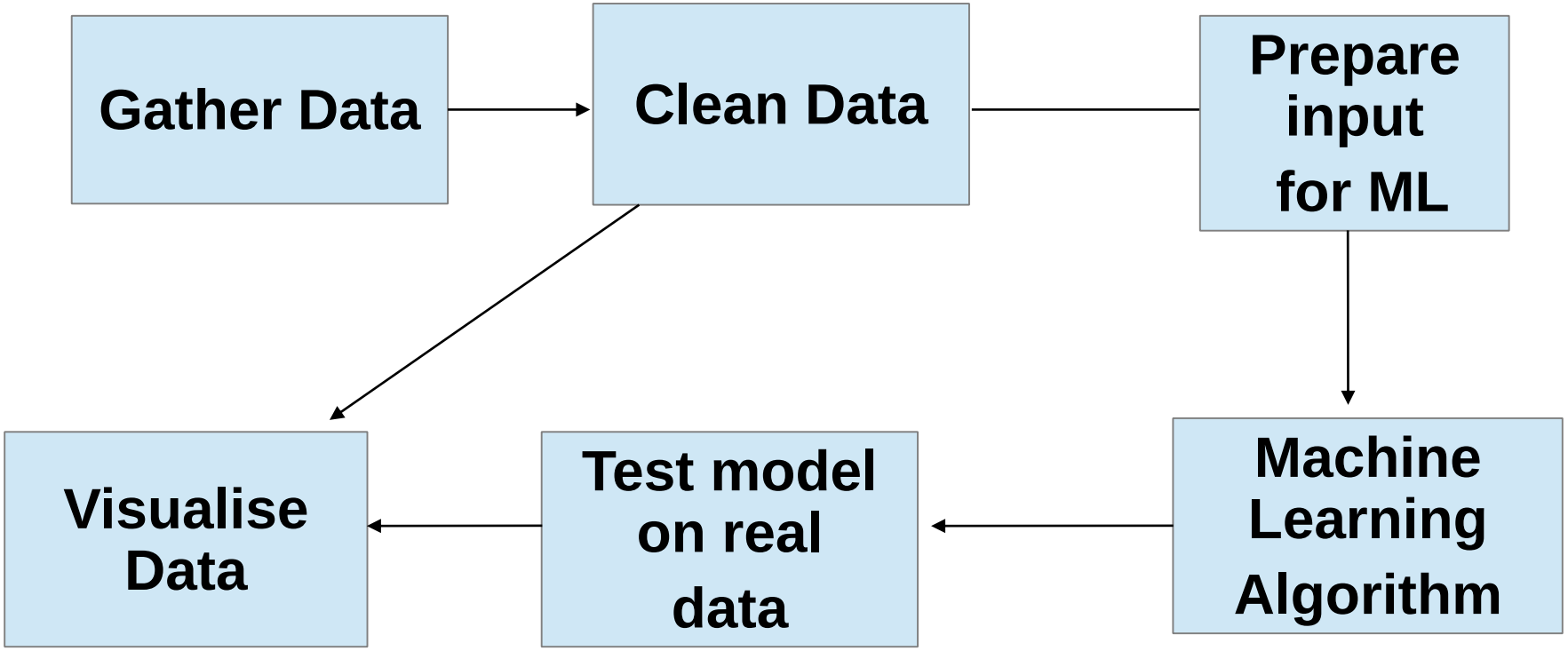
- To computer, experience is all about :

