Neural Network Theory and Applications
神经网络理论及应用

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Course Mechanics

- Programming exercises : each student will do 6 of these, including one of own devising (in consultation with instructor).
- Grading:
  - 40% programming exercises;
  - 40% final project;
  - 20% quiz and class participation.
- Deadline of final Project: <u>June 30, 2019</u>

Instructor and Slides

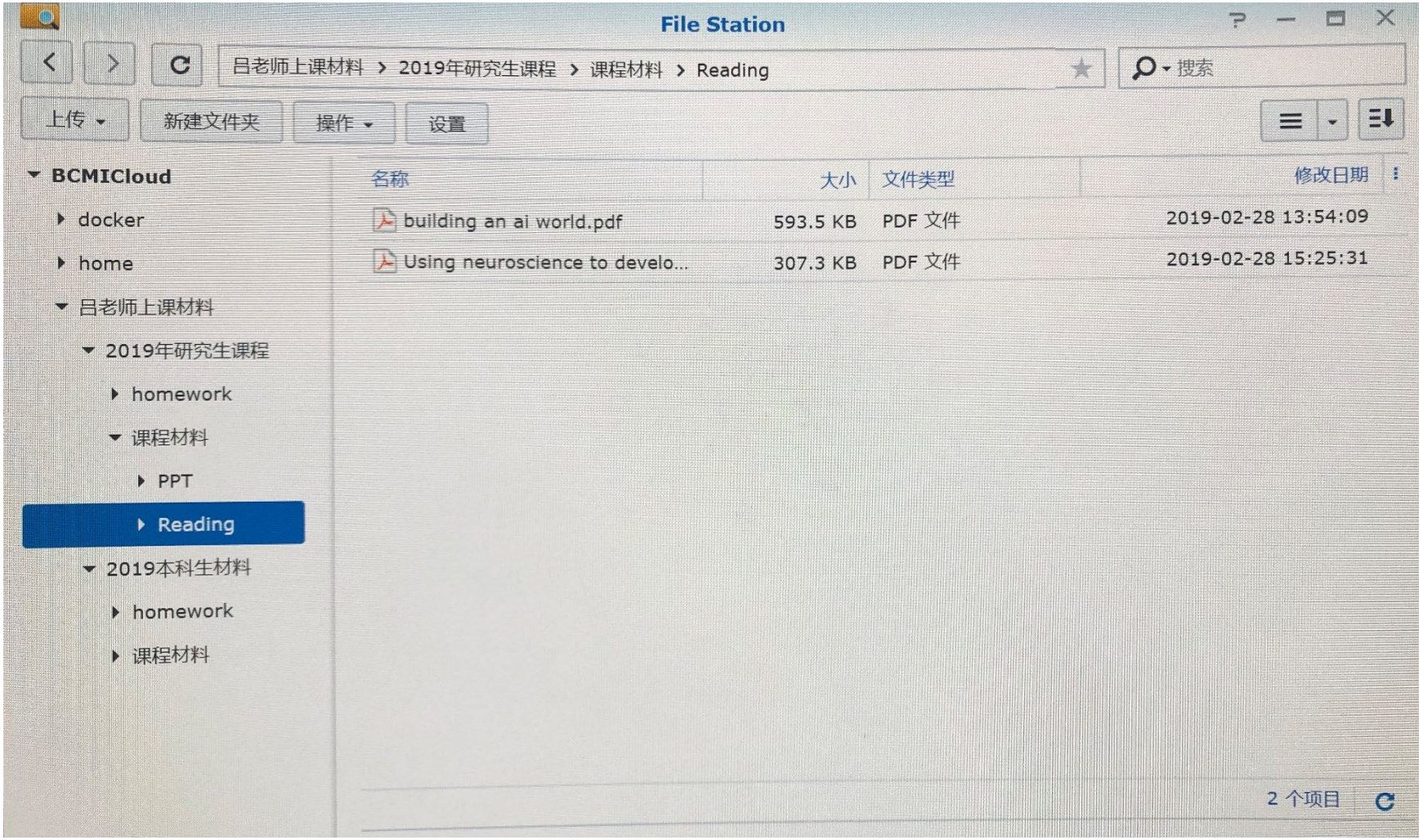
- My Ph.D. students：
  - Wei Liu （刘伟）; liuwei@liujr.com
  - Yun Luo （罗赟）; angeleader2012@163.com
- Send email to Yun Luo （罗赟）：
  - Your name; Your student ID
- You can download the slides from:

  http://gofile.me/4gVYW/24rlP0NRX
- You can upload your home work using

  http://bcmicloud.quickconnect.to/sharing/ADcAbLdi8

  PASS: sjtubcmi

BCMI Cloud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Using neuroscience to develo...
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2 个项目

Goals for the Course

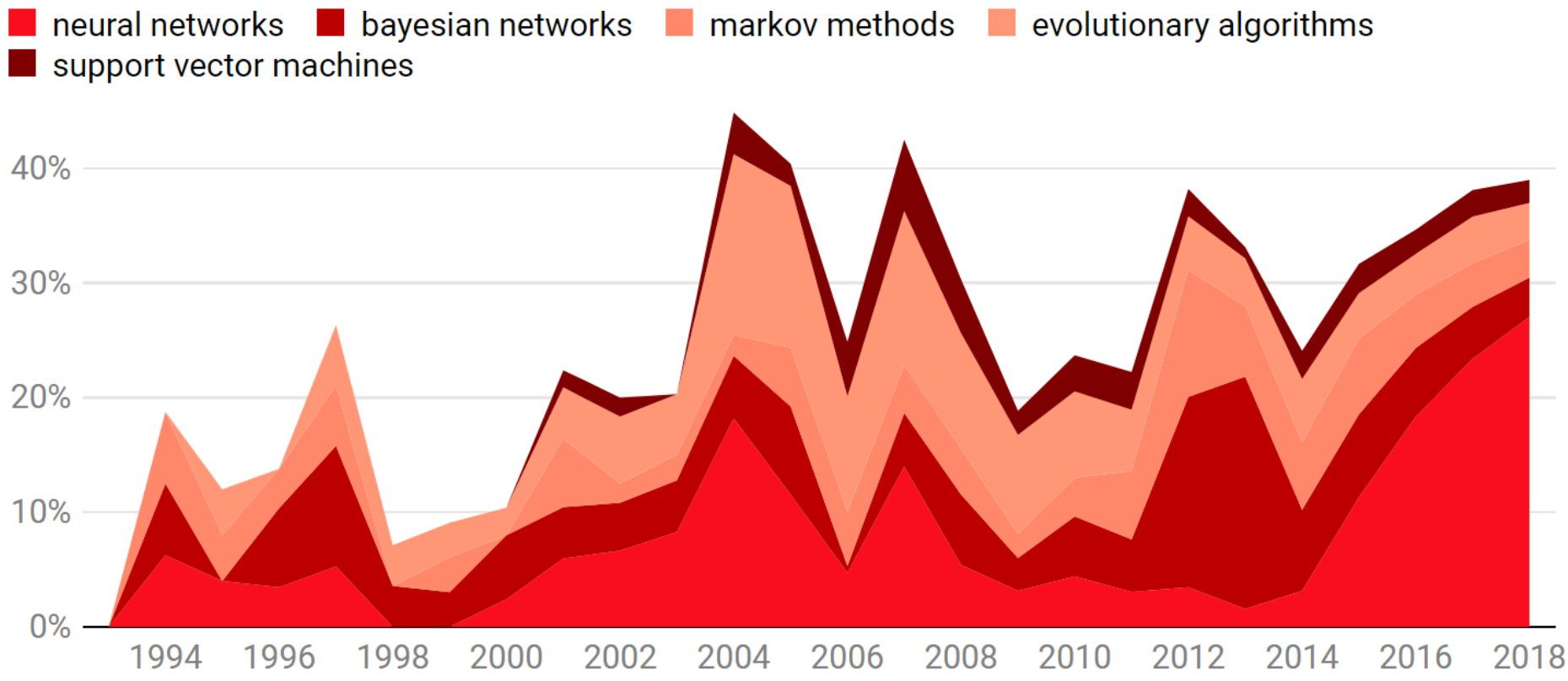
- Learn the theories, algorithms, methods and foundational ideas of NN
- Prepare to apply NN
- Prepare to do research in NN and related fields
- Learn some new ways of thinking about AI, machine learning, and Intelligent information processing
  - The biological perspective
  - The systematical perspective
  - The skeptical perspective

Outline of the Course

- Introduction
- Perceptron, Multilayer Perceptron
- Min-Max Modular Network
- Support Vector Machine
- Unsupervised Learning: Self-Organization Map
- Auto-encoder
- Transfer Learning
- Convolutional Neural Network (CNN)
- Long and Short-Term Memory (LSTM)
- Generative Adversarial Networks (GAN)
- Reinforcement Learning

Neural networks take over other machine-learning methods

Percentage of papers that mention each method



Hover over the chart areas to see their labels.

Chart: MIT Technology Review • Source: arXiv.org • Created with Datawrapper

AlphaGo掀起了新一轮AI浪潮！

- 2016年1月，Google在Nature上发文，表示他们的AlphaGo系统在正式比赛中打败了欧洲围棋冠军。
- 2016年3月，AlphaGo成功挑战韩国围棋九段李世石，比分为4:1
- 2017年年初Master横扫人类棋手！
- AlphaGO:强化学习+深度学习+搜索技术

AlphaGo Zero

- **AlphaGo Zero is a version of AlphaGo, which is created without using data from human games and stronger than any previous version.**
- **AlphaGo's Zero is trained without datasets derived from human experts. All of the training data are generated by playing games against itself.**

2017年10月19日凌晨，在国际学术期刊《自然》（Nature）上发表的一篇研究论文中，谷歌下属公司Deepmind报告新版程序AlphaGo Zero：从空白状态学起，在无任何人类输入的条件下，它能够迅速自学围棋，并以100:0的战绩击败“前辈”。

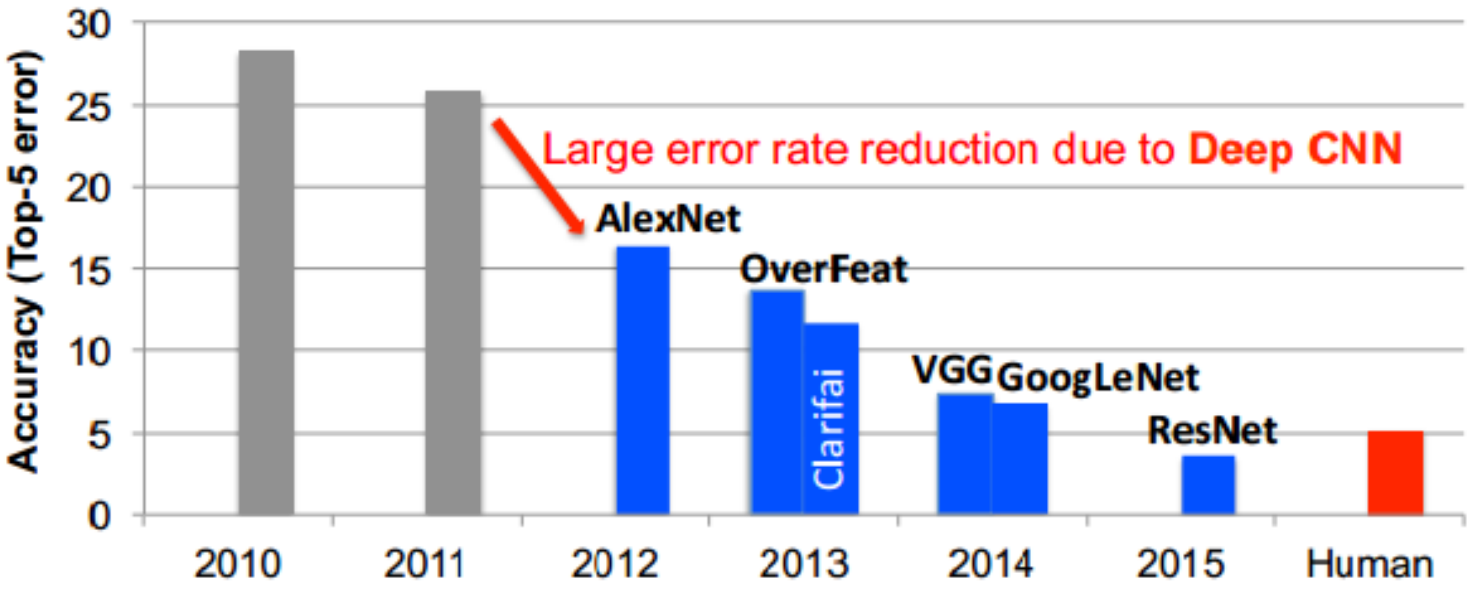
ImageNet

- **Information**
  - Total number of non-empty synsets: 21841
  - Total number of images: 14,197,122
  - Number of images with bounding box annotations: 1,034,908
  - Number of synsets with SIFT features: 1000
  - Number of images with SIFT features: 1.2 million
- **The contest contains 1000 different categories, including animals, fruits, vegetables and so on.**
  - Training set: 1.2 millon
  - Test set: 100 k
  - Validation: 50 k

ImageNet

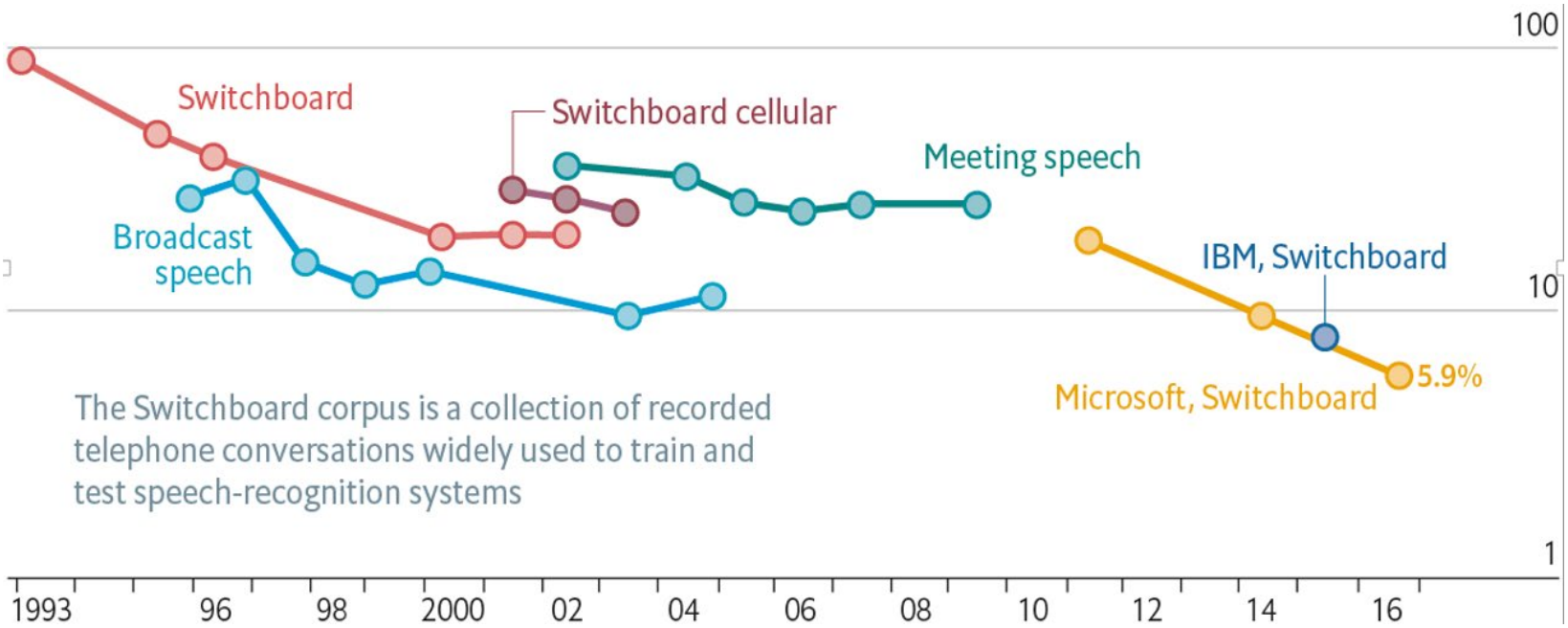
ImageNet and Deep Learning

- **The top-5 error rate has reduced drastically when the deep learning methods were adopted to solve ImageNet classification problems. The error rates are smaller than human's judge in recent methods.**

