Introduction of the Course

吴思
心理与认知科学技术学院
麦戈文脑科学研究所
北大--清华生命科学联合中心
北京大学
Email: siwu@pku.edu.cn

助教：褚天昊、王超名

微信公众号：

吴思Lab计算神经科学及类脑计算

About Myself

Education:

- Bsc. in Physics, BNU, 1990
- Msc. in General Relativity, BNU, 1992
- PhD in Statistical Physics, BNU, 1995

Academics:

- 1995-2000: Postdoc at HKUST, Limburg Univ., RIKEN
- 2000-2008: Lecturers at Sheffield, Sussex Univ.
- 2008-2011: PI at Institute of Neuroscience, CAS
- 2011-2017: Professor, PI at McGovern Institute @BNU
- 2018-present: Professor, PI at McGovern Institute @PKU

Social:

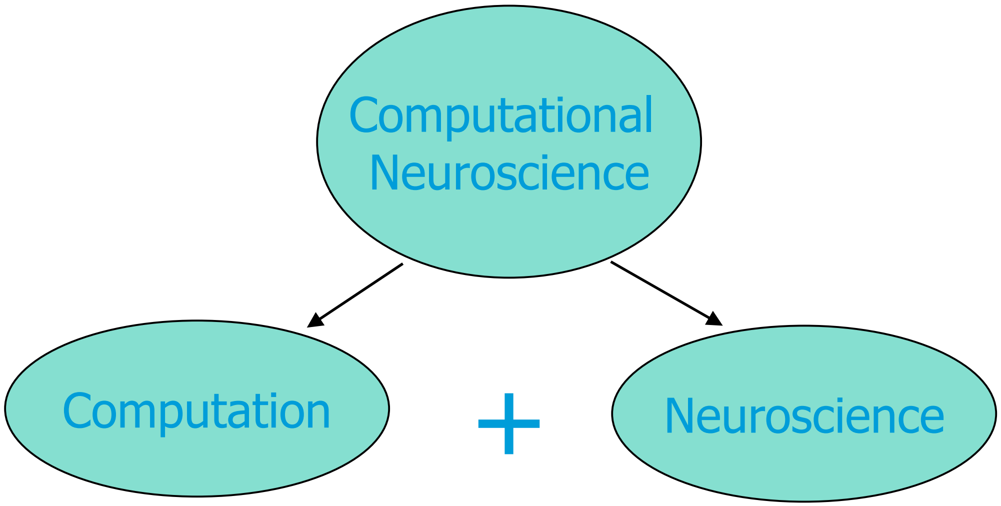
- Front. Computational Neuroscience, Co-Editor-in-Chief

My History of Neural Network

Prof. Shun-ichi Amari
Information Geometry (1985)
Amari-Hopfield model (1970s, 1982)
Continuous attractor neural network (1977, 1990s)
Stochastic gradient descent (1967, 1986)
Natural gradient (1998)
Many others

Prof. Kunihiko Fukushima
Neocognitron (1980)

What is Computational Neuroscience



- A newly emergent (1980s) and vastly developing field.

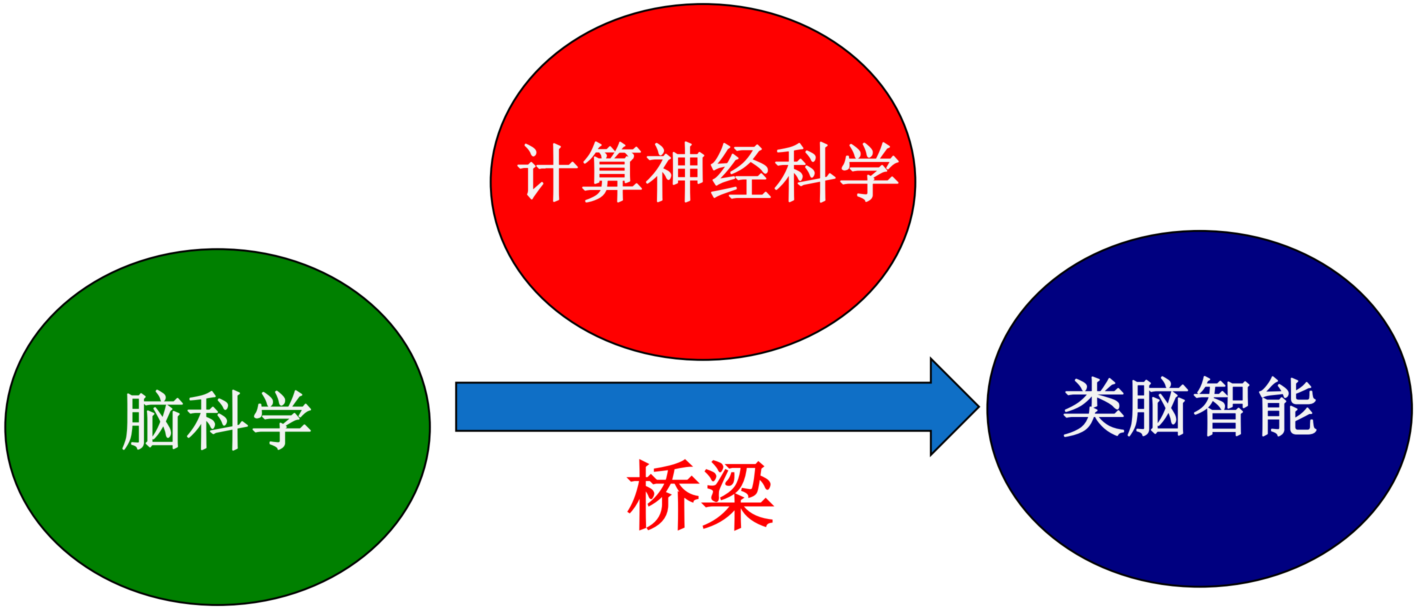
- Highly multidisciplinary, related to biology, physics, mathematics, computer science, engineering, and AI.

- Two aims:
  - ✓ Using mathematical models/approaches to elucidate brain functions
  - ✓ Developing brain-style computational algorithms.

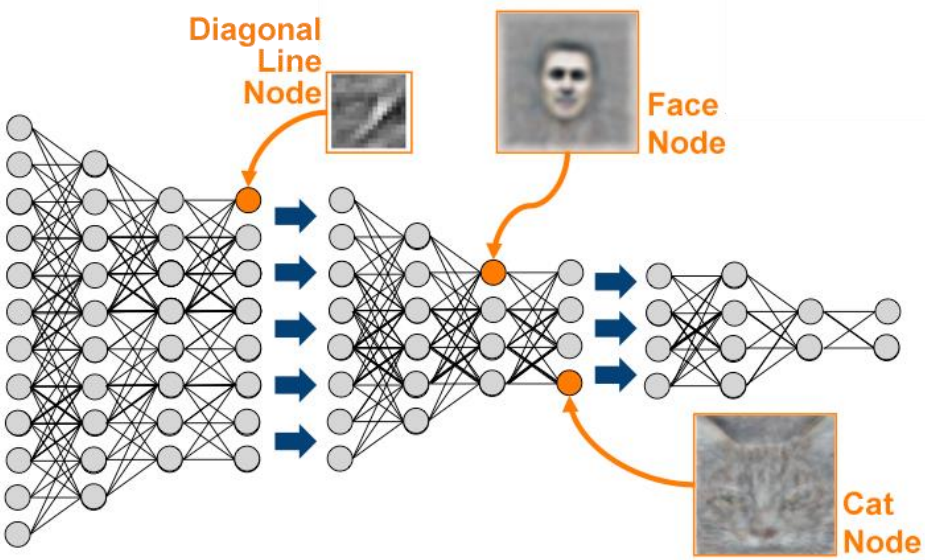
- Challenges: data + math; infant of physics; theoretical physics