DATA

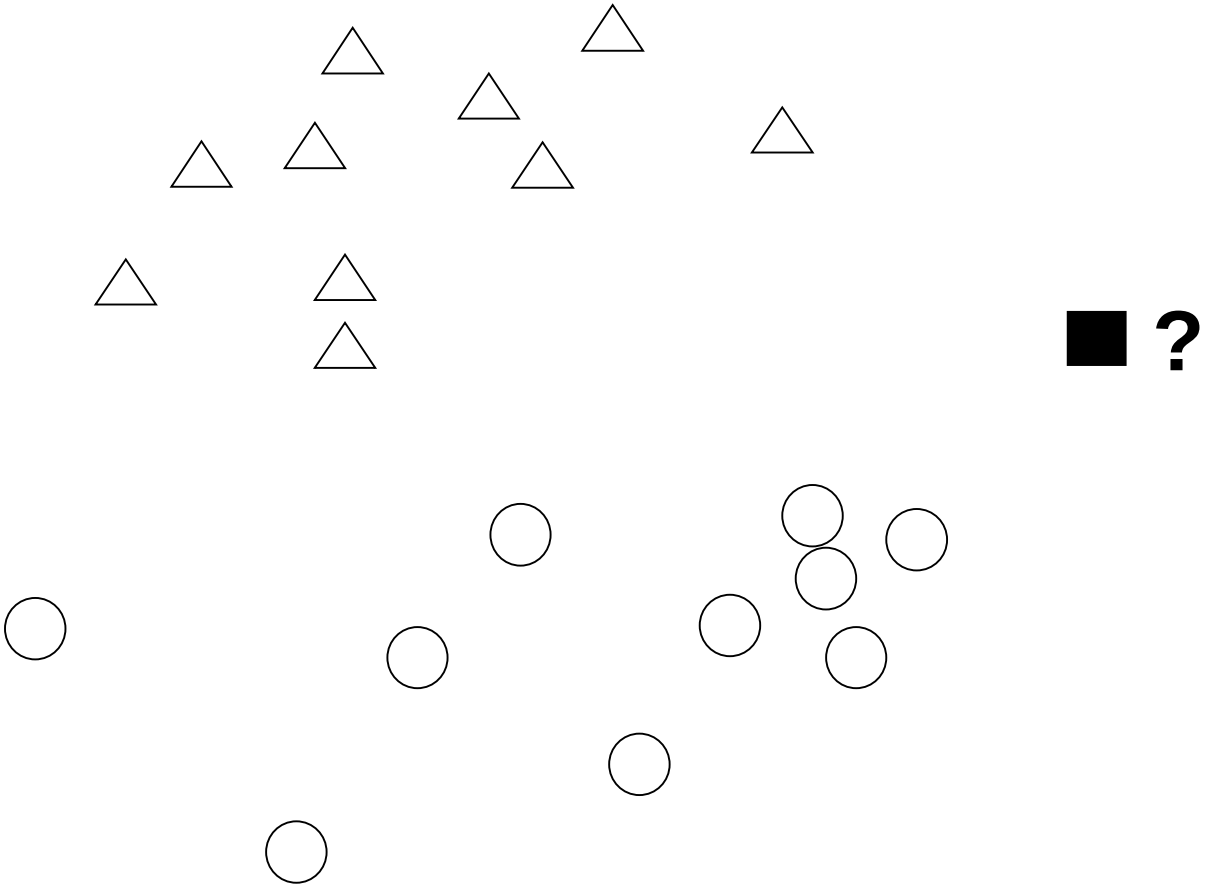
Machine Learning Paradigms

- rote learning
- learning by being told (advice-taking)
- learning from examples (induction)
- learning by analogy
- concept learning
- clustering
- discovery
- …

What is Machine Learning ? How?