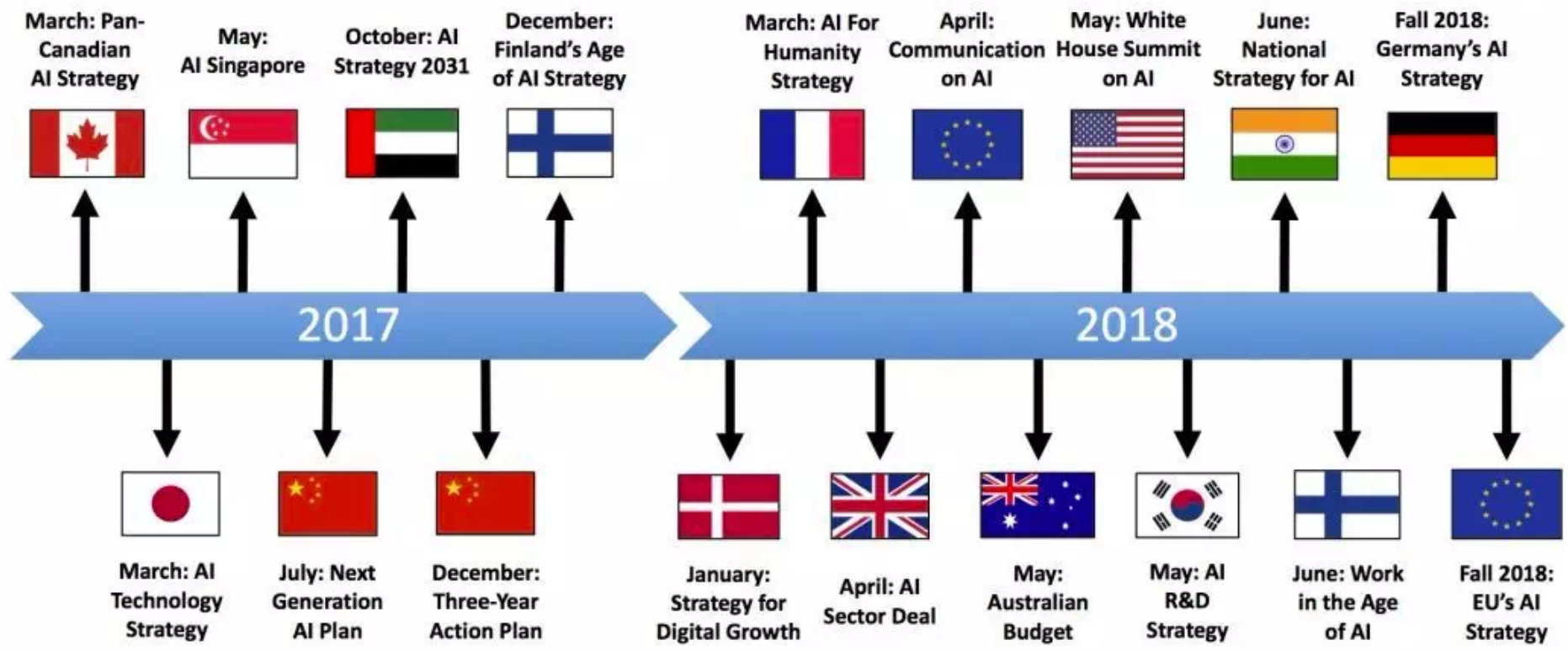


Speech Recognition and Deep Learning

- **The error rate of speech recognition has a high value before 2010. The application of deep learning in this field makes the error rate drastically reduced.**

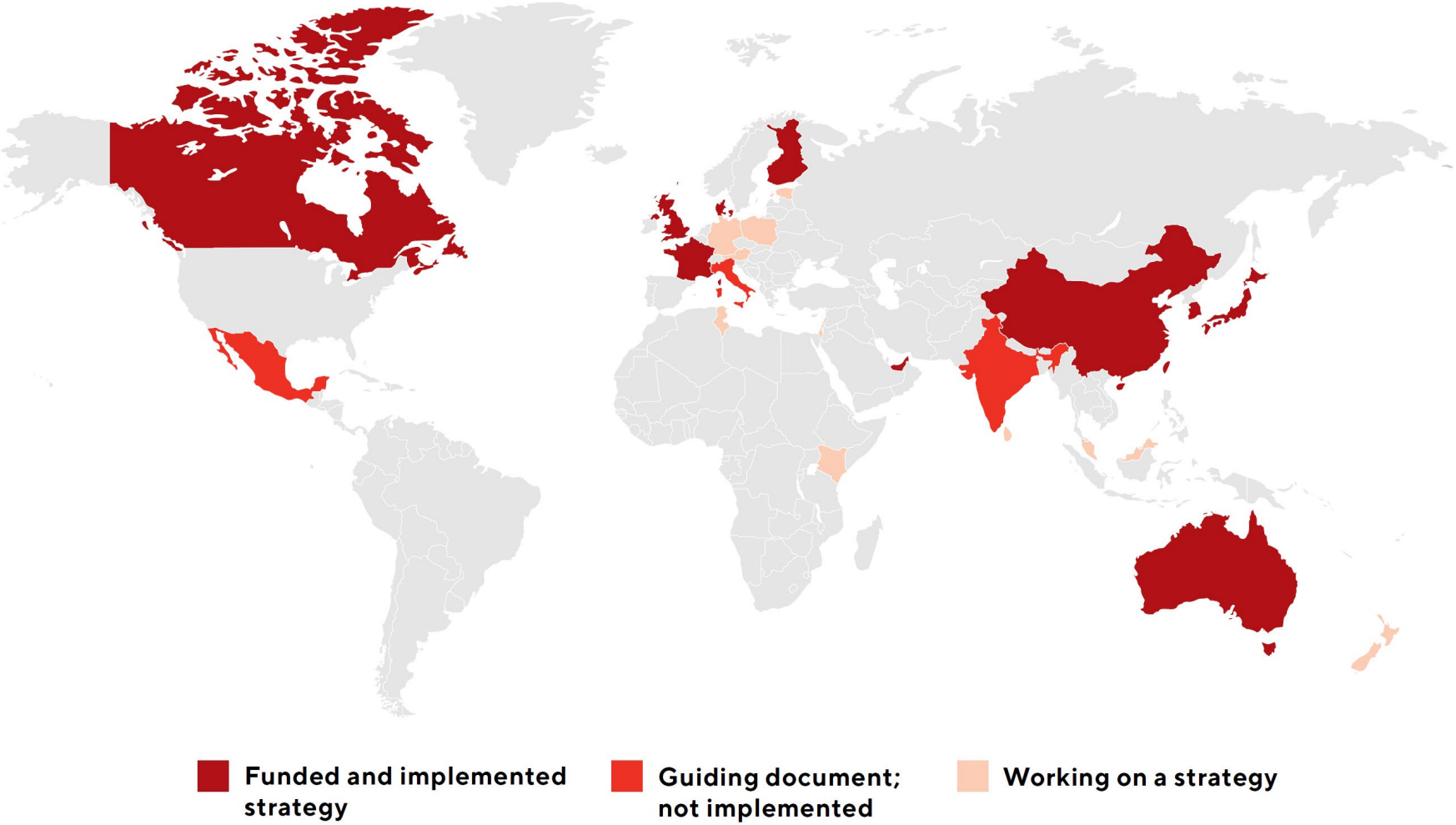


National Artificial Intelligence Strategies



Report on National and Regional AI Strategies

Figure 1: Current Landscape of AI Strategies



From CIFAR Report

Table 2: Guiding Documents

Country/ Region	Release Date	Guiding Document	Implemented? (As of November 2018)
Japan	March 2017	Artificial Intelligence Technology Strategy	Yes
China	July 2017	A Next Generation Artificial Intelligence Development Plan	Yes
UAE	October 2017	UAE Strategy for Artificial Intelligence	Yes
Finland	December 2017	Finland's Age of Artificial Intelligence	Yes
Italy	March 2018	Artificial Intelligence at the Service of Citizens	Partially
Sweden	May 2018	National Approach for Artificial Intelligence	Yes
India	June 2018	National Strategy for Artificial Intelligence: #AIforAll	No
Mexico	June 2018	Towards an AI Strategy in Mexico: Harnessing the AI Revolution	No
Germany	July 2018	Key points of the Federal Government for an AI Strategy	No

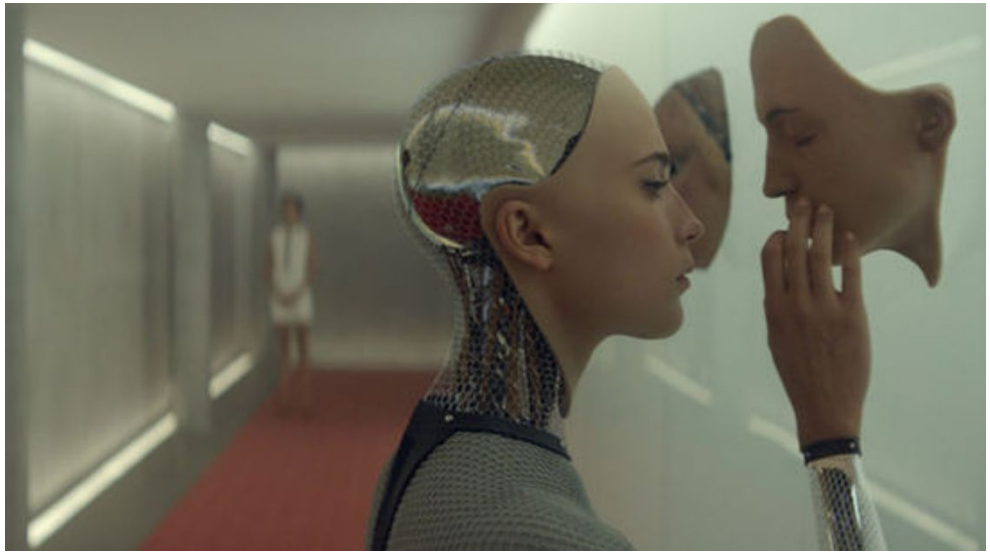
From CIFAR Report

Artificial General Intelligence

通用人工智能
强人工智能

Ethics of artificial intelligence

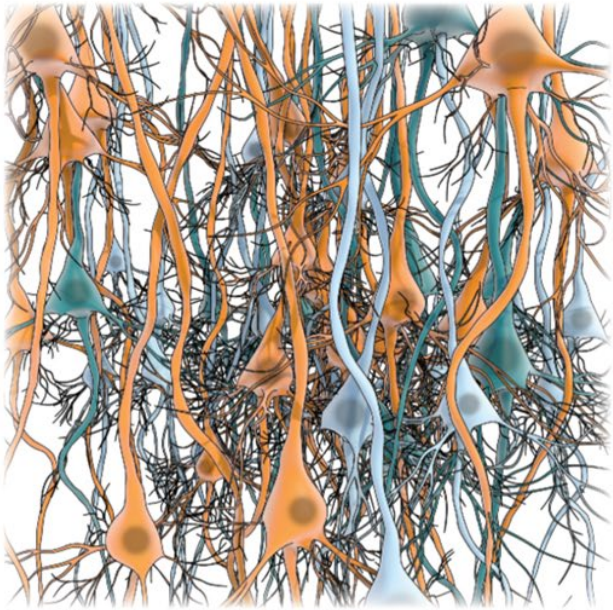
- With the rapid developments of the AI-based systems, large amount of questions related to the social impact, governance, and ethical implications of these technologies have emerged .
- The Berkman Klein Center (Harvard) and the MIT Media Lab have set up the Ethics and Governance of Artificial Intelligence Fund to solve the ethics problems caused by AI.



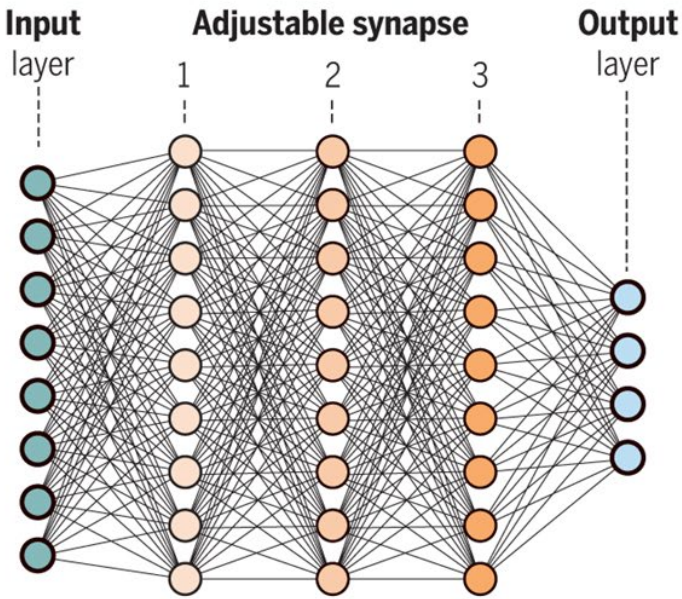
Using neuroscience to develop artificial intelligence

Brain circuitry and learning

A major open question is whether the highly simplified structures of current network models compared with cortical circuits are sufficient to capture the full range of human-like learning and cognition.



Complex neural network
Connectivity in cortical networks includes rich sets of connections, including local and long-range lateral connectivity, and top-down connections from high to low levels of the hierarchy.



Informed AI network
Biological innate connectivity patterns provide mechanisms that guide human cognitive learning. Discovering similar mechanisms, by machine learning or by mimicking the human brain, may prove crucial for future artificial systems with human-like cognitive abilities.