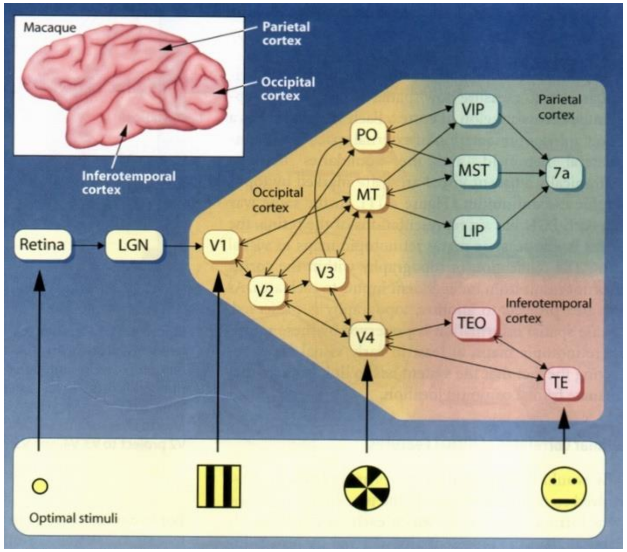
A Bridge from Brain Science to AI

为类脑智能提供新思想和新模型



深度学习的成功

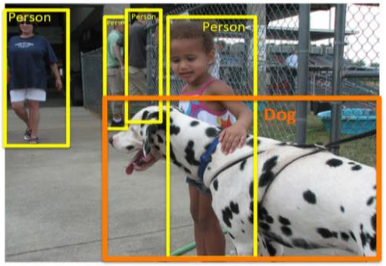




IMAGENET Large Scale Visual Recognition Challenge (ILSVRC) 2010-2014

~~20 object classes~~ ~~22,591 images~~

200 object classes	456,567 images	DET
1000 object classes	1,431,167 images	CLS-LOC



http://image-net.org/challenges/LSVRC/

AlphaGo

深度学习的局限

➢ 对抗样本：

$+ .007 \times$

$=$

熊猫

长臂猿

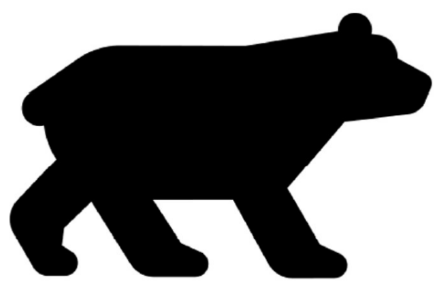
➢ 小样本学习

➢ 举一反三

➢ 运动识别

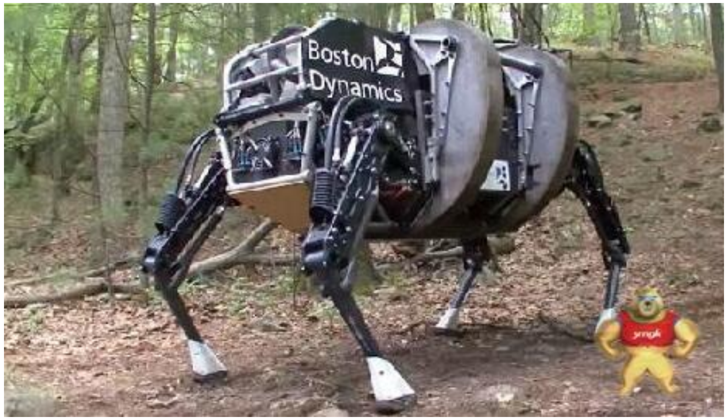
➢ 图像理解

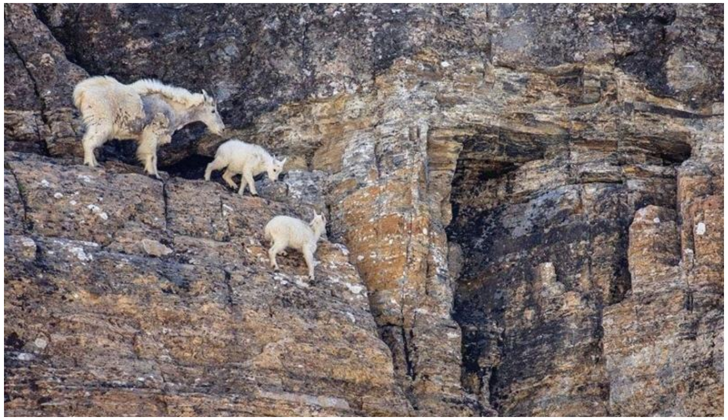
全局认知



(a)

We are far from understanding Intelligence





什么是智能？

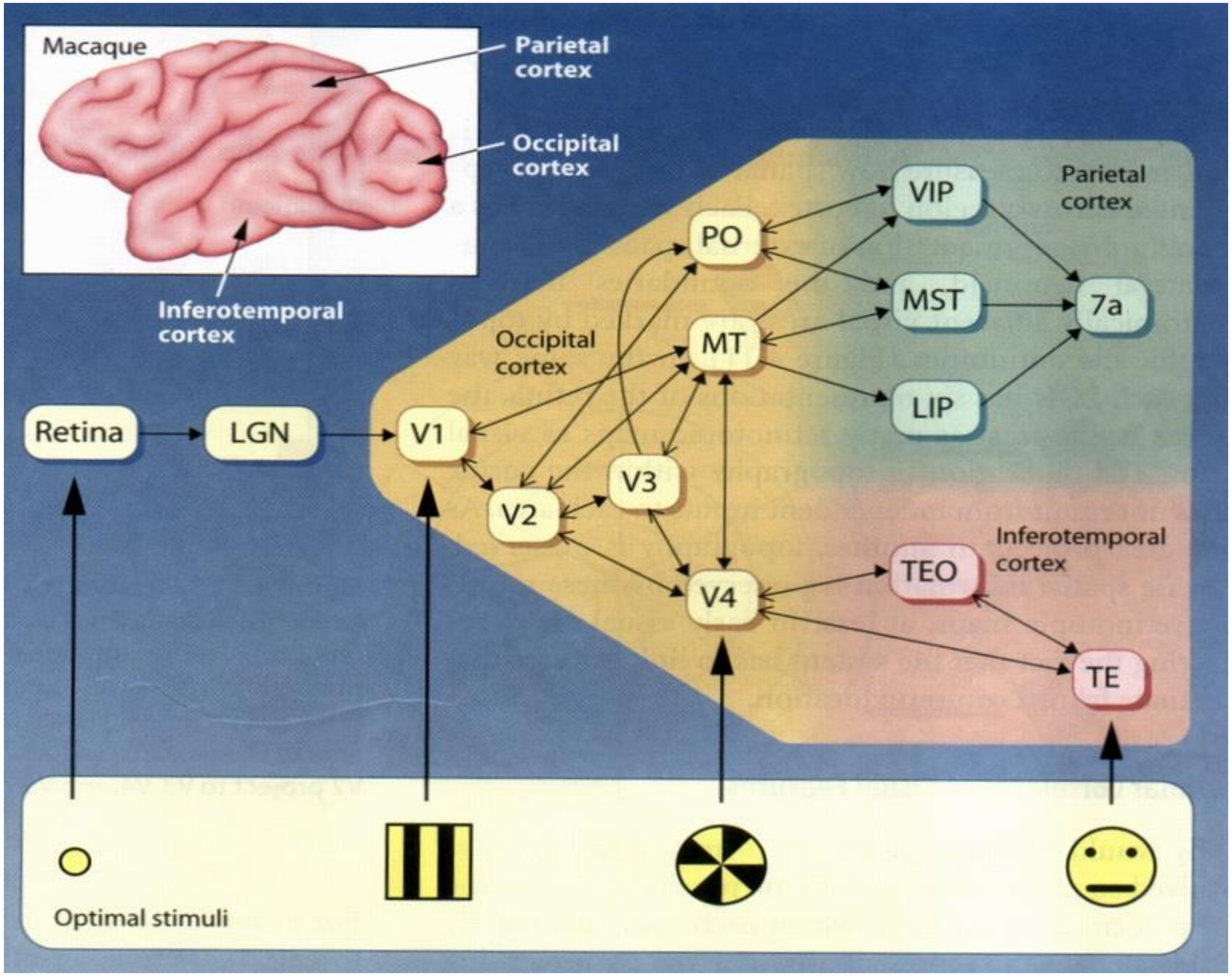
- 智能的发生：
  - 皮亚杰：智能就是当你不知道怎么办时，调用的东西
- 智能的体现：
  - Hawkins、郭爱克：智能就是感知-预测-抉择过程
- 智能的结果
  - 智能就是人类不断把一个个很“智能”的事情变成不再那么“智能”的行为活动（吴思）