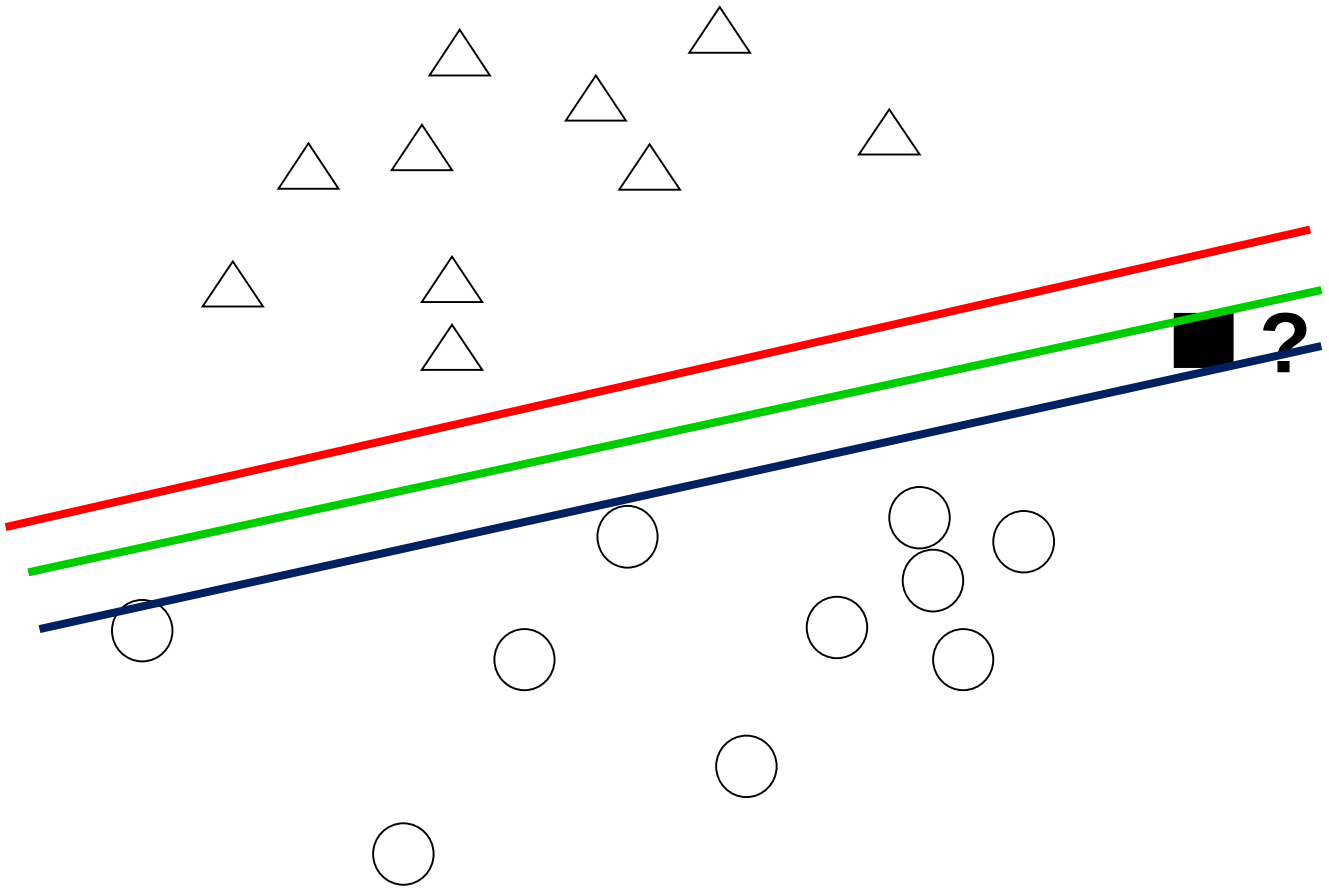


Example: Train an linear classifier



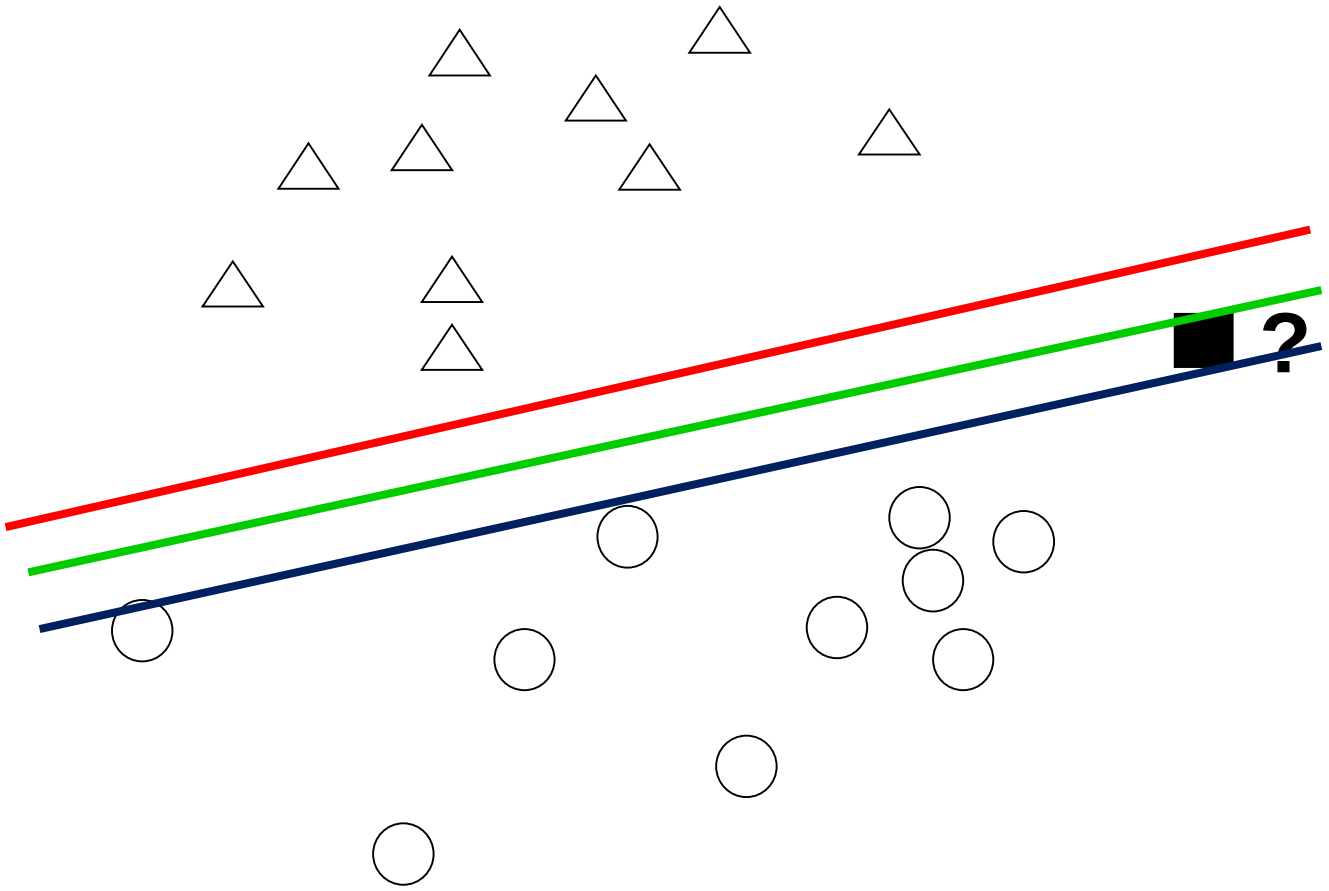
Example: Train an linear classifier