SCIENCE, Feb. 2019, Shimon Ullman

大脑：通用人工智能的唯一参照物

- 物理大脑：
  - ~1.3升，~1.5公斤，占体重2%
  - 功耗~20W，占全身20%
- 神经大脑：
  - 神经元数约1000亿（860亿）
  - 1~2M个功能柱（6层），每柱约1万神经元，人脑突触总数约100T
  - 每个神经元通过数千至上万突触与其他神经元相联
  - 神经元典型发放频率不超过100Hz
  - “除人脑外，没有任何一个自然或者人工系统能够具有对新环境与新挑战的自适应能力、新信息与新技能的自动获取能力、在复杂环境下进行有效决策并稳定工作直至几十年的能力。没有任何系统能够在多处损伤的情况下保持像人脑一样好的鲁棒性，在处理复杂任务的同时，没有任何系统能媲美人脑的低功耗性”
    ——HBP建议书

日本脑科学研究计划（1996-2016）

- 理解脑 （Understanding the Brain)领域
  - 神经细胞机能部（4）
  - 神经网络机理部（4）（伊藤正男教授）
  - 认知脑科学部（2）

- 保护脑 (Protecting the Brain)领域
  - 发生与分子化学研究部（2）
  - 病因遗传基因研究部（3）

- 创造脑 (Creating the Brain)领域
  - 脑型器件与脑道研究部（2）（松本元教授）
  - 脑型信息系统研究部（3）（甘利俊一教授）

- 先端技术开发中心（2）

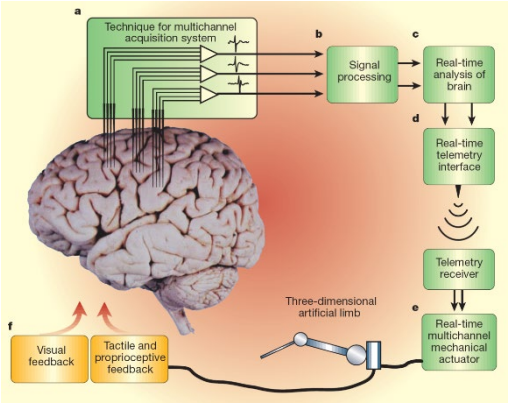
（1997年当时实验室22个；鼎盛时期发展到近50个实验室）

2013年欧美的脑科学研究计划

- 欧盟未来新兴旗舰技术项目（21>6>2)
  - 石墨烯；人脑工程
- 人脑工程
  - 2013年9月启动；10年将投入10亿欧元
  - 瑞士洛桑联邦理工学院教授马克拉姆牵头
  - 87个世界各地研究团队承担
  - 2023年前完成
  - 目标：在治疗帕金森氏症、研发超级计算机和智能机器人等领域取得重大突破
- 奥巴马政府实施了一项为期10年的科学研究，检查人脑的活动，并绘制一张全面的人脑活动图(Brain Activity Map)，希望能在大脑研究领域做出类似人类基因组计划 (Human Genome Project)为遗传学所做的贡献（纽约时报）

Brain Science and Technology Institute (Nov. 19, 2015)

- Three Centers
  - Mental heath
  - Brain-inspired Computing
  - Brain Diseases
- Brain-inspired Computing
  - Brain-inspired computing theory
  - Brain-computer interaction
  - Brain-inspired chip and device
- Brain computer Interaction
  - Brain function rehabilitation
  - Diagnosis of mental diseases such as attention deficit hyperactivity disorder (ADHD)
  - Drowsy driving prediction
  - Affective brain-computer interaction
- China Brain research Project (2016-2030) will started this year ?



Outline of Lecture 1

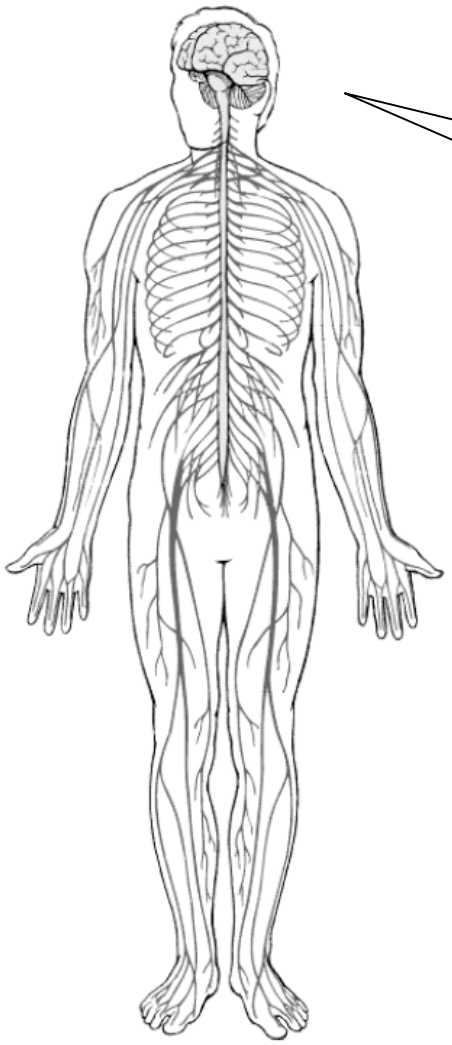
- Computer and Brain
- What is a neural network ?
- What can neural networks help ?
- What can neural networks do ?
- Biological neural networks
- Simple neuron model
- Neural network history
- Network architectures
- Learning paradigms
- Learning tasks
- Applications in my lab
- Recommended textbooks
- Neural network journals and conference

Comparing Brains with Digital Computers

	Computer	Human Brain
Computational units	1 CPU, 10^5 gates	10^{11} neurons
Storage units	10^9 bits RAM, 10^{10} bits disk	10^{11} neurons, 10^{14} synapses
Cycle time	10^{-8} sec	10^{-3}
Bandwidth	10^9 bit/sec	10^{14} bit/sec
Neuron updates/sec	10^5	10^{14}

A Very Short Introduction to Brain

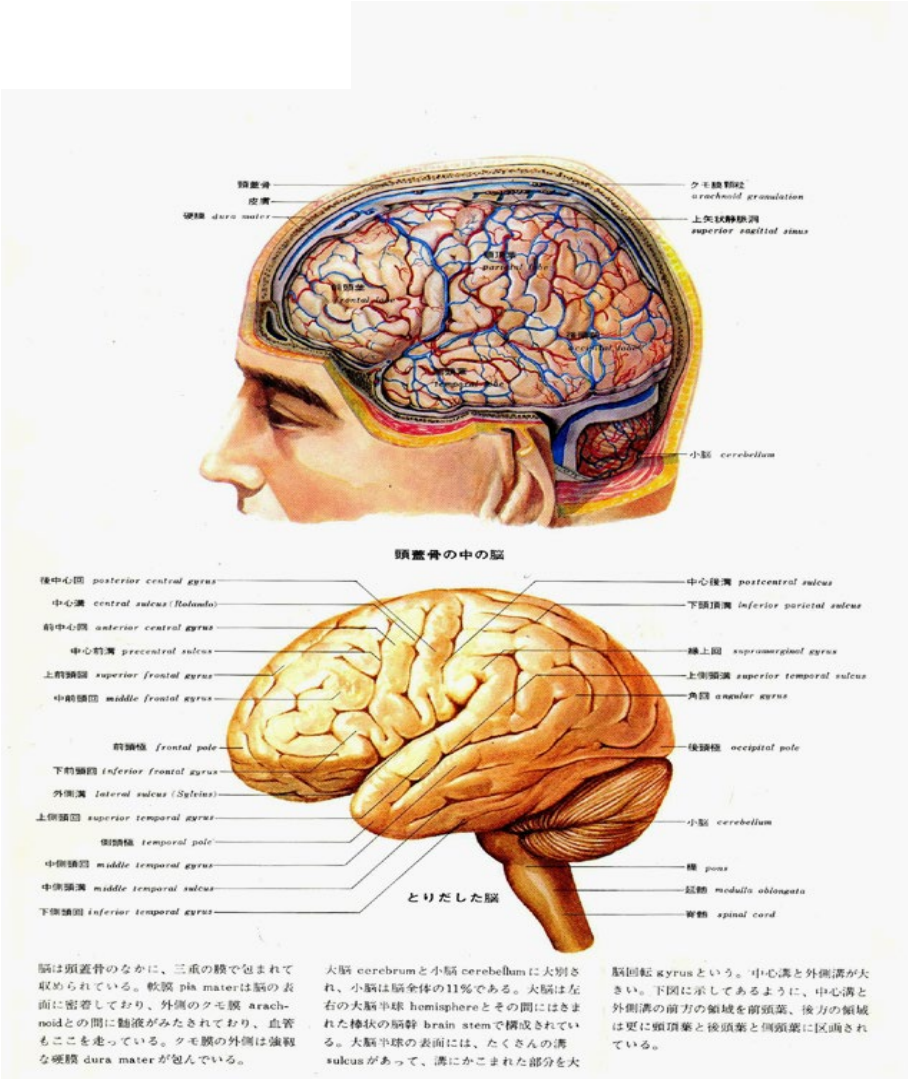
The Nervous System



Central nervous system
(Brain & spinal cord)

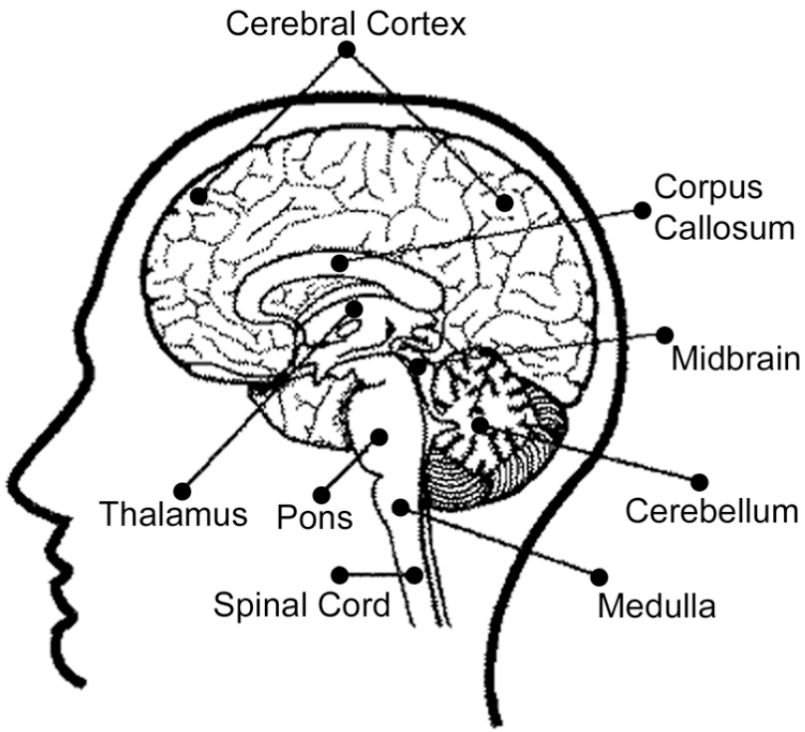
Peripheral nervous system

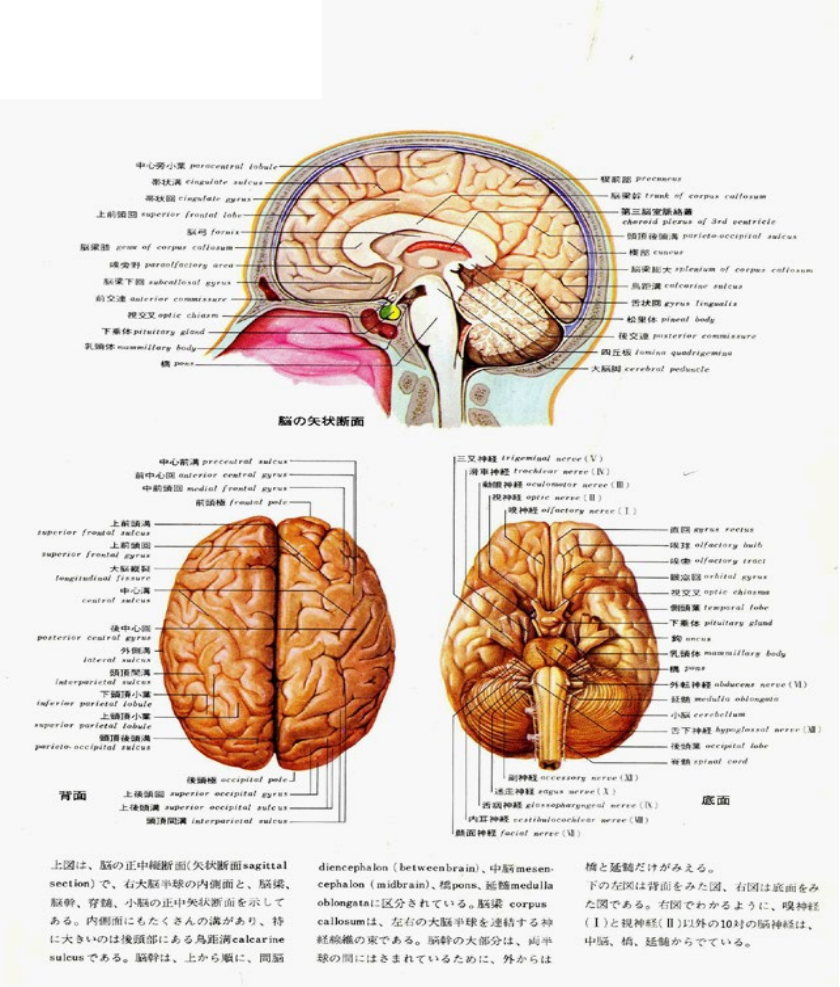
The Human Brain



- The brain contains about 100 billons neurons
- 10000 connections per neuron

Parts of the Human Brain





上図は、脳の正中縦断面(矢状断面sagittal section)で、右大脳半球の内側面と、脳梁、脳幹、脊髄、小脳の正中矢状断面を示してある。内側面にもたくさんの溝があり、特に大きいのは後頭部にある鳥距溝calcarine sulcusである。脳幹は、上から順に、間脳diencephalon (betweenbrain)、中脳mesencephalon (midbrain)、橋pons、延髄medulla oblongataに区分されている。脳梁 corpus callosumは、左右の大脳半球を連結する神経線維の束である。脳幹の大部分は、両半球の間にはさまれているために、外からは橋と延髄だけがみえる。

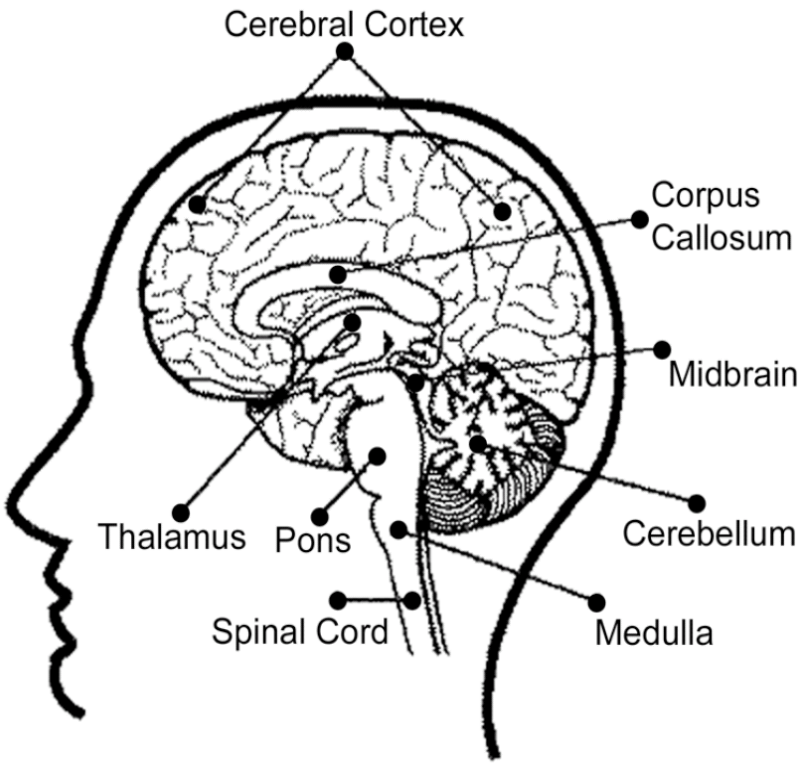
下の左図は背面をみた図、右図は底面をみた図である。右図でわかるように、嗅神経(Ⅰ)と視神経(Ⅱ)以外の10対の脳神経は、中脳、橋、延髄からでている。