大脑是智能的基础

- Baby sea squirt swim, having brain

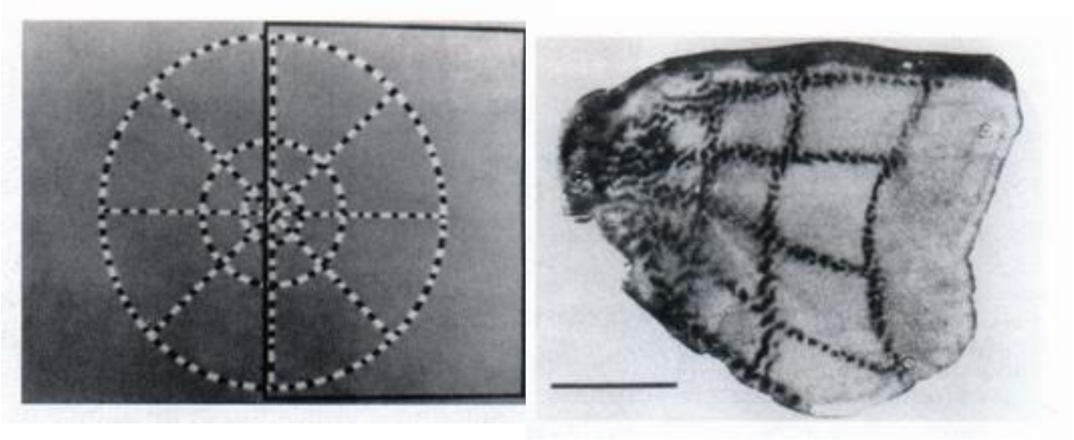
- Adult sea squirt no movement, without brain