Based on samples, train a model (y = x*a + b) parameter: a, b



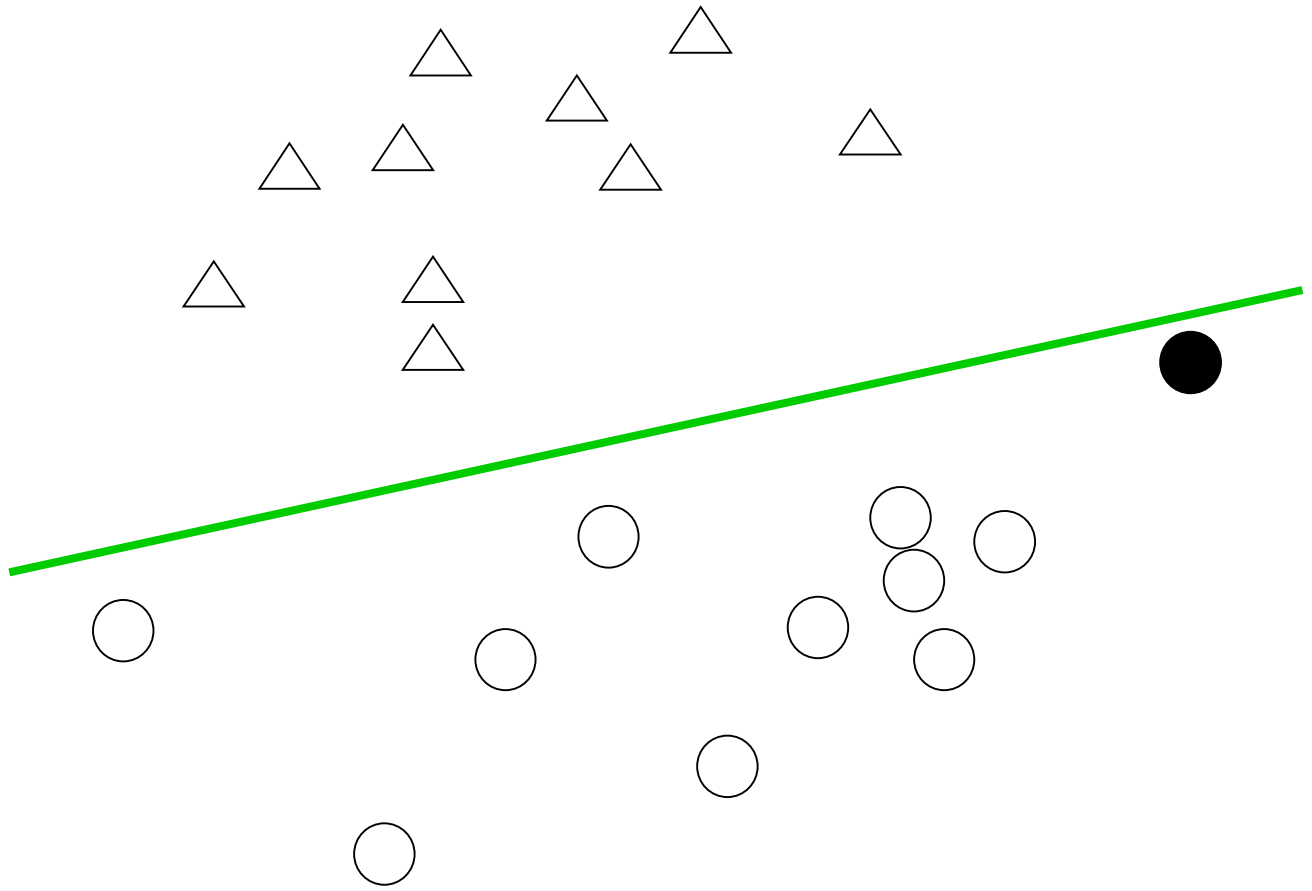
Example: Train an linear classifier

Which model is better ?