Cerebral Cortex 大脑皮层

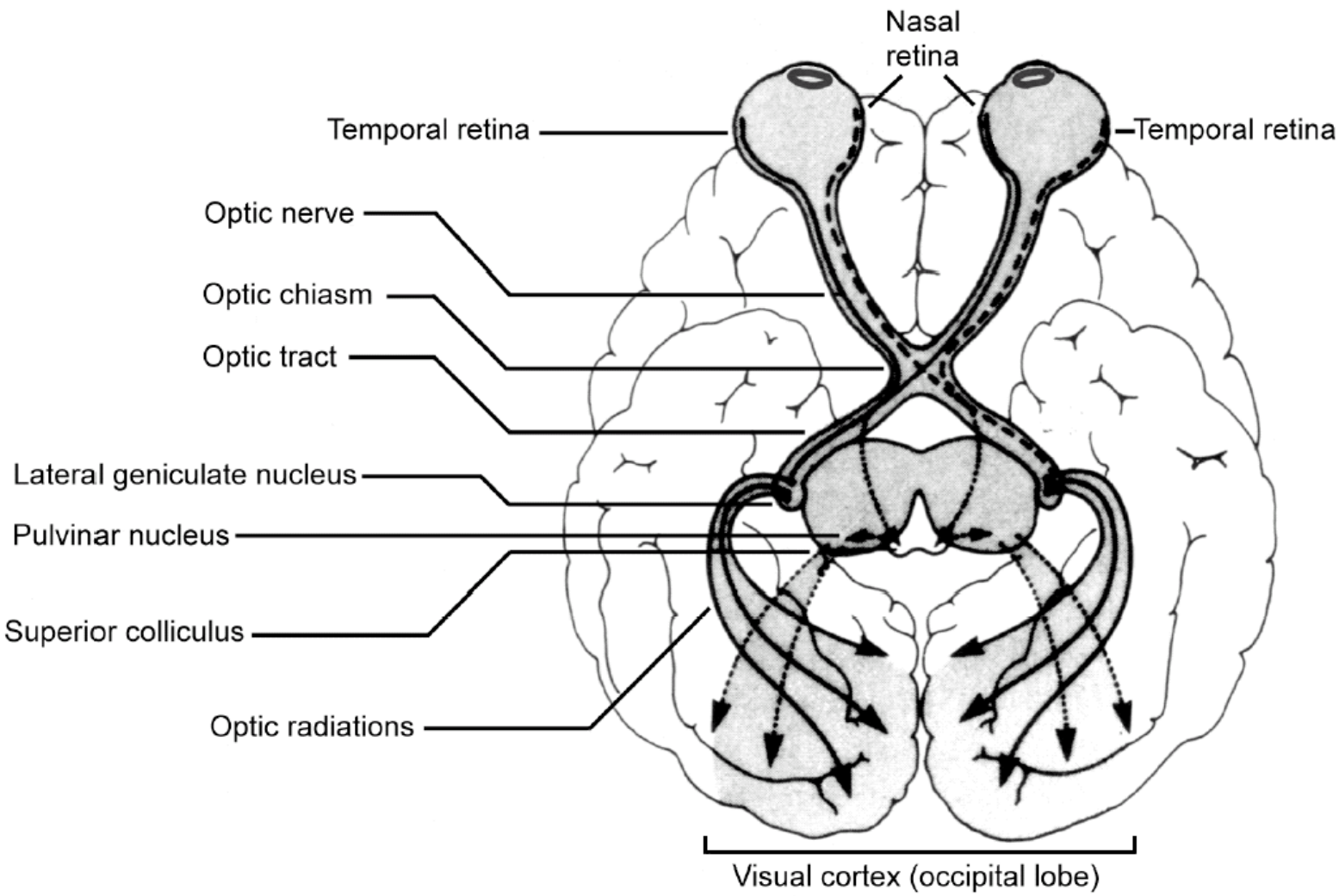
- “Cortex” from the Latin for “bark” (of a tree)
- The cortex is a sheet of tissue that makes up the outer layer of the brain (2 to 6mm)
- The right and left sides of the cerebral cortex are connected by a thick band of nerve fibers
- FUNCTIONS: Thought, voluntary movement, language, reasoning, perception

Cerebellum 小脑

- "Cerebellum" from the Latin for "little brain"
- FUNCTIONS: Movement, balance, posture

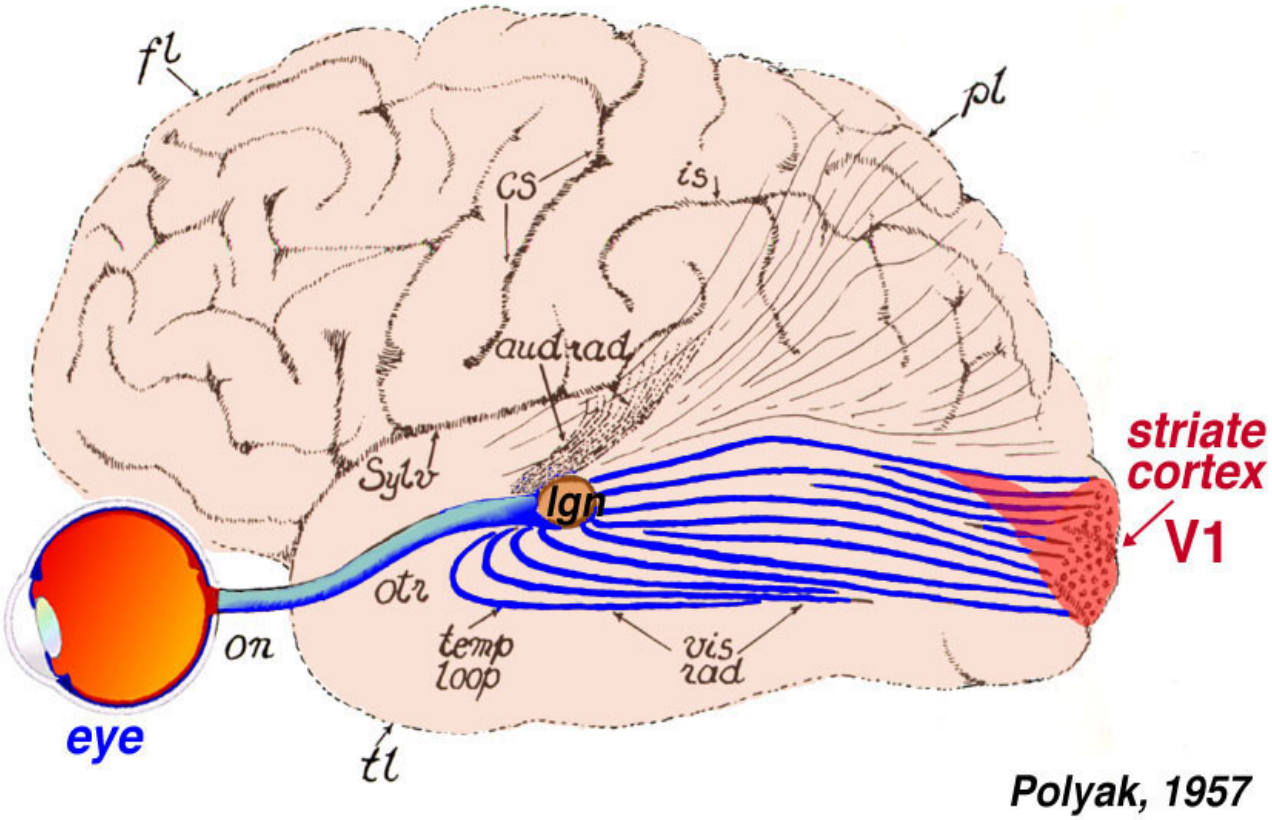


Visual Cortex



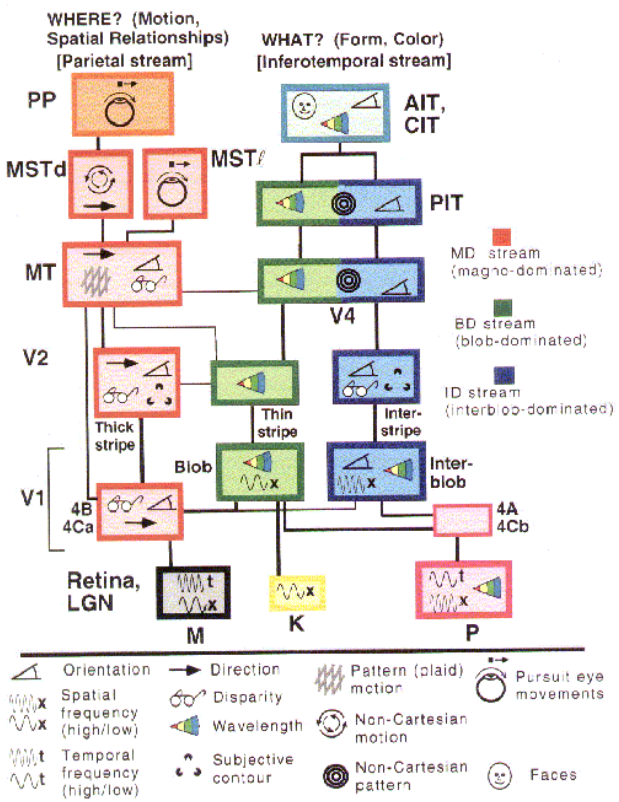
Visual Cortex （视觉皮层）

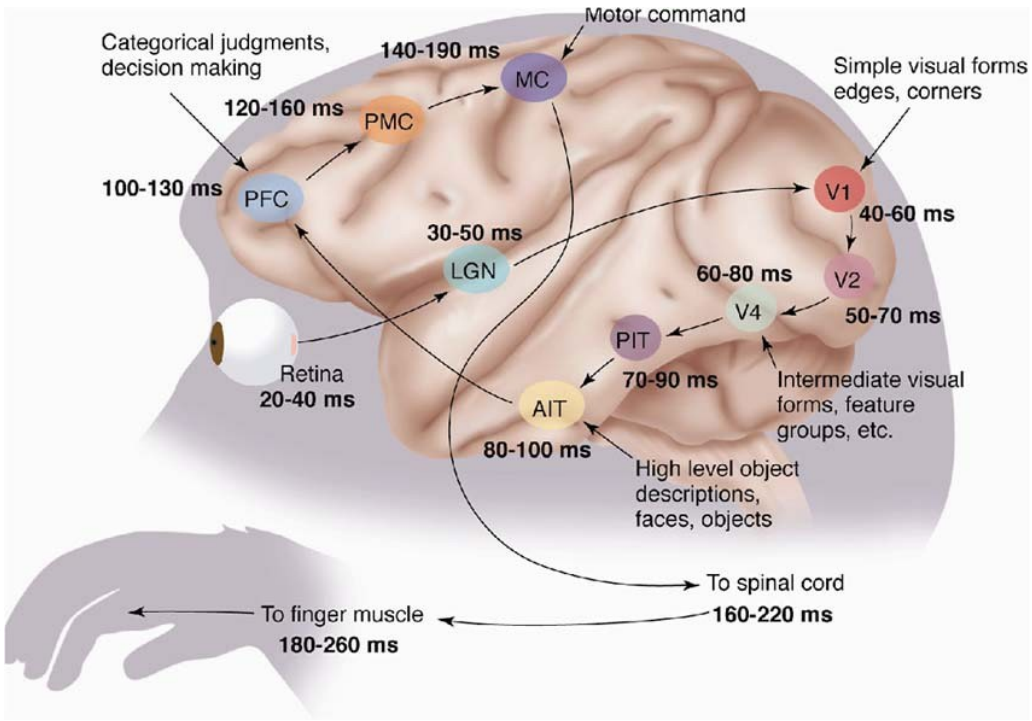
- 至少有70～80%以上的外界信息是由视觉系统接受、处理和感知的；
- 人类大脑皮层约一半的区域参与视觉信息的分析。

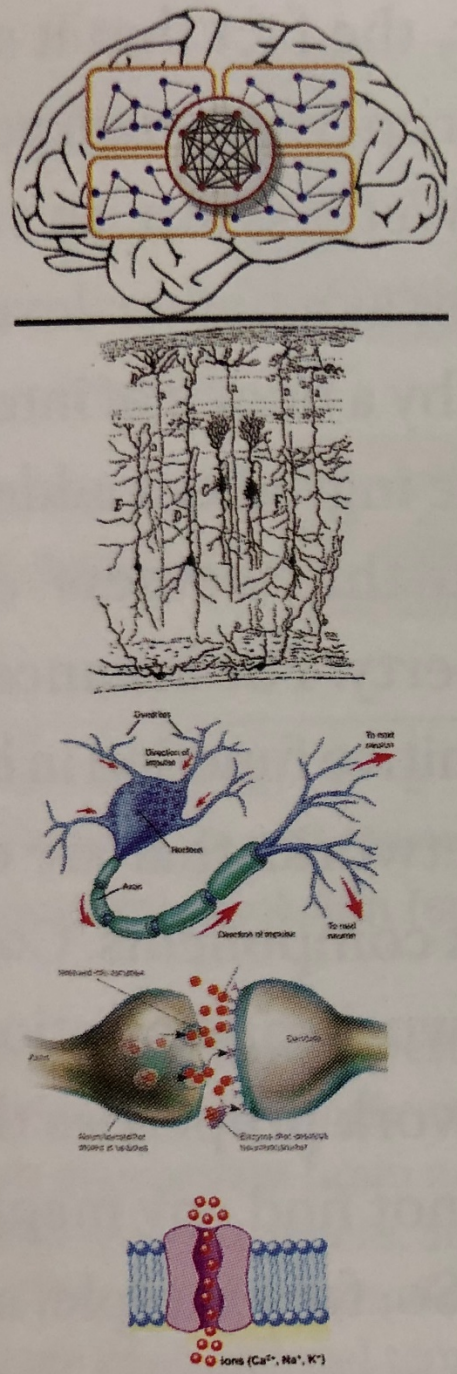


The Mammalian Visual cortex is Hierarchical

- The ventral (recognition) pathway in the visual cortex has multiple stages
- Retina - LGN - V1 - V2 - V4 - PIT - AIT ....
- Lots of intermediate representations

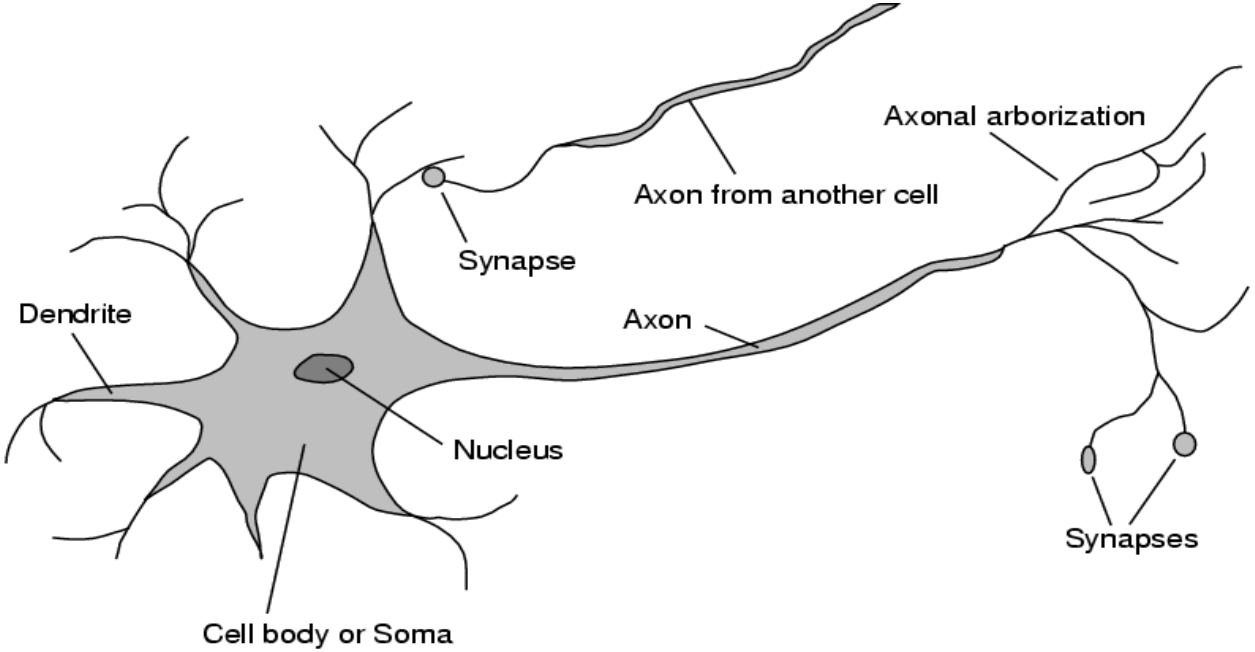





Systems (visual, auditory, motor, etc.)
Circuits
Macroscale (cm)
Mesoscale (mm)
Microscale (μm)
Neurons
Synapses
Proteins

What is a Neuron ?