Feature Extraction from Simple to Complex

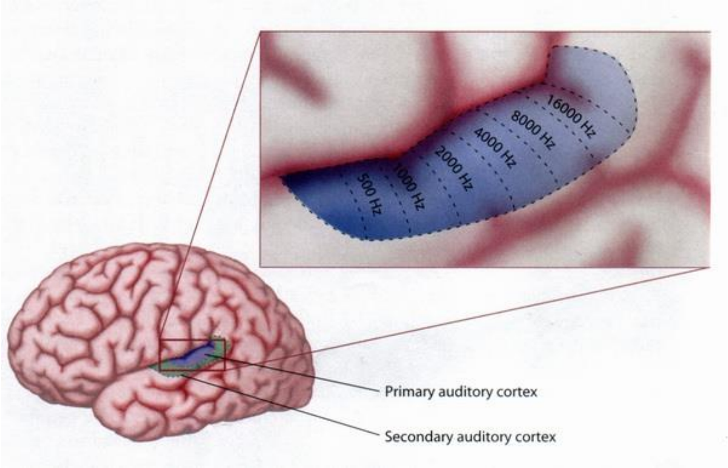


Topographic Maps

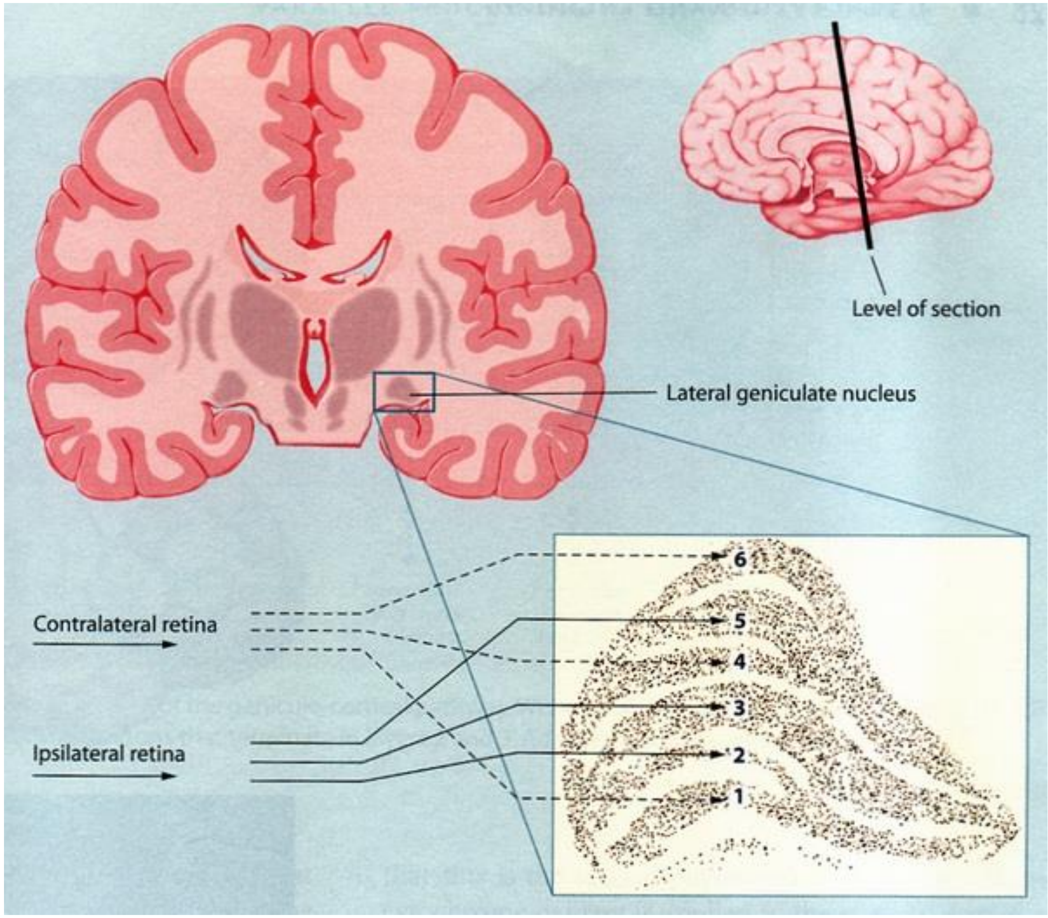
Retinotopic map



Tonotopic map

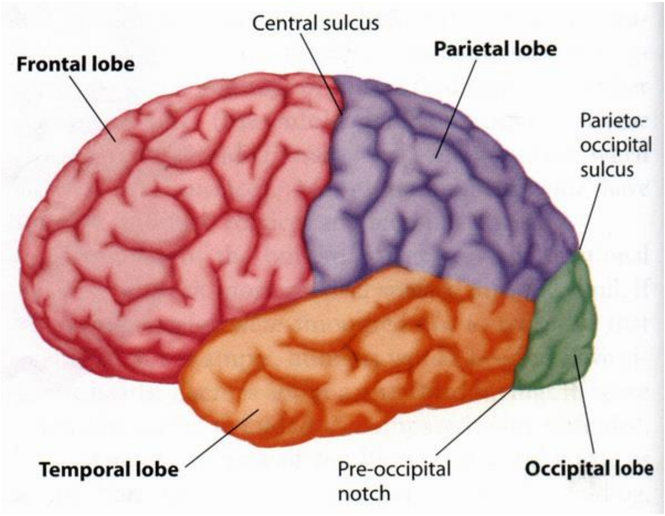


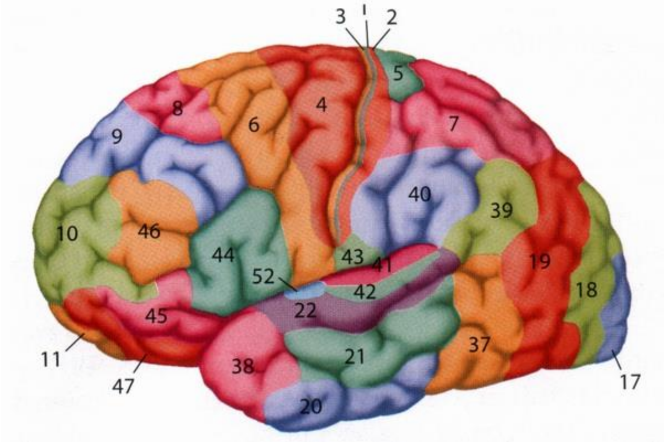
Divide-and-Conquer & Feature Binding

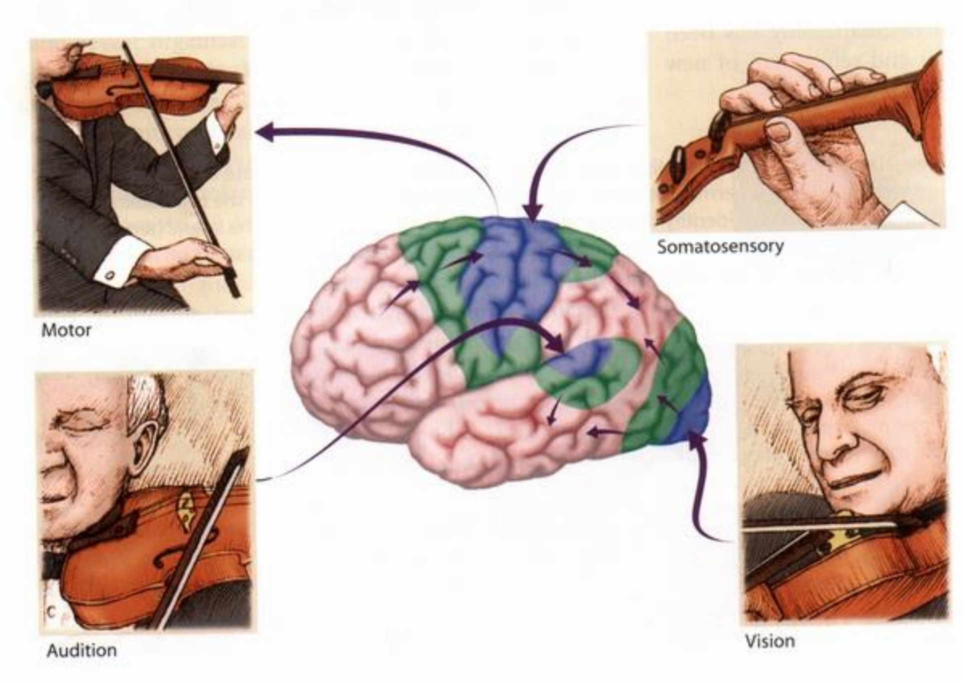


Six distinct copies of the same visual information maintained at LGN

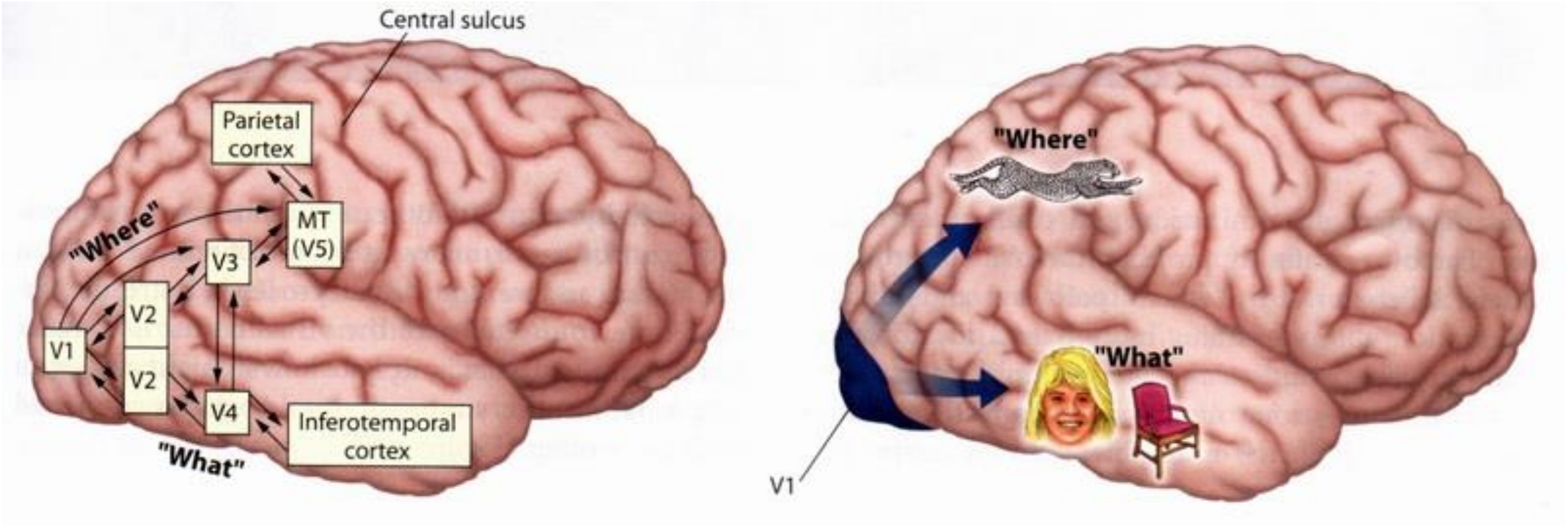
Brain Function Localization & Collaboration







‘Where’ and ‘What’ Visual Pathways



‘Where’: the motion and spatial location
‘What’: the detailed features, form, and object identity

Global vs. Local Perception

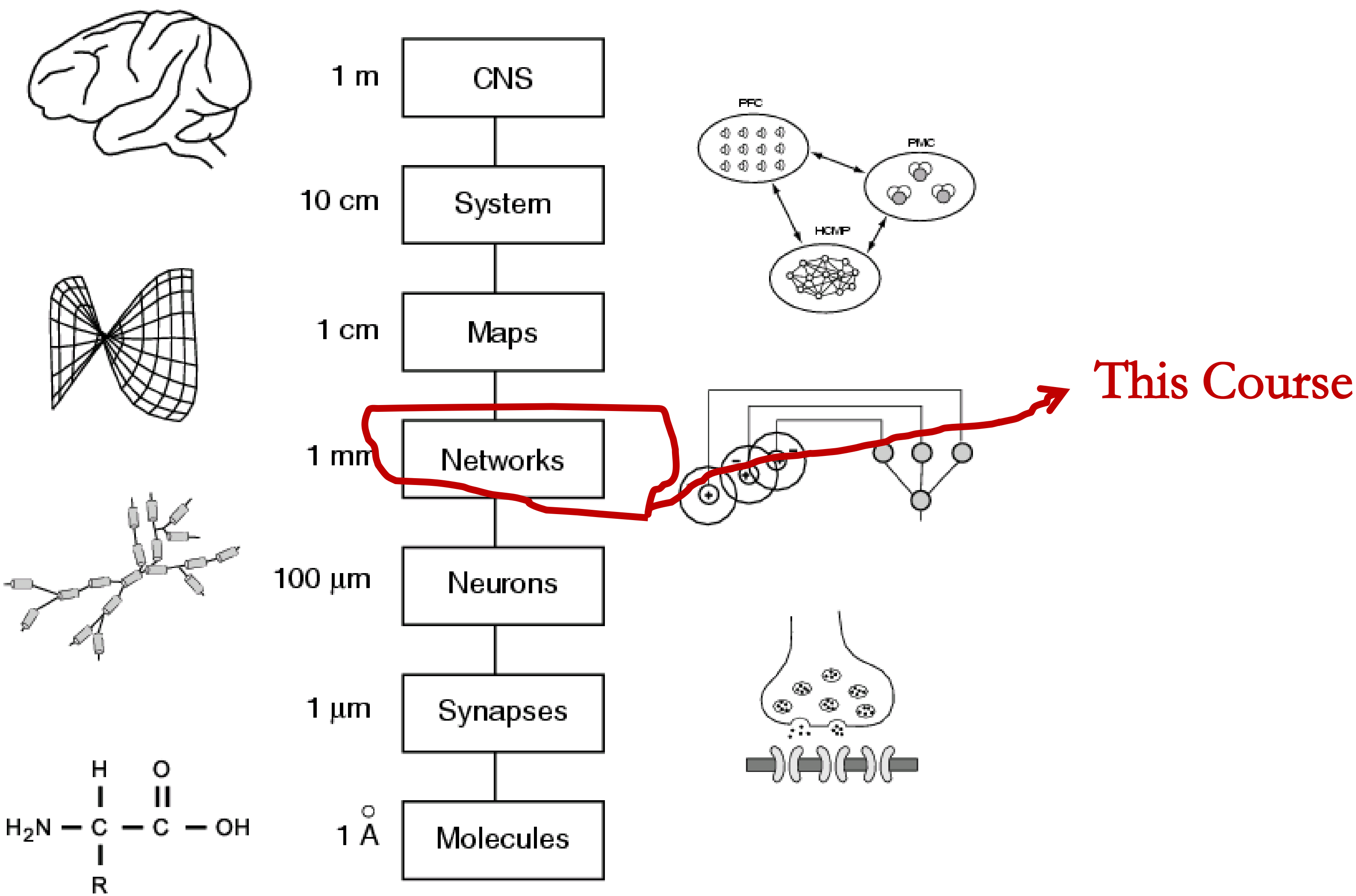
Who is this guy?