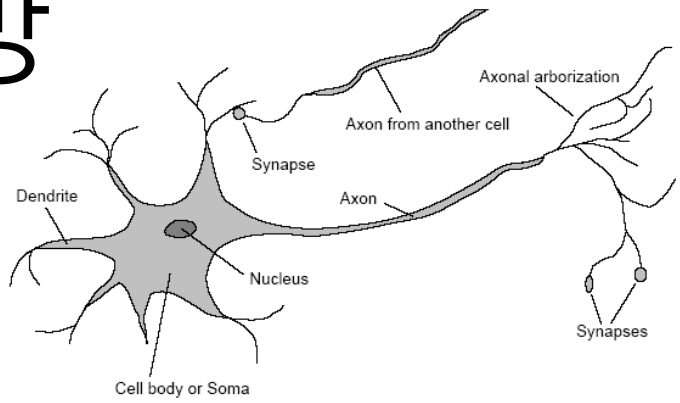


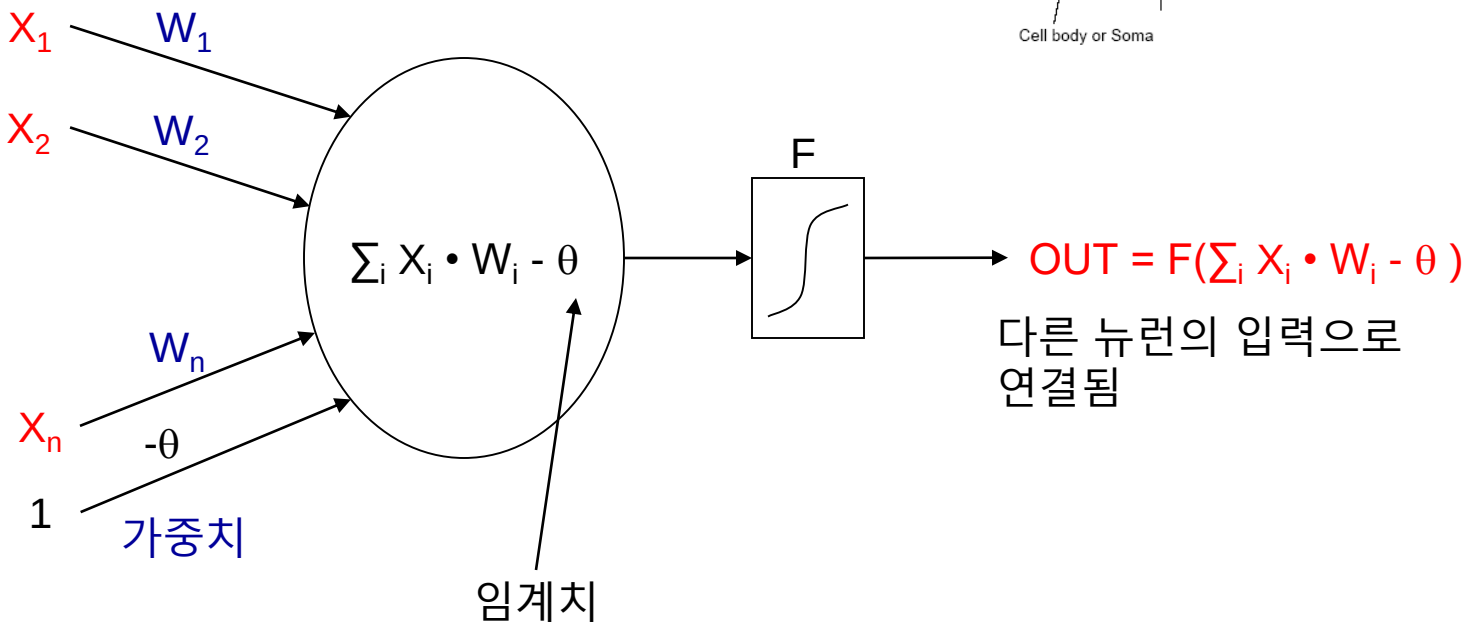
Example: Train an linear classifier

Which model is better ?