- Cells of the nervous system are called neurons (nerve cells)
- The human brain has about 100 billion neurons



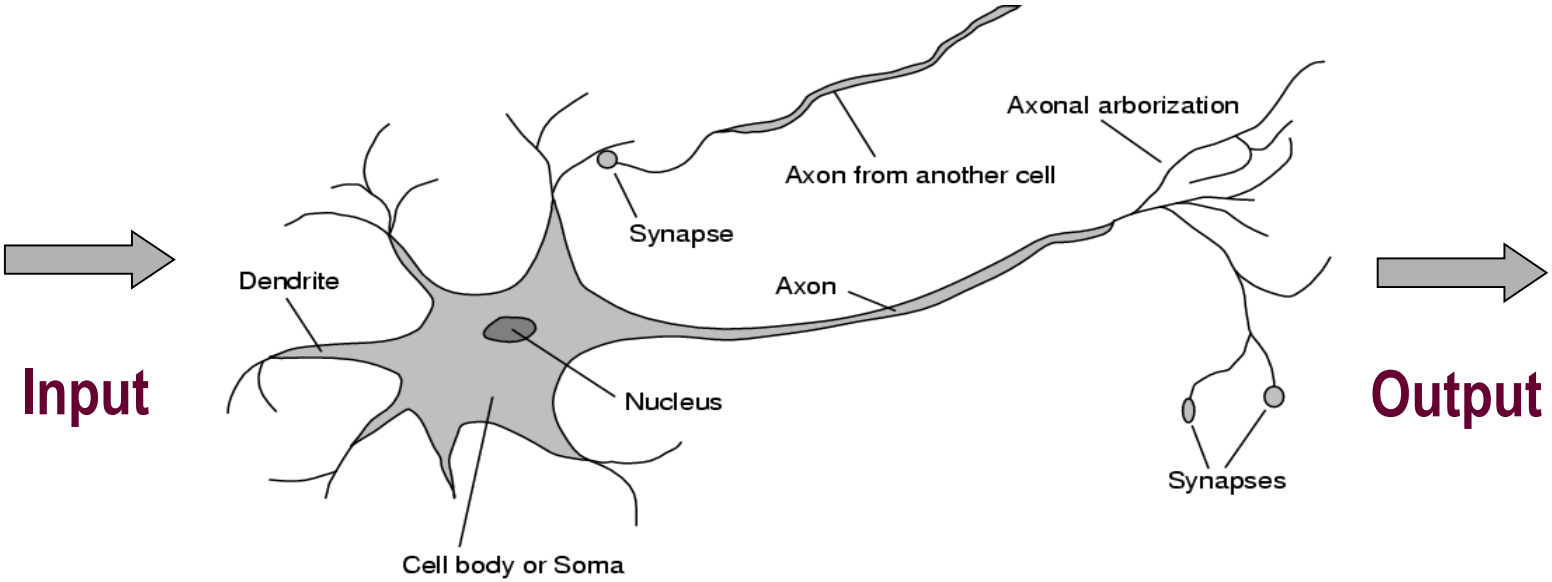
Axon : 轴突

Dendrite: 树突

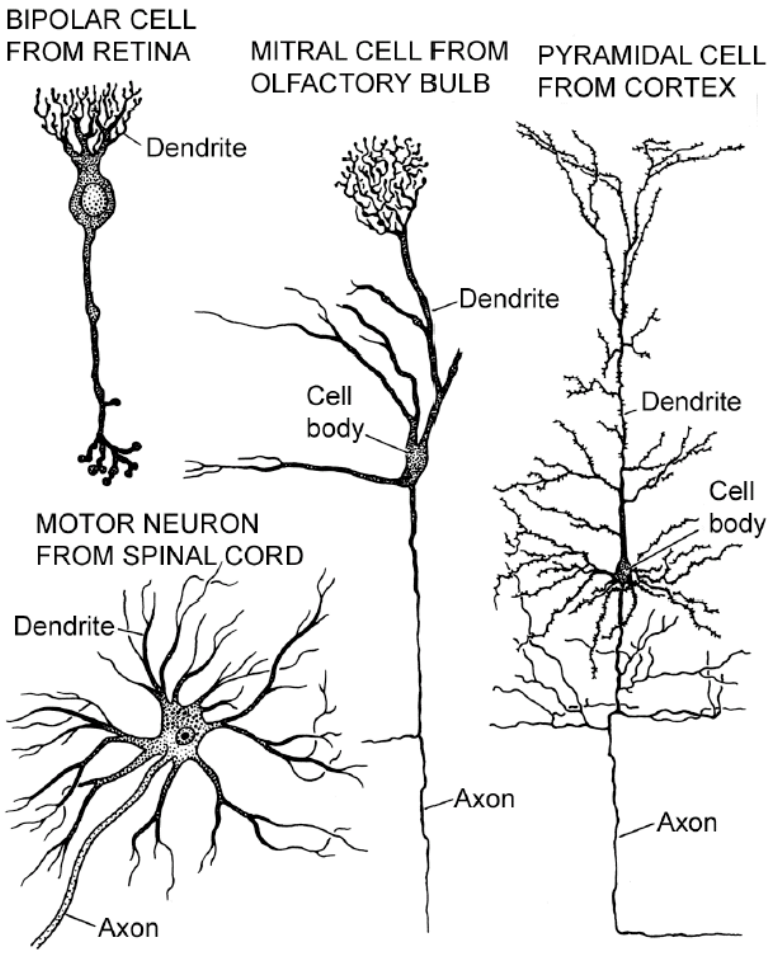
Synapse: 突触

Neurons vs. Other Cells

- Specialized extensions: dendrites and axons
- Neurons communicate with each other through an electrochemical process



Different Neurons

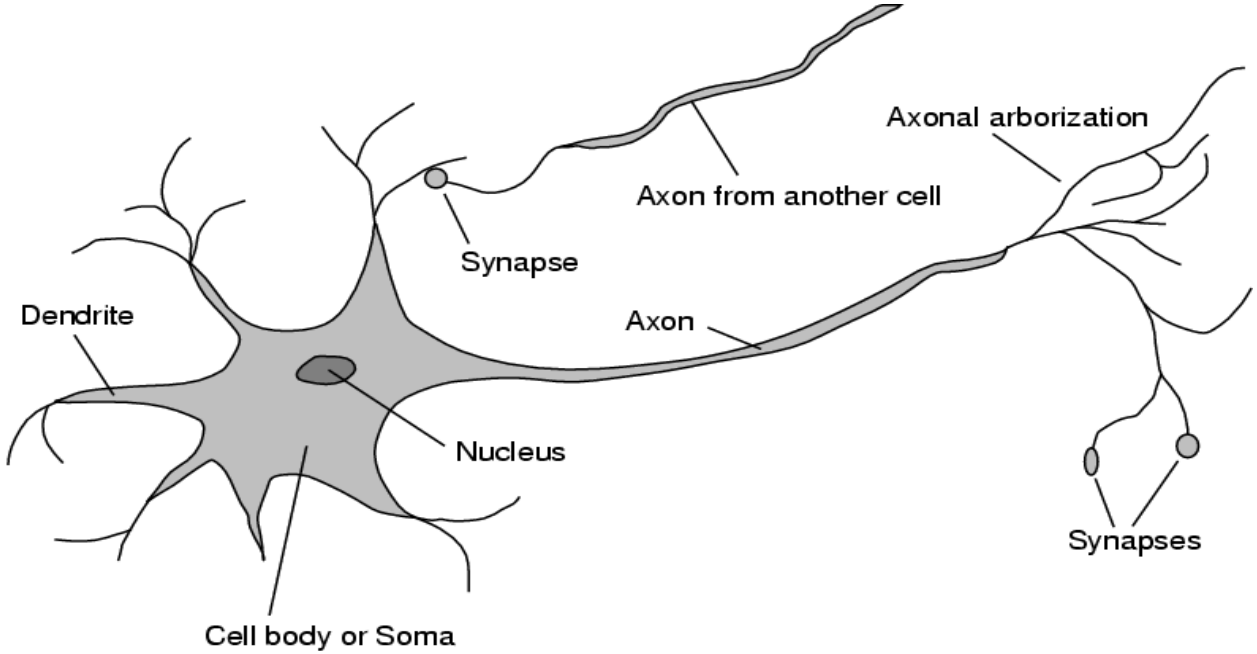


- Neurons come in many different shapes and sizes
- Some of the smallest neurons have cell bodies that are only 4 microns wide, while some of the biggest neurons have cell bodies that are 100 microns wide

Micron=100万分之一米

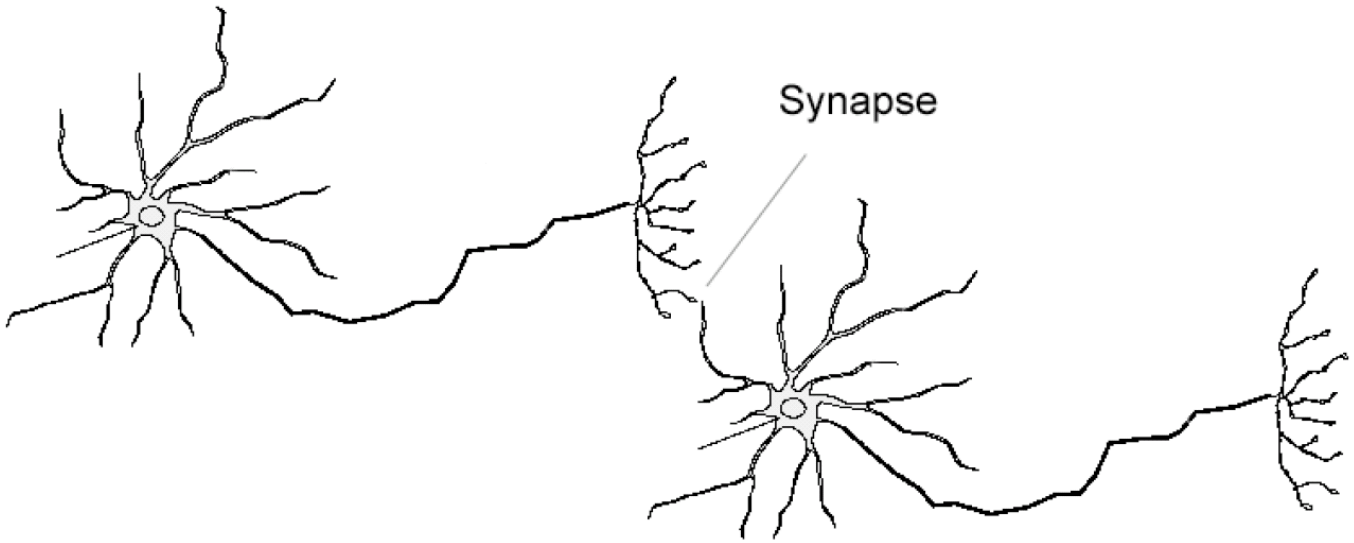
Axons and Dendrites

- Dendrites branch and terminate *in the vicinity of the cell body*, rarely more than a millimeter long and often much shorter
- Axons can extend to *distant targets*, more than a meter away in some instance