Who is this guy?

Aims of the Course

- Basic knowledge and programming skills in Computational Neuroscience
- Critical thinking is more important than acquiring facts
- Knowing how is more than important knowing what
- Laying foundation for future research in Computational Neuroscience and Brain-inspired Intelligence
  - What are the right questions to address, in order to decipher brain functions?
  - Whether the questions are biological meaningful?
  - Whether the questions are computationally interesting?
  - Whether the questions are technically feasible?

Structure Levels of Neural Systems



Research Levels of Computational Neuroscience

- **Computational theory**
- **Representation & Algorithm**
- **Implementation**

This Course

From David Marr

Contents of the Course

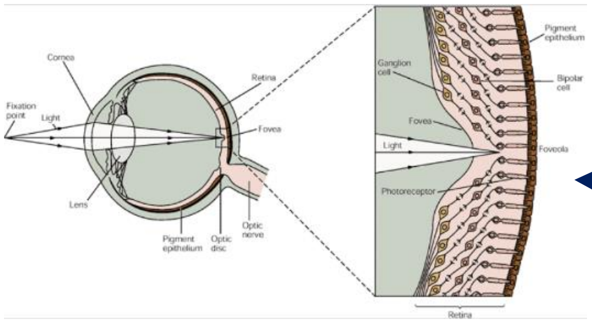
- Introduction of the course
- Programming tool--BrainPy
- Neural coding: basics, population coding, adaptive coding
- Attractor networks: Hopfield, CANN
- Synaptic computation: short-term plasticity, shunting inhibition
- Reservoir computing: SVM, temporal information processing
- Delay compensation & anticipative tracking
- Multi-sensory integration & segregation
- Push-pull feedback
- Visual stability
- Decision-making & application
- Neural experiments
- Neuromorphic computing

Assessment

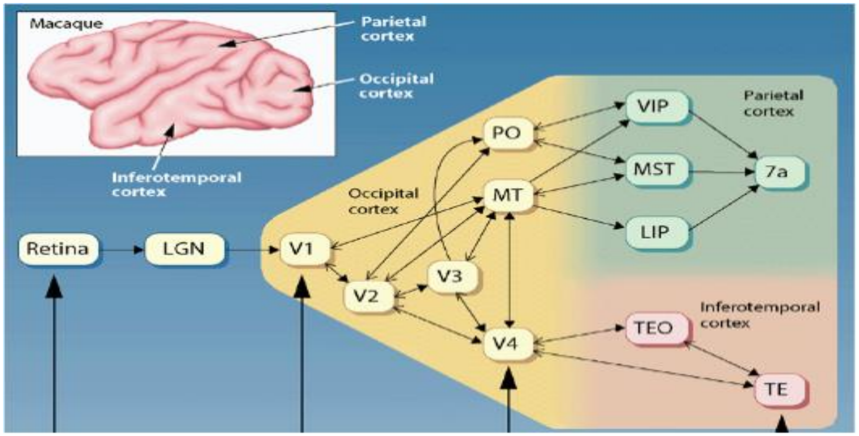
- **Coursework 60%**
  - Single neuron model 20%
  - CANN 20%
  - Selecting one from below 20%
    - E-I balanced network
    - Hopfield model
    - CANN+SFA
    - Coupled CANNs
    - Short-term plasticity
    - Decision-making

- **Final Report 40%**
  - An essay > 2000 words
  - Any topic covered by the course and related to Computational Neuroscience

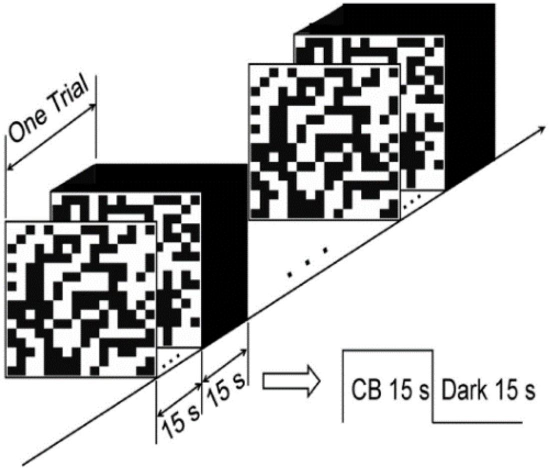
Adaptive Neural Coding



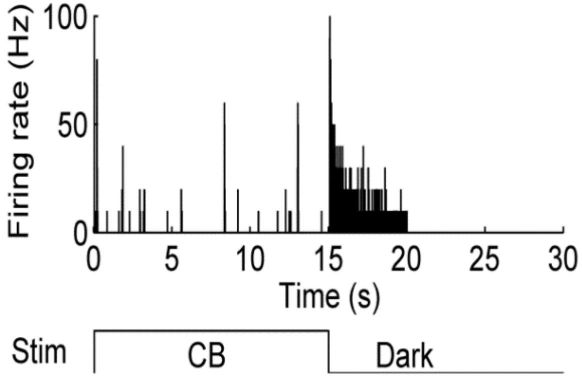
Retina



Where is the stimulus information in neural adaptation?