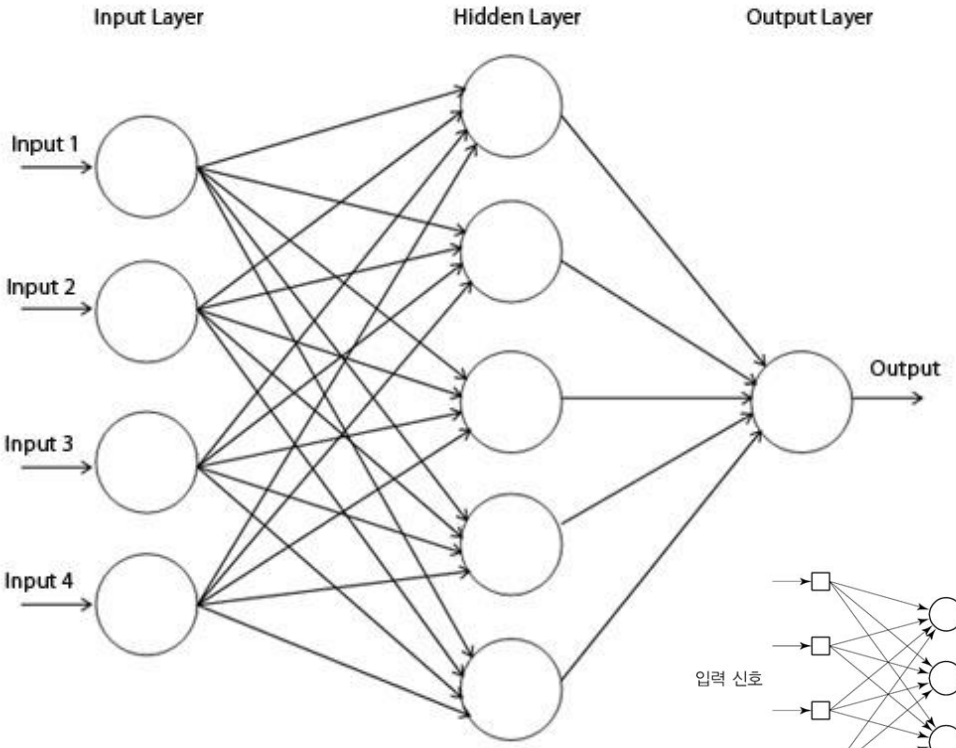
인공신경망

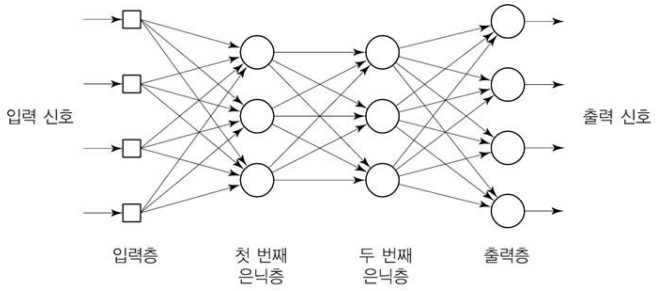

Axonal arborization
Axon from another cell
Synapse
Dendrite
Axon
Nucleus
Synapses
Cell body or Soma


X_1
W_1
X_2
W_2
W_n
X_n
$-\theta$
1
가중치
$\sum_i X_i \bullet W_i - \theta$
임계치
F
$OUT = F(\sum_i X_i \bullet W_i - \theta)$
다른 뉴런의 입력으로
연결됨