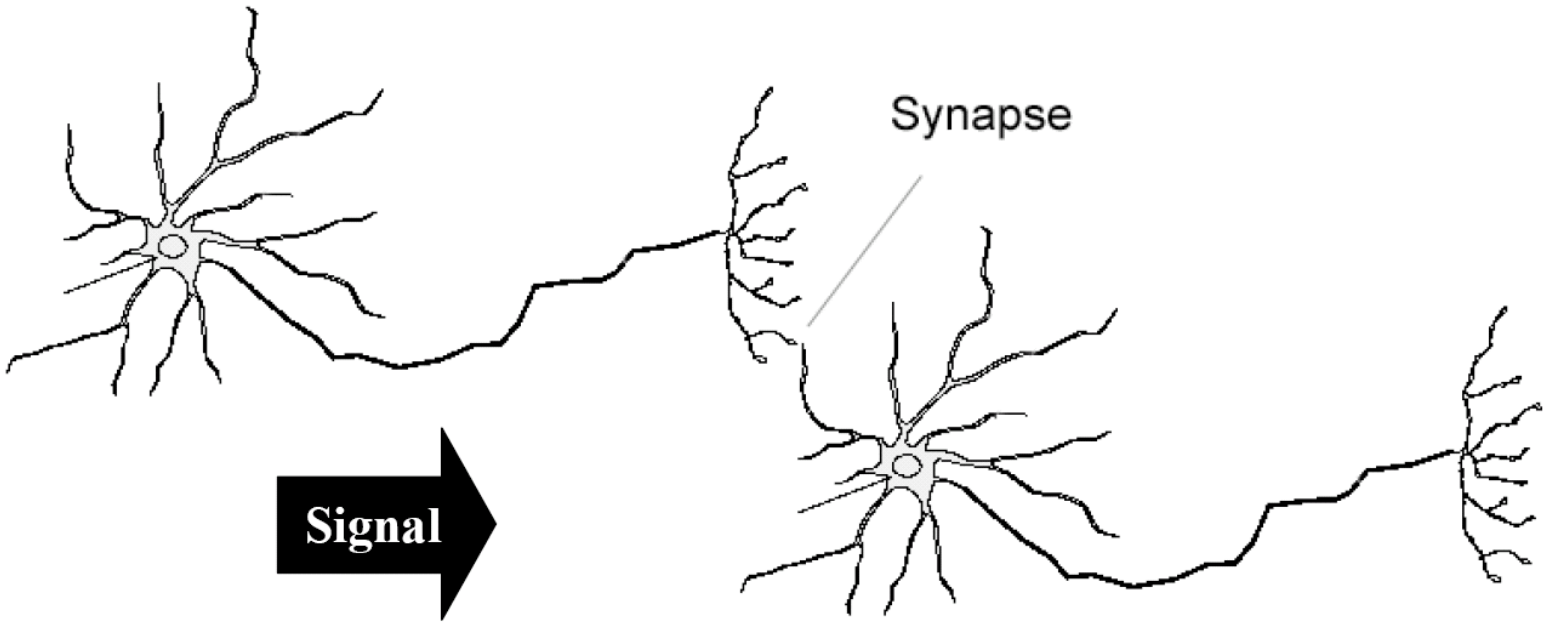
Synapses

- Neurons communicate through specialized junctions called *synapses*

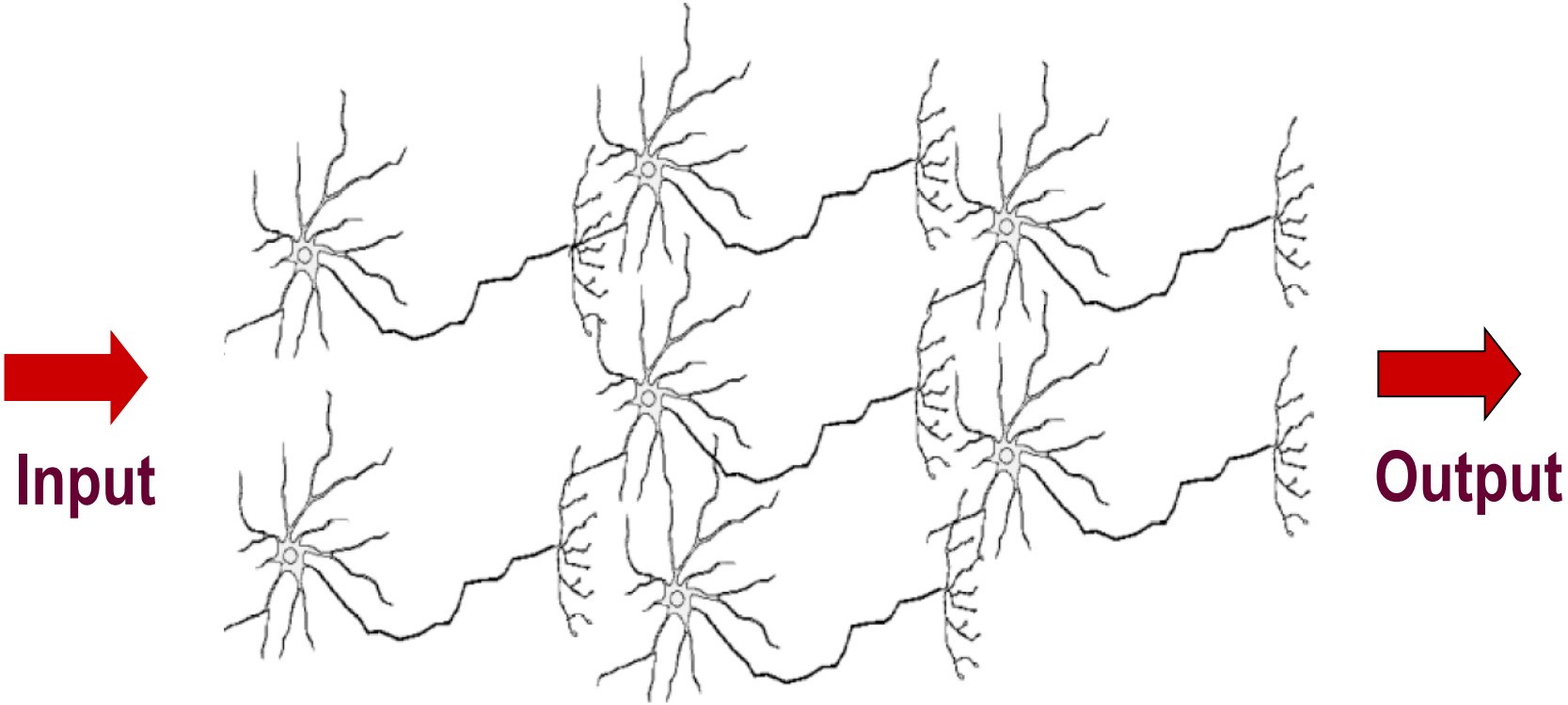


Axonal Signals

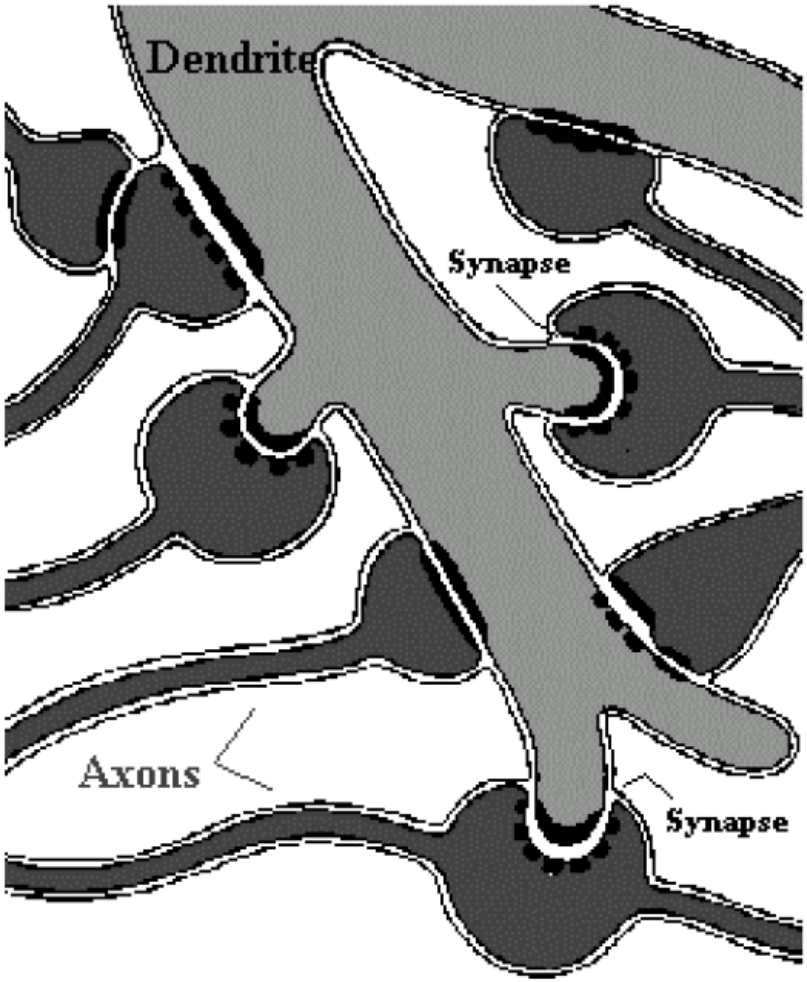
- An electrical signal
- 20 m/s to 100 m/s



A Neural Network

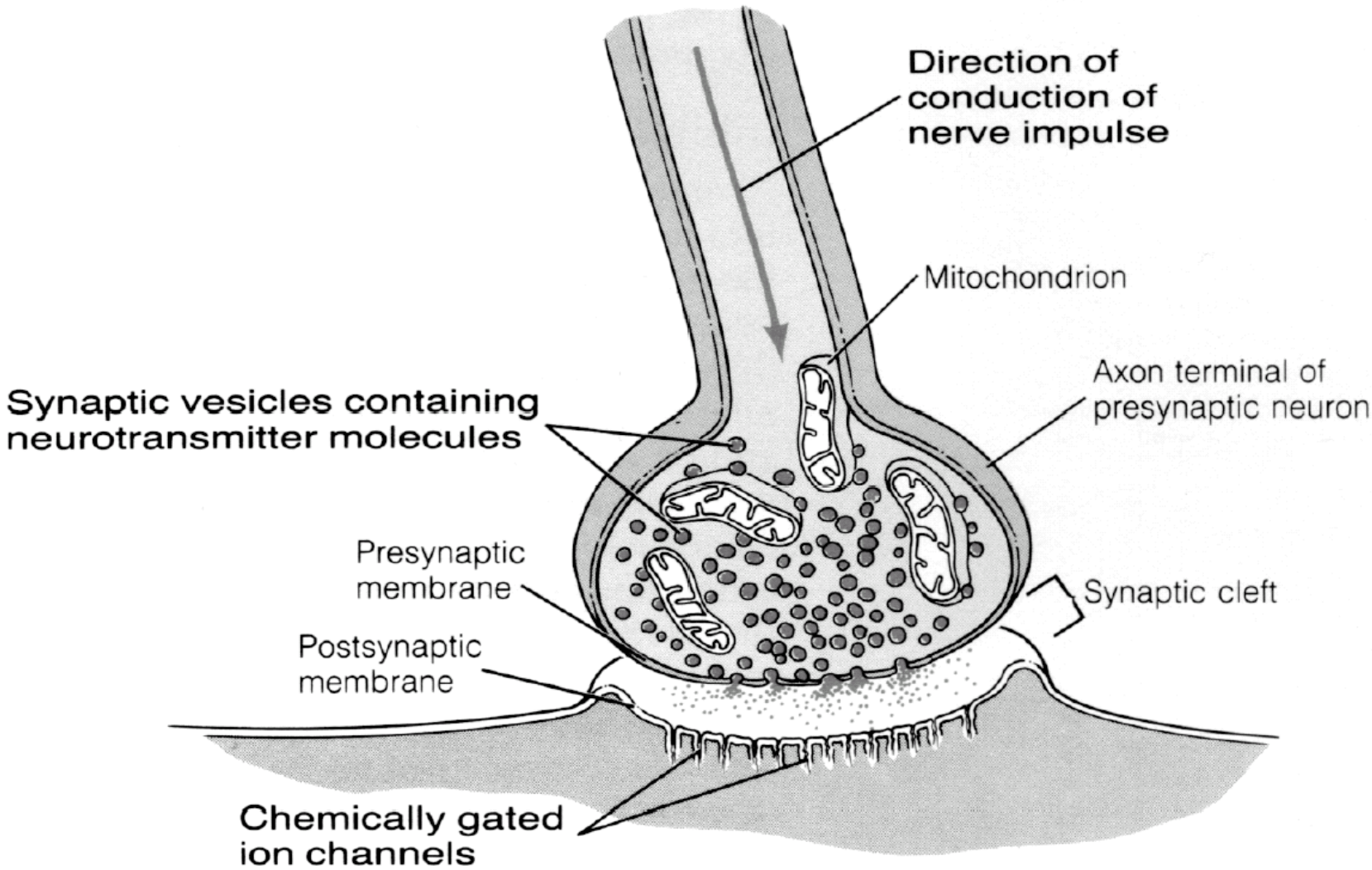


Synapses and Dendrites

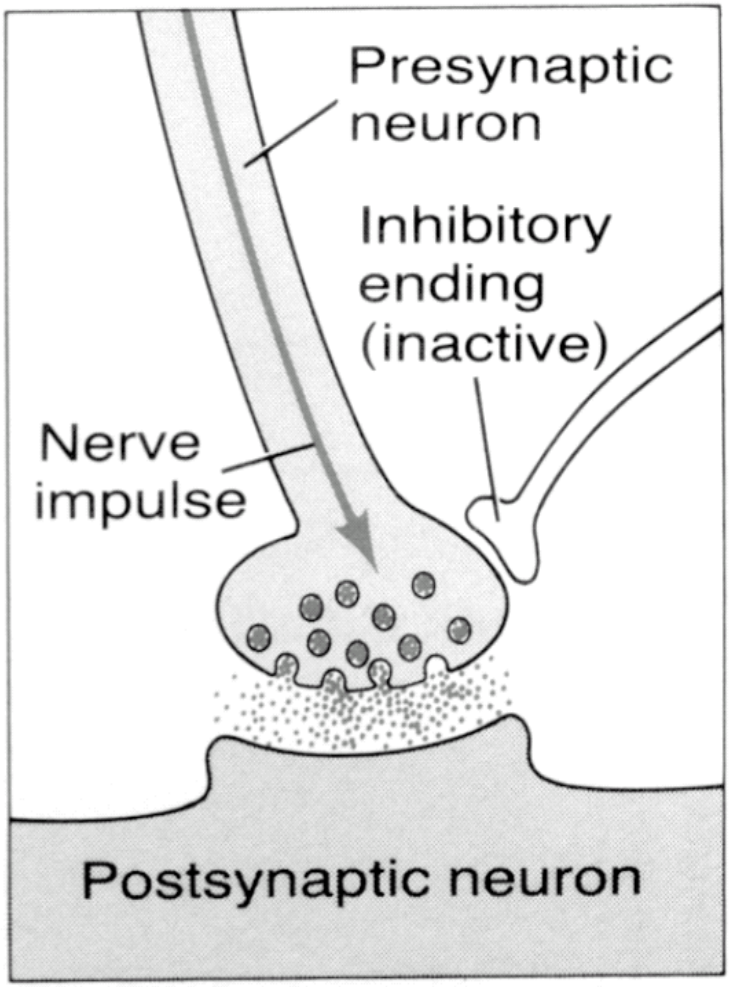


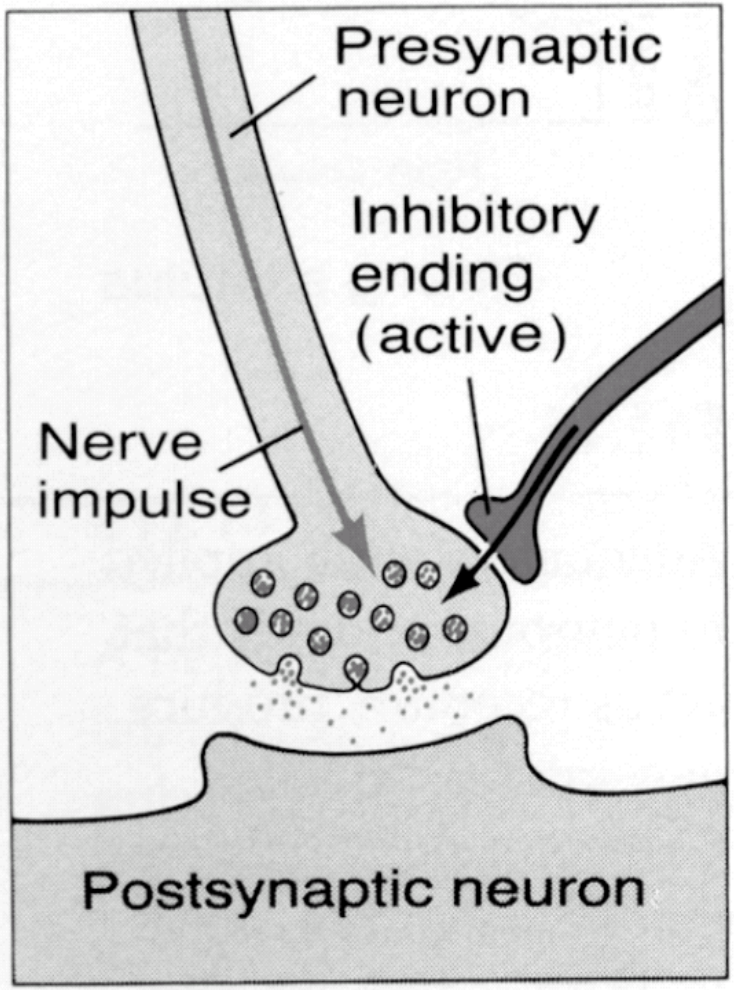
- Axon releases chemical transmitters into the synaptic cleft