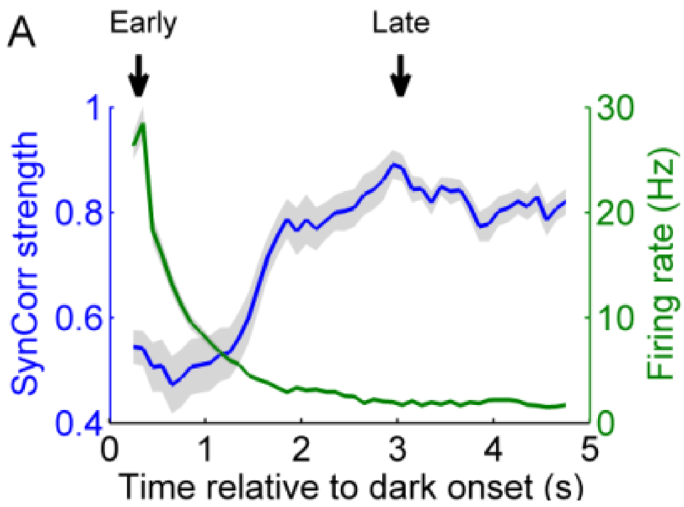
Bullfrog retina experiment



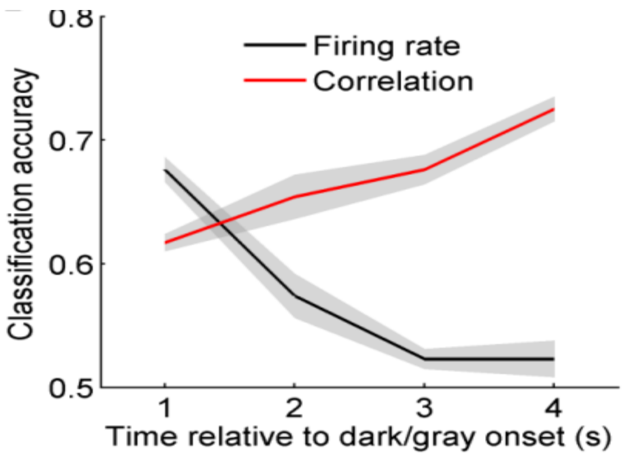
Visual Adaptation

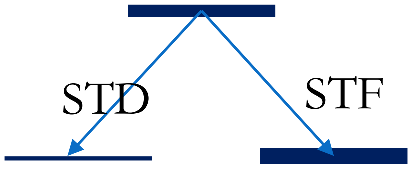
From Rate to Correlation Code

Neural synchronization increasing over adaptation



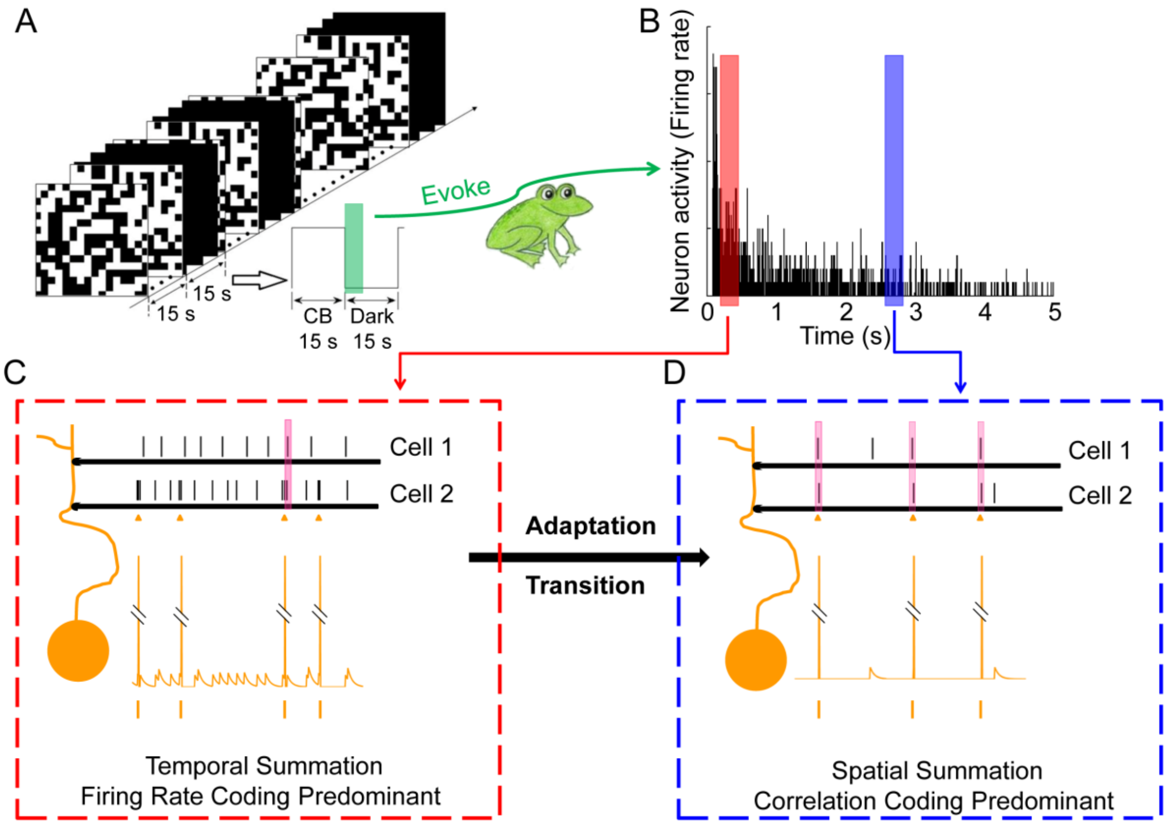
Stimulus information shift to correlation over adaptation





The underlying mechanism:
Synaptic short-term plasticity (STP)
(dynamical synapse)

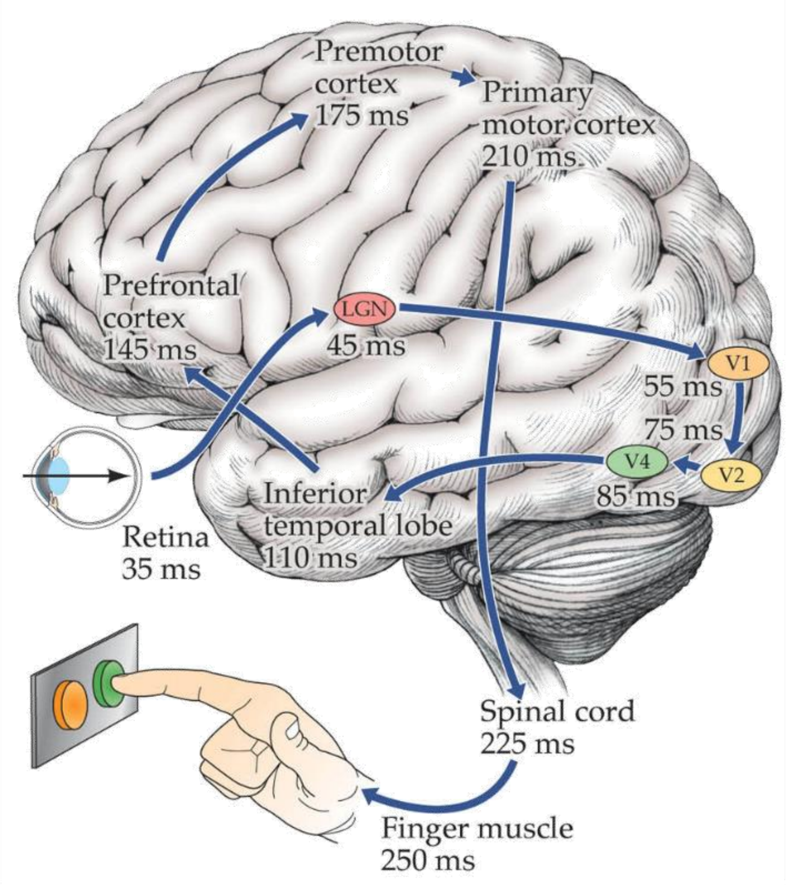
Why Adaptive Neural Encoding?