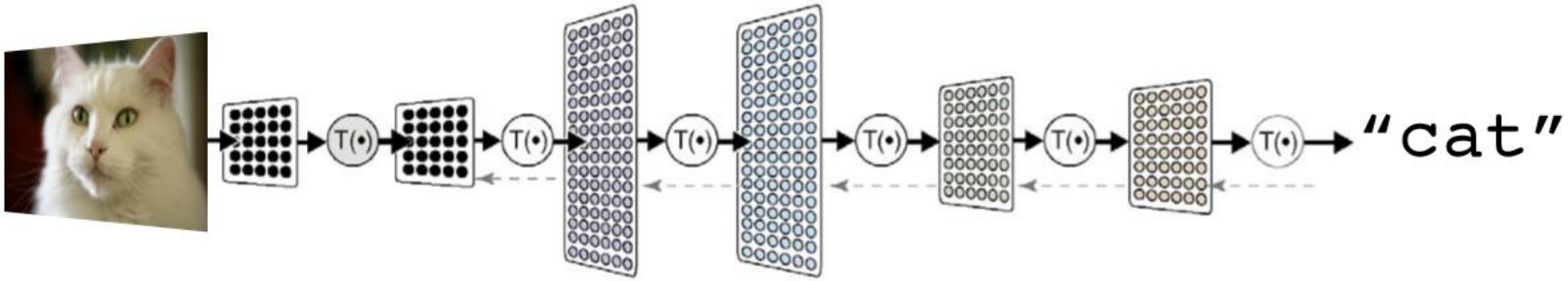
입력

다층 신경망 (MLP : Multi-Layer Perceptron) 1980~



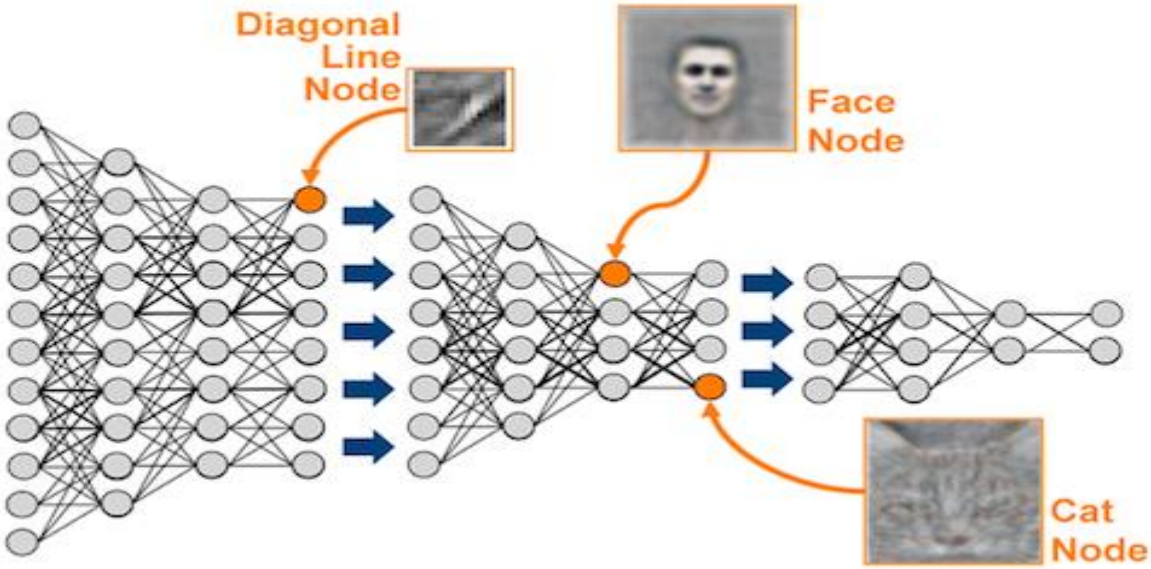


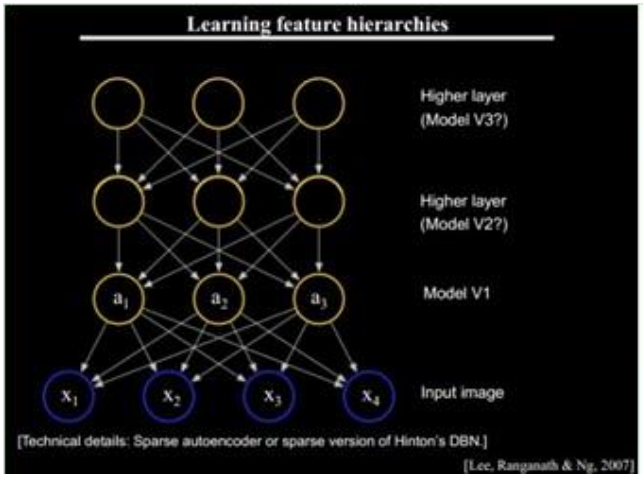
심층 신경망

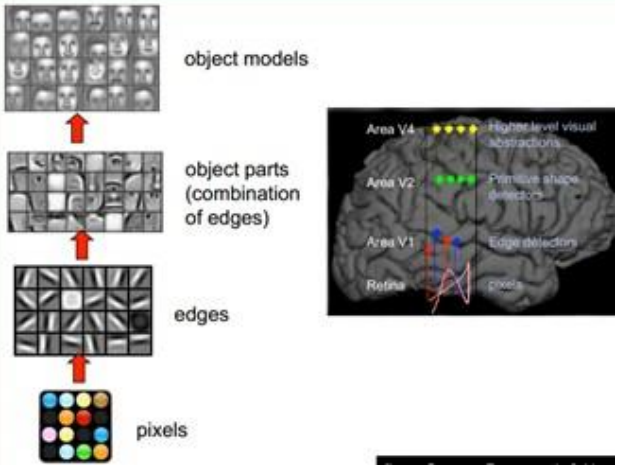


- 여러 층을 효율적으로 학습 시킬 수 있는 방법들이 등장!
- 방대한 데이터와 빠른 성능의 컴퓨터

심층 신경망

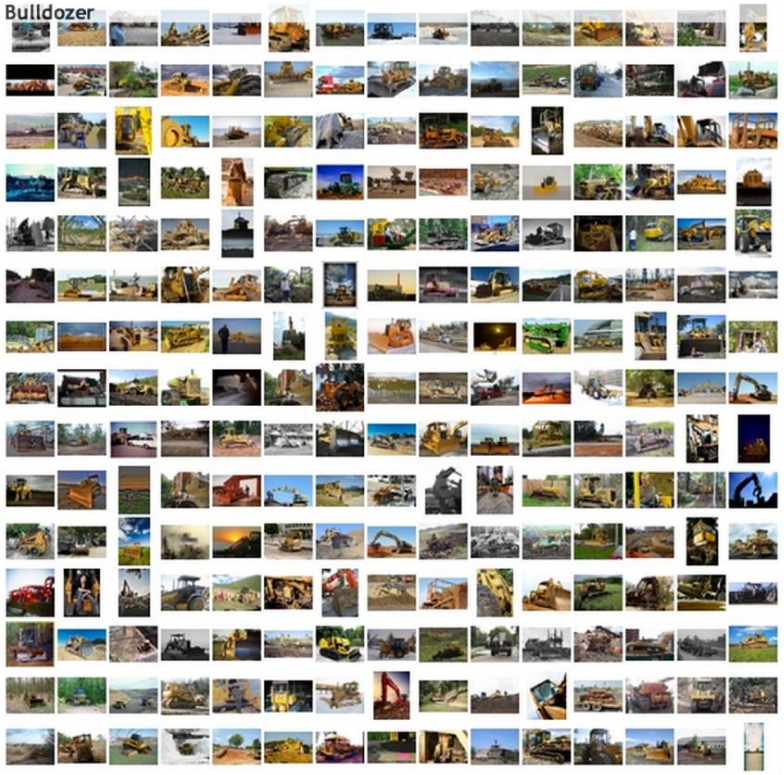

Diagonal
Line
Node
Face
Node
Cat
Node


Learning feature hierarchies
Higher layer
(Model V3?)
Higher layer
(Model V2?)
Model V1
Input image
[Technical details: Sparse autoencoder or sparse version of Hinton's DBN.]
[Lee, Ranganath & Ng, 2007]