Synapse


Direction of conduction of nerve impulse
Mitochondrion
Axon terminal of presynaptic neuron
Synaptic vesicles containing neurotransmitter molecules
Presynaptic membrane
Synaptic cleft
Postsynaptic membrane
Chemically gated ion channels

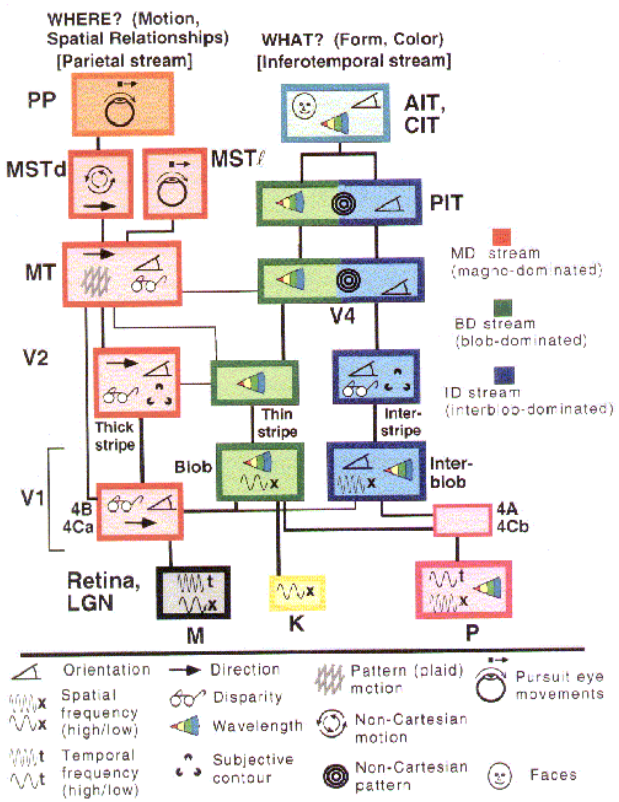
Inhibition

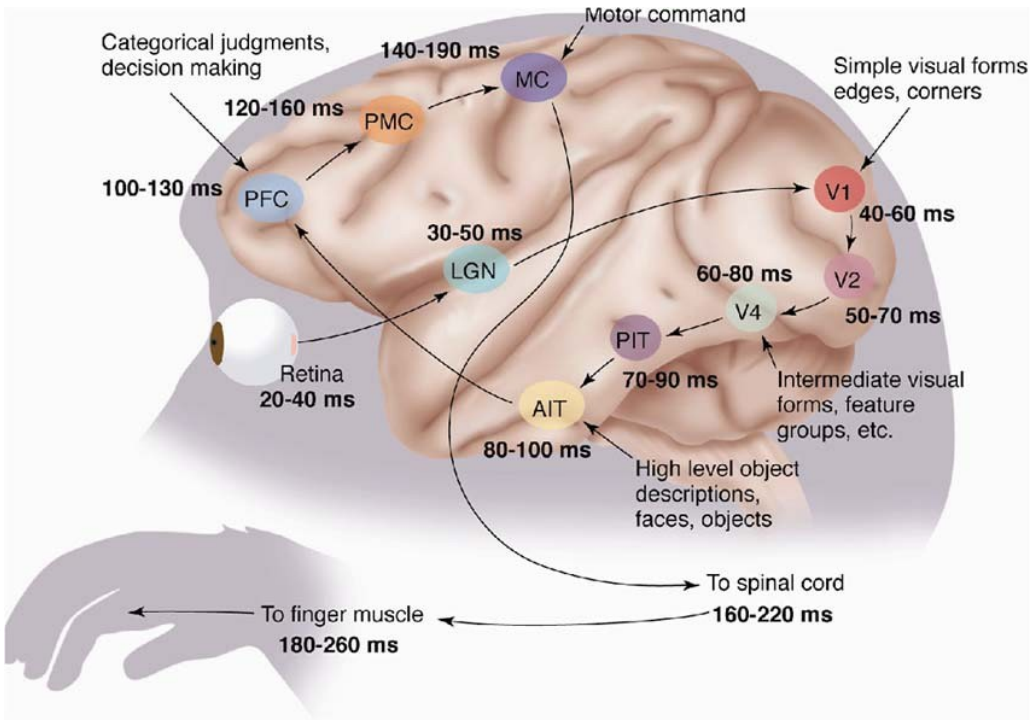

Presynaptic neuron
Inhibitory ending (inactive)
Nerve impulse
Postsynaptic neuron

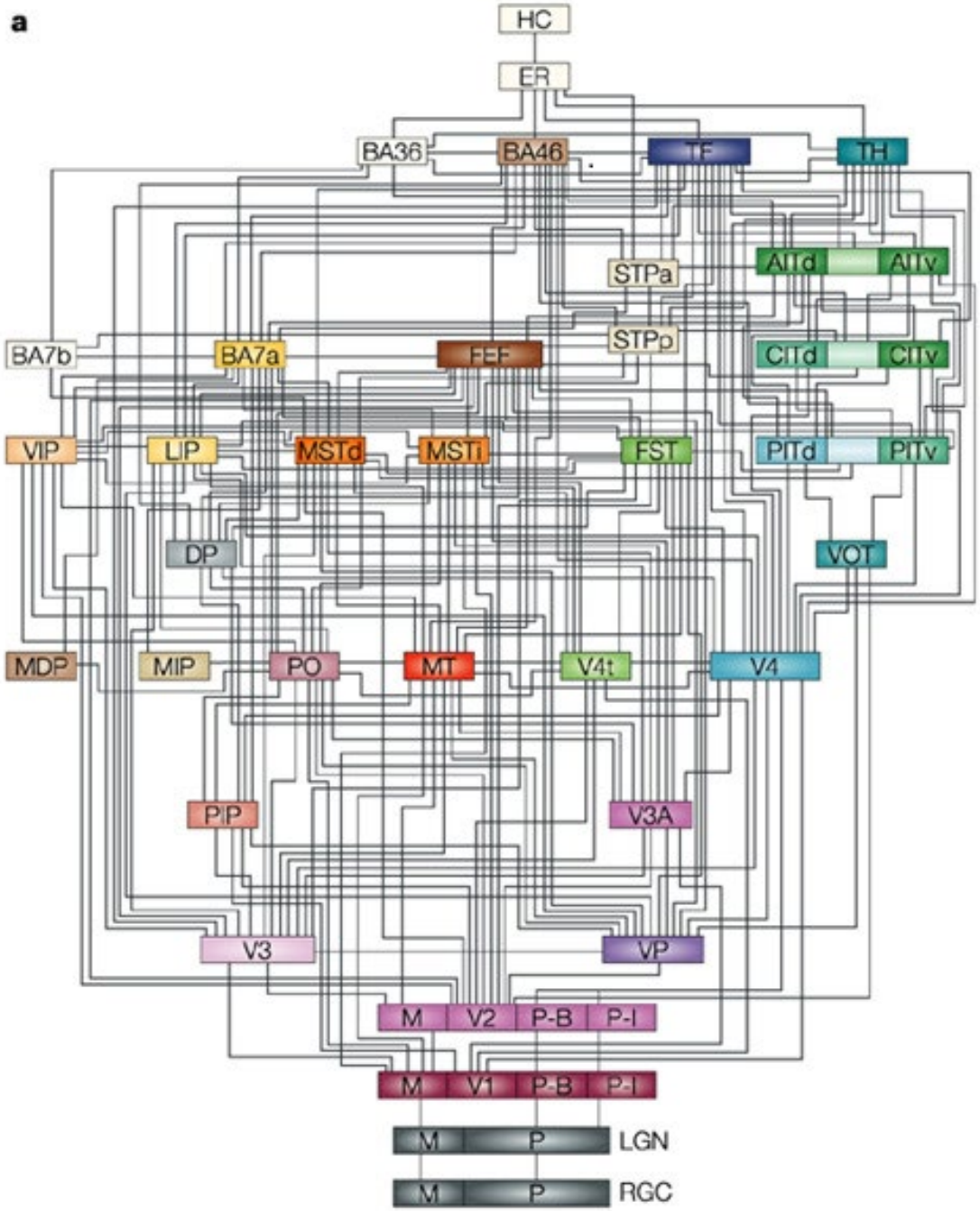

Presynaptic neuron
Inhibitory ending (active)
Nerve impulse
Postsynaptic neuron

The Mammalian Visual cortex is Hierarchical

- The ventral (recognition) pathway in the visual cortex has multiple stages
- Retina - LGN - V1 - V2 - V4 - PIT - AIT ....
- Lots of intermediate representations

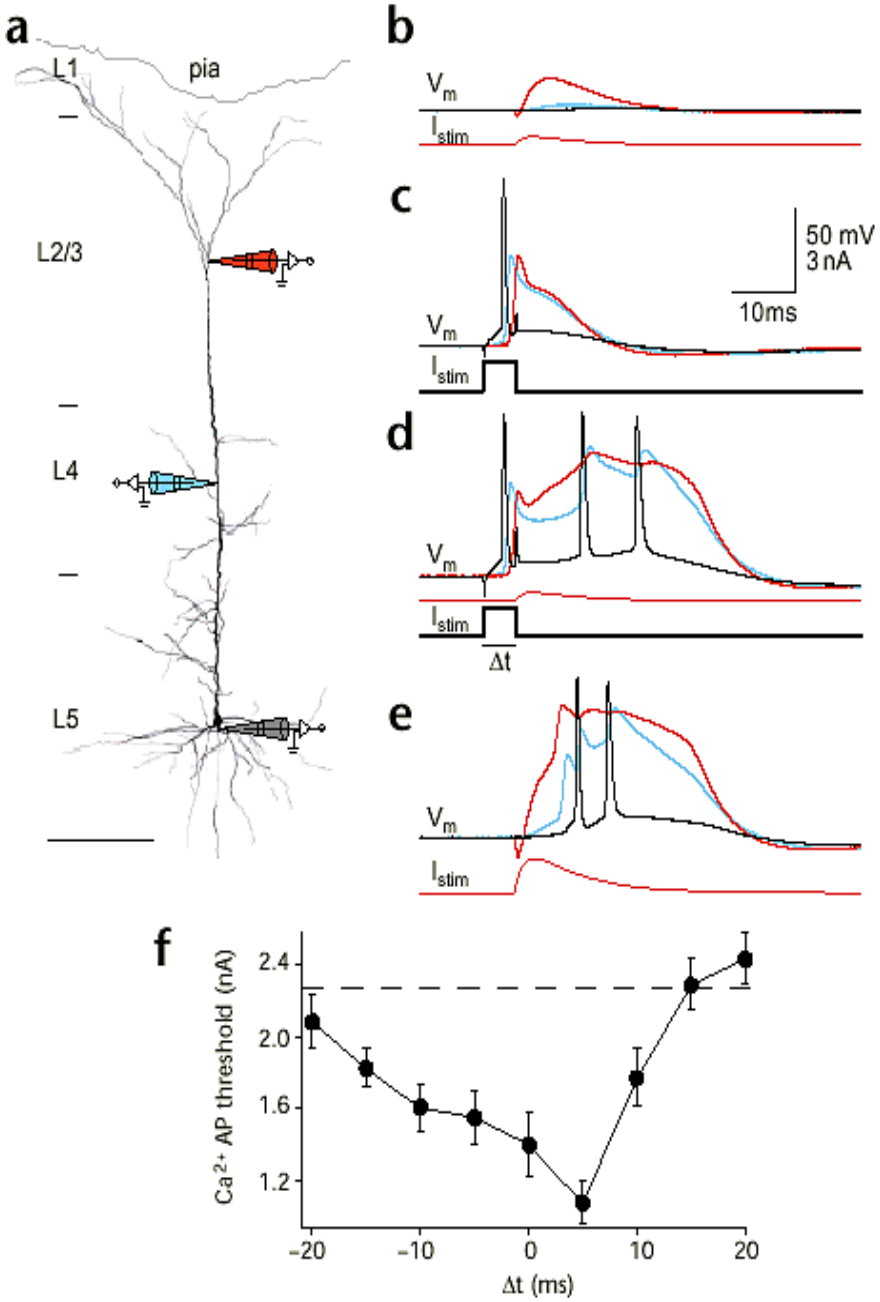


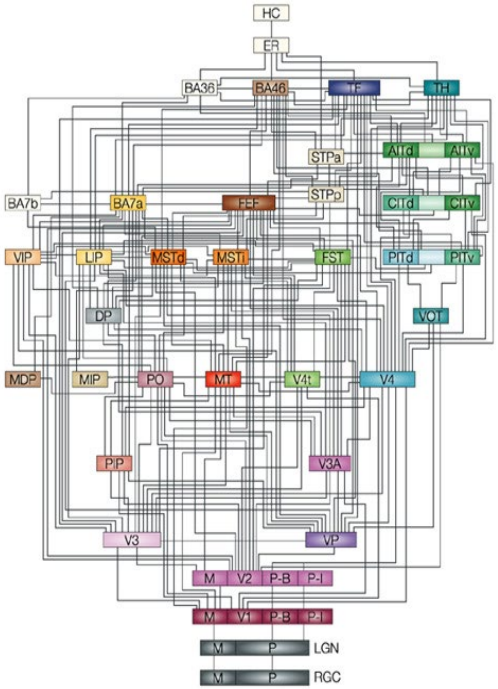


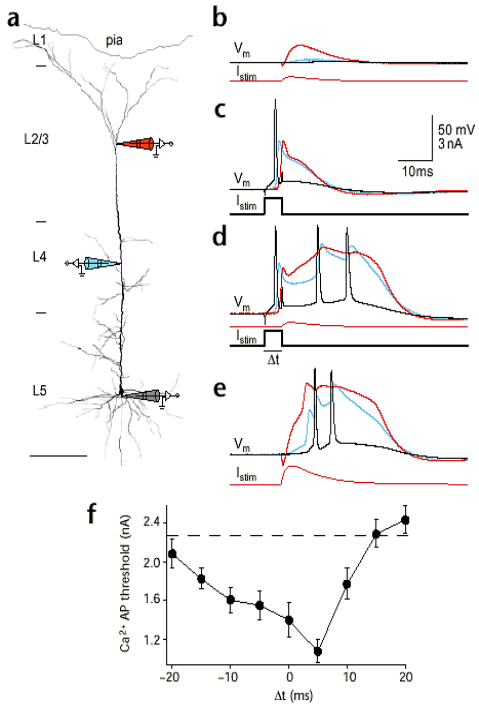


猴视觉皮层既平行又分级的30多个视觉皮层区域间连接的示意图

- 30多个视皮层区
- 10多个等级
- 305条视觉联系

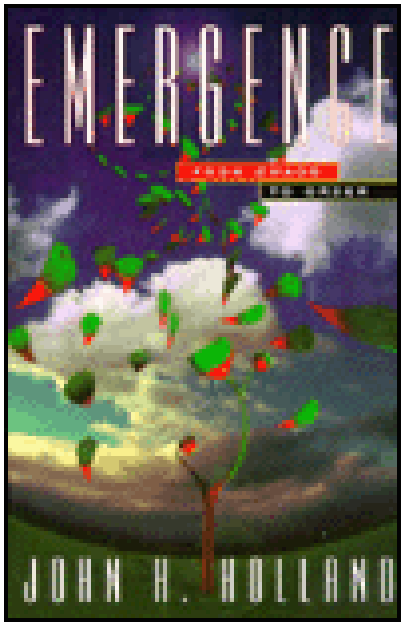

a
L1
pia
L2/3
L4
L5
b
V_m
I_{stim}
c
50 mV
3 nA
10ms
V_m
I_{stim}
d
V_m
I_{stim}
Δt
e
V_m
I_{stim}
f
Ca^{2+} AP threshold (nA)
2.4
2.0
1.6
1.2
-20
-10
0
10
20
Δt (ms)





Our knowledge of organizing neurons in system level is rather poor !