Two advantages:

- Responding fast to a novel object with strong independent firing-rate code
- Encoding information efficiently with low frequency but correlation code lately

Predict to Compensate Time Delays



(e.g. Maunsell and Gibson 1992; Raiguel et al. 1989; Nowak et al. 1995; Schmolesky et al. 1998; Thorpe, Fize, & Marlot 1996)

From retina to V1 ~50ms

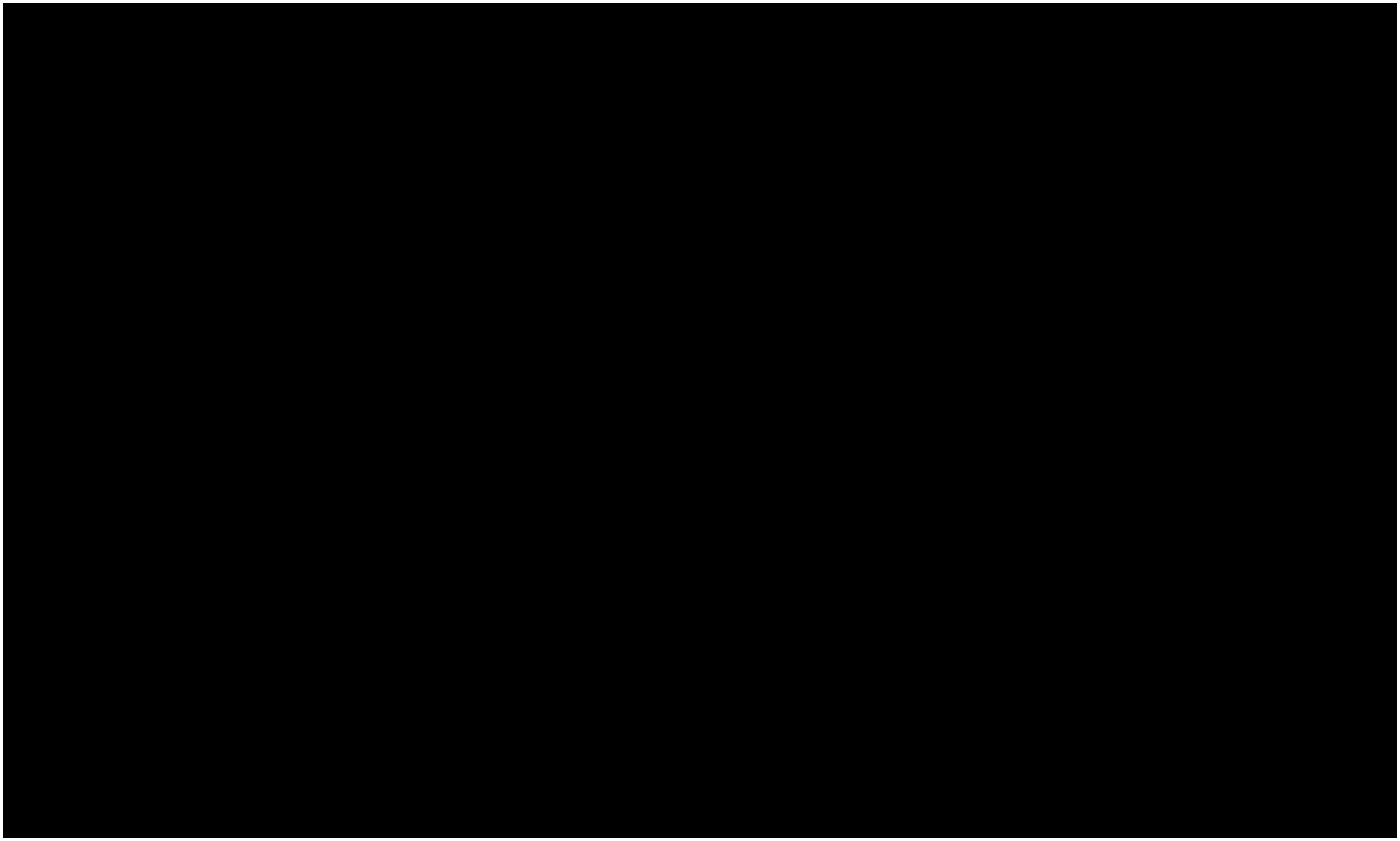
- Federer’s serve speed: ~200km/h
- 50 ms delay implies displacement ~ 3 m!

A Life or Death Issue

- Escaping from a predator

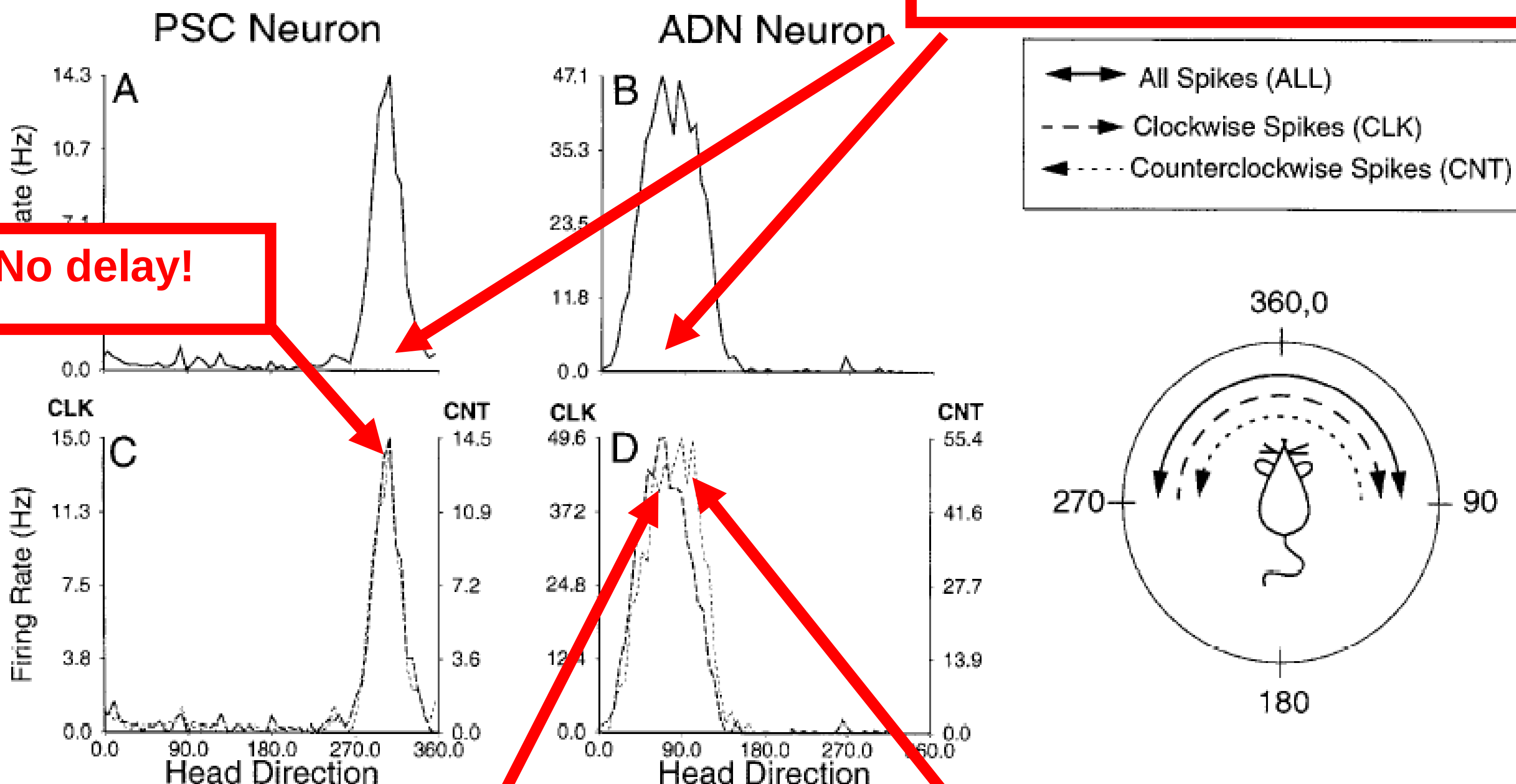
- Catching a prey

Flash-lag Effect



Predict to Compensate

Rat facing this direction



No delay!

Turning anticlockwise: earlier!