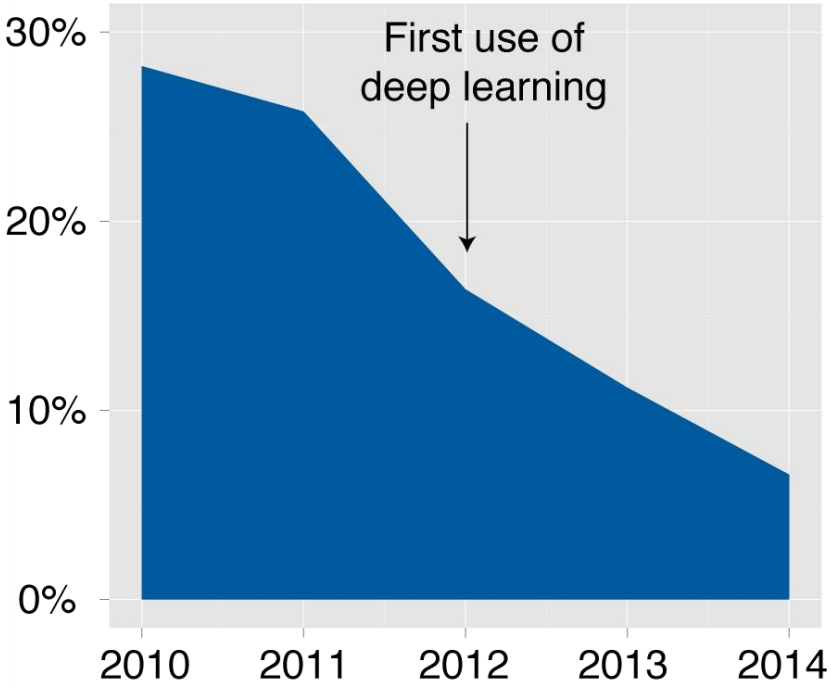

object models
object parts
(combination
of edges)
edges
pixels
Area V4
Area V2
Area V1
Retina

인식 성능이 급속도로 향상

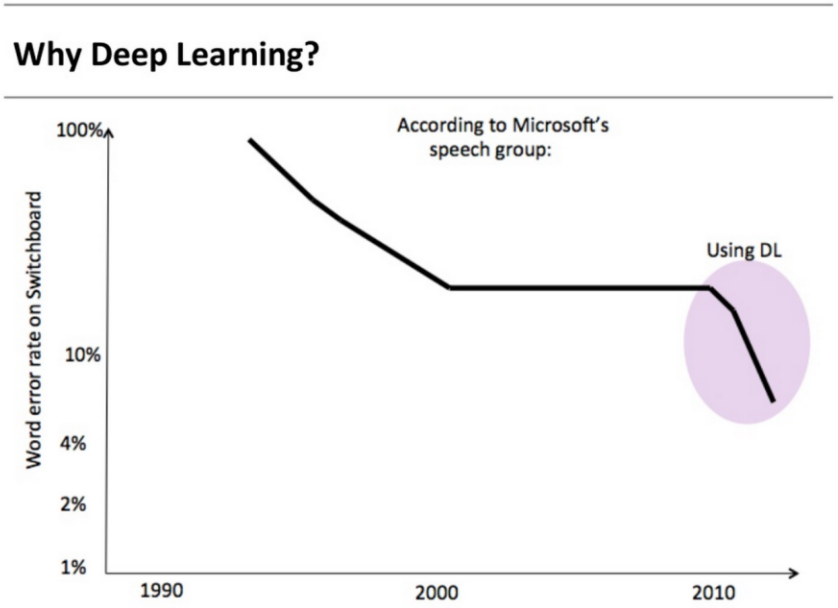
ImageNet examples



Objection classification error rate



이미지 인식 이외의 분야로 확장



음성 인식도 급격하게 에러율 내려감



AlphaGo (2016)
강화 학습으로 방대한 탐색 공간에 대한 고수준 전략을 수행할 수 있게됨

목 차

- 지능정보시대
- 인공지능의 발달과 학습
- 인간의 학습과 기계학습
- **맺는말**

Human learning vs. Machine learning

- Huge data pools (Big Data) are processed with various types of highly complex algorithms to produce digital knowledge without conventional programming.

- In spite of the fact that computers can perform “neural network” processes, they are inspired by the neurons of the brain but are not self-organizing and adaptive.

- It is proven that machine based knowledge far exceeds the capacity of the human brain as far as memorizing knowledge, understanding and comprehending are concerned.

- Human vs. AI ?
- Human with AI

THANK YOU
FOR YOUR ATTENTION!