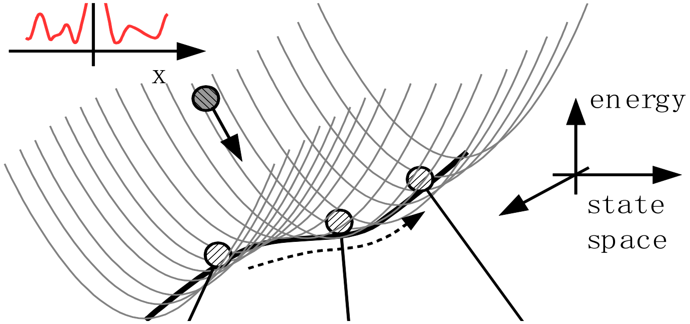
Turning clockwise: earlier!

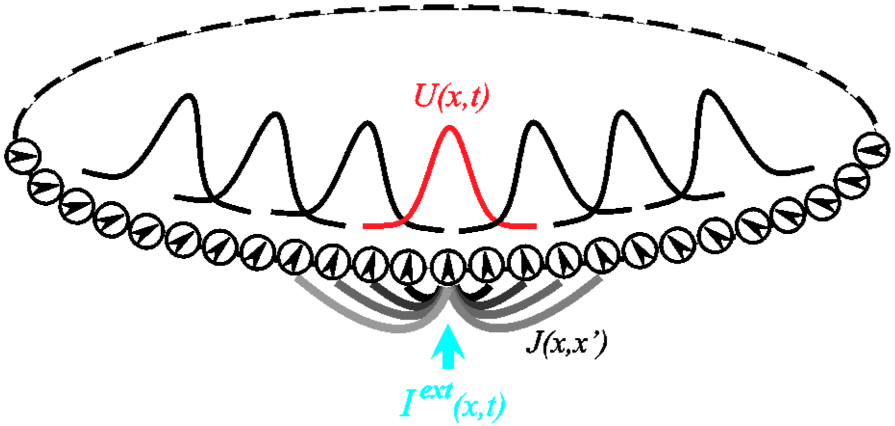
Blair and Sharp, J. Neurosci. (1995)

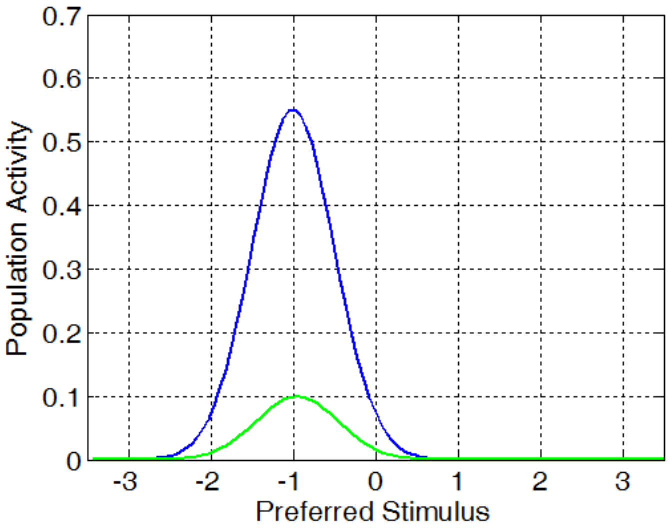
Continuous Attractor Neural Network (CANN)

$$\tau \frac{dU(x,t)}{dt} = -U(x,t) + \rho \int dx' J(x-x') r(x',t) + I^{ext}(x,t)$$

$$r(x,t) = \frac{U(x,t)^2}{1 + k\rho \int dx' U(x',t)^2}; \quad J(x-x') = \frac{J}{\sqrt{2\pi a}} \exp\left[-\frac{(x-x')^2}{2a^2} \right]$$





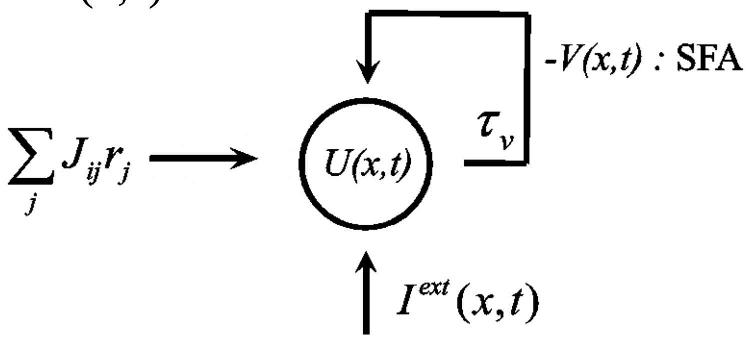


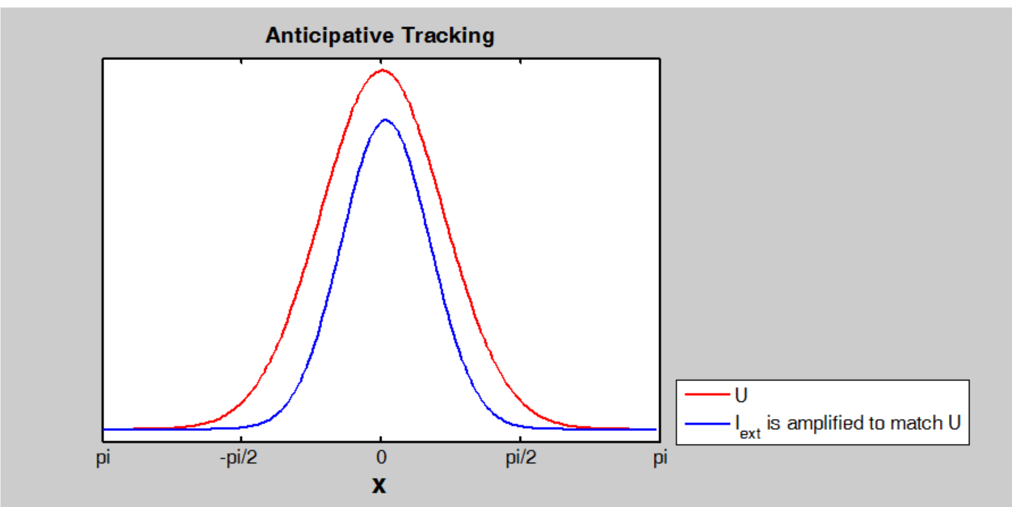
1. Amari, 1977, 2. Ben-Yishai et al., 1995, 3. Zhang, 1996, 4. Seung, 1996,
5. Deneve et al, 1999, 6. Wu et al, 2002, 2005, …

A CANN with Negative Feedback Modulation

$$\tau \frac{dU(x,t)}{dt} = -U(x,t) + \rho \int dx' J(x-x') r(x',t) - V(x,t) + I^{ext}(x,t)$$

$$\tau_v \frac{dV(x,t)}{dt} = -V(x,t) + mU(x,t)$$





Negative Feedback Modulation:

- Spike frequency adaptation
- Short-term depression
- Negative feedback across layers

Advantages:

- Constant anticipative time
- Robust to speed
- Network computation

Mi et al., NIPS 2014

Why Neural Delays?

- **Advantages**
  - To integrate temporal information over time for reliable responding
  - To integrate multiple sensory cues
  - To implement temporal code
  - And many others
- **Disadvantages**
  - Delayed response to fast moving objects or varying temporal information

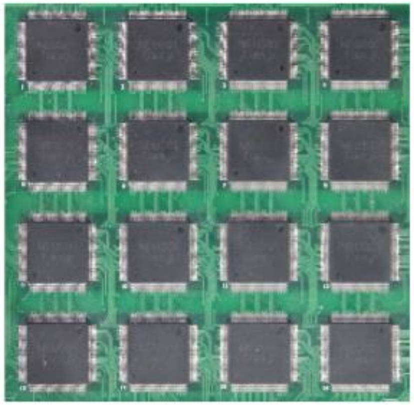
The art of being slow

Two sides of the same coin

- Every animal adopts to its own optimal time scale suitable for its own survival in the natural environment
- The brain co-evolves strategies to compensate delays

CANN for Object Tracking

"Tianji" Chip



In collaboration with Tsinghua Univ.