Emergence: From Chaos to Order



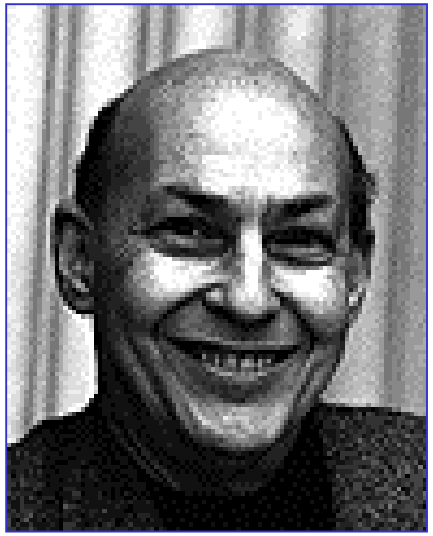
John H. Holland (1998)

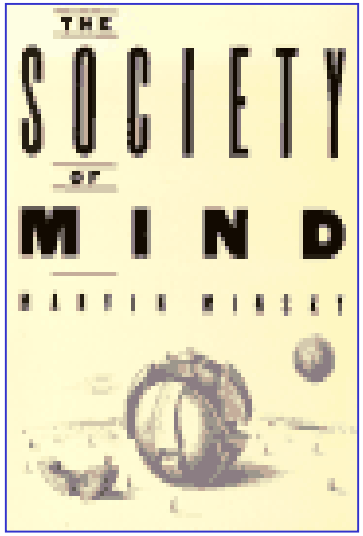
A Theory of Emergence

"We are everywhere confronted with emergence in complex adaptive systems: ant colonies, network of neurons, Internet…, where the behavior of the whole is much more complex than the behavior of the parts."

J. H. Holland, Emergence: From Chaos to Order (1998)

Marvin Minsky (1986)



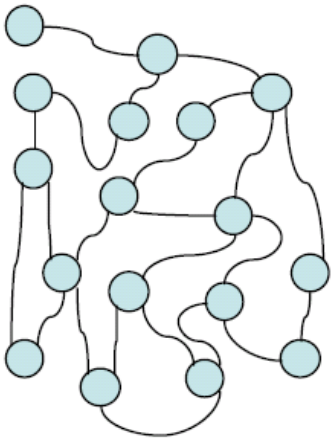


Emergence of Intelligence

“This book tries to explain how minds work. How can intelligence emerge from non-intelligence ? To answer that, we’ll show that you can build a mind from many little parts, each mindless by itself”

What is a Neural Network ?

- A neural network is a network of many simple processors (neurons, units)
  - The units are connected by *connections*
  - Each connection has a number weight associated with it
  - The units operate only locally – on their weights and the inputs they receive through the connection



- Connectionism
- Parallel distributed processing
- Neural computation
- Neurocomputing

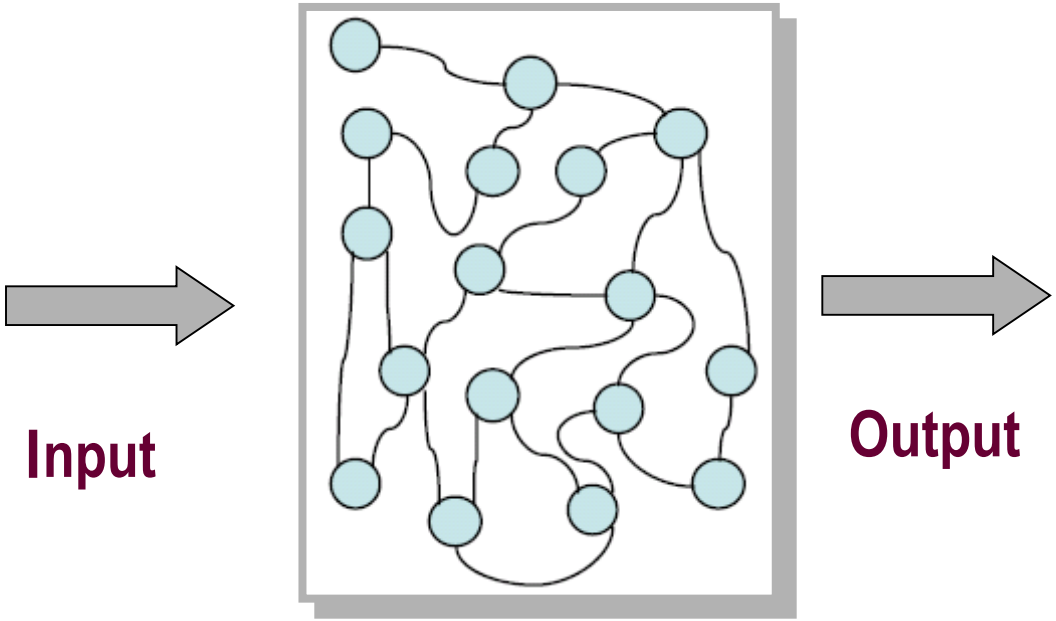
What is a Neural Network? (Cont.)

- A NN is a massively parallel distributed processor made up of simple processing unit, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects:
  - Knowledge is acquired by the network from its environment through *a learning process*
  - Interneuron connection strengths, known as *synaptic weights*, are used to store the acquired knowledge

What is a Neural Network ? (Cont.)

- Some NNs are models of biological NNs and some are not
- The inspiration for the field of NNs came from the desire to produce artificial systems capable of sophisticated computations similar to those that the human brain routinely performs, and thereby also to enhance our understanding of the brain

Information Processing



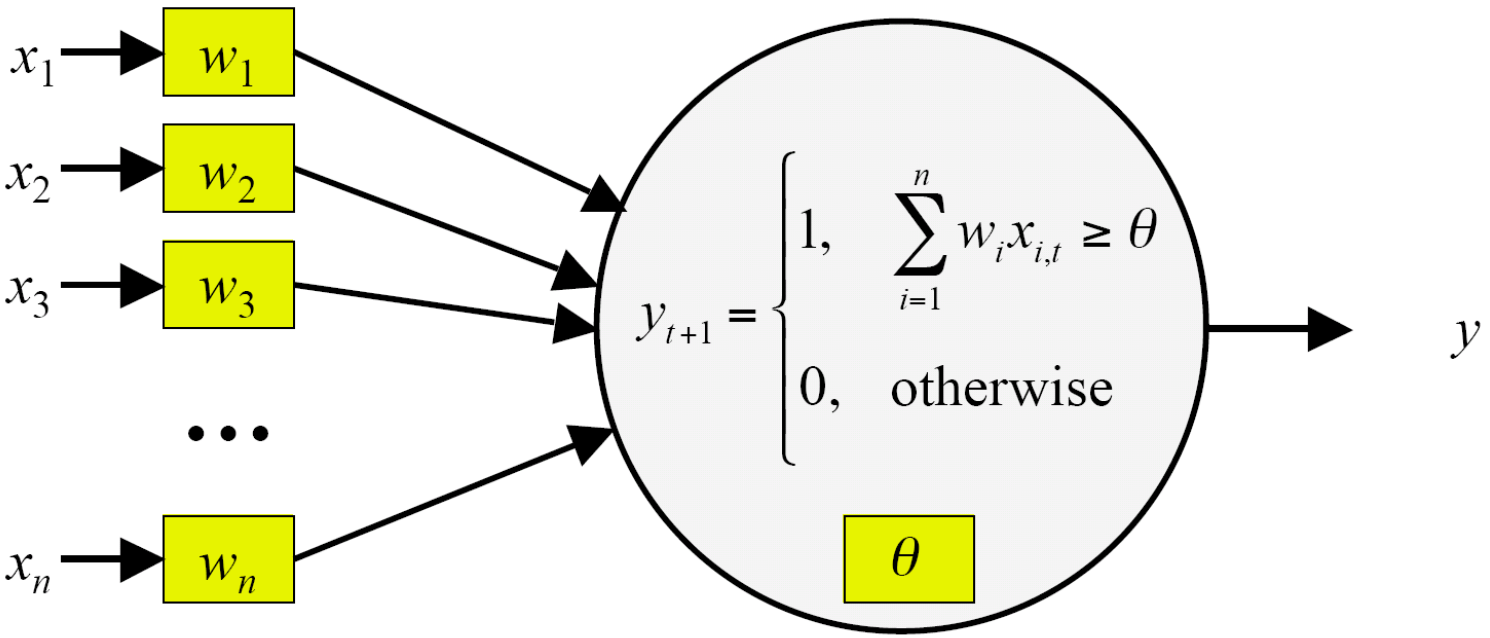
Neural Network History

- 1943: McCulloch and Pitts Model
- 1949: Hebb's rule
- 1962: Rosenblatt's learning Perceptron
- 1969: Minsky and Papert published their book "Perceptrons" on the limitations of perceptrons
- 1970s: Kohonen, Anderson, Grossberg, Amari, Fukushima
- 1980s: Rumelhart and McClelland, Hopfield, etc.
- 1990s: NNs have found many practical applications
- 2006: Hinton, LeCun, Bengio, etc. deep learning

Professors Amari and Fukushima in ICONIP2011

Neural Network History -1

- 1943: McCulloch and Pitts develop basic models of neurons
  - The first artificial neuron



Neural Network History -2

1943: Warren McCulloch and Walter Pitts

Networks of logical threshold units (all or nothing responses) can perform logic calculations. Any finite logical expression can be realized by these McCulloch-Pitts neurons.

Describes a true connectionist model, with simple computing elements, arranged largely in parallel, doing powerful computations with appropriately constructed connections.

Neural Network History -3

1949: Donald O. Hebb

The organization of behavior was the first explicit statement of a physiological learning rule for synaptic modification (since become known as the Hebb rule).

"When an axon of cell A is near enough to excite a cell B and repeatedly or persistently takes part in firing it, some growth process or metabolic change takes place in one or both cells such that A's efficiency, as one of the cells firing B, is increased."

Neural Network History -4

1950-1970: Many papers on associative memory models (Taylor, Willshaw, Longuet-Higgins, Anderson, Kohonen, Nakano).

Correlation matrix memories

1956: F. Rosenblatt

The perceptron model and the perceptron convergence algorithm

Described a learning machine with simple computing elements that was potentially capable of complex adaptive behaviors.

1960: Widrow and Hoff

Introduced the least mean square error algorithm (gradient descent) which is the basis for most modern "error correction rules".

Neural Network History -5

1969: Minsky and Papert

Used elegant mathematics to demonstrate that there are fundamental limits on what a one-layer perceptron can compute.

"In the popular history of neural networks, first came the classical period of the perceptron, when it seemed as if neural networks could do anything. A hundred algorithms bloomed, a hundred schools of learning machines contended. Then cam the onset of the dark ages, where, suddenly, research on neural networks was unlived, unwanted, and most important, unfunded. "

Neural Network History -6

1973; 1976: Christoph van der Malsburg

Demonstrated self-organization in computer simulations motivated by topologically ordered maps in the brain.

1980s: Stephen Grossberg

Adaptive resonance theory

1982: John Hopfield

Used the idea of an energy function to formulate a new way of understanding the computation performed by recurrent networks with symmetric synaptic connections. He established the relation between such recurrent networks and an Ising Model used in statistical physics.

1982: Teuvo Kohonen

Self-organizing maps

Neural Network History -7

1983: Sutton, Barto and Anderson

Introduced reinforcement learning and showed that a reinforcement learning system could learn to balance a broomstick in the absence of a helpful teacher.

1986: Rumelhart, Hinton and Williams

Developed the backpropagation algorithm which solved the credit assuagement problem for multi-layer networks, which emerged as the most popular algorithm for the training of neural networks. It was discovered independently also by Parker and LeCun.

Neural Network History -8

2006: Hinton, LeCun, and Bengio

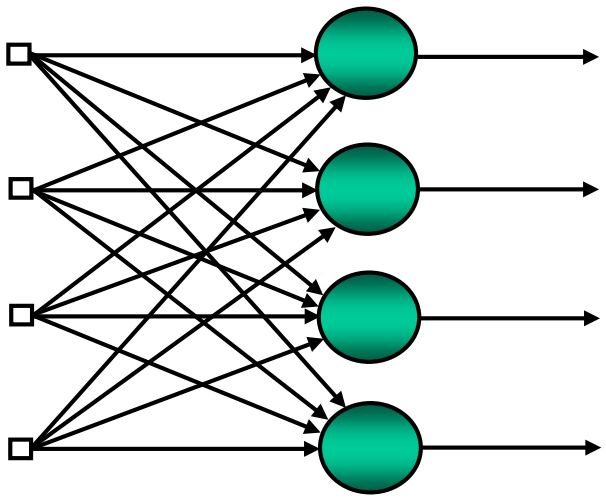
Developed deep learning algorithms and successfully applied to unsupervised feature learner.

This Lesson: Part 2

- Network architectures
- Learning paradigms
- Learning tasks

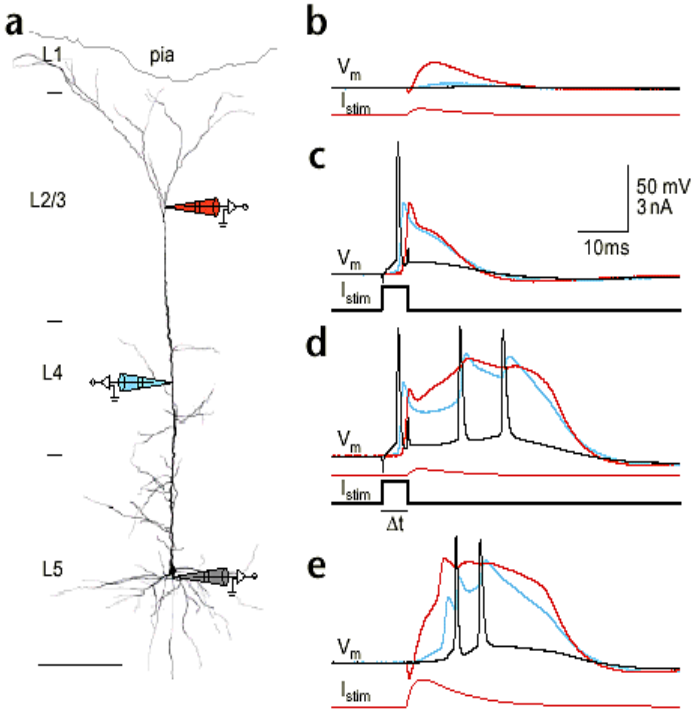
Network Architectures

- Single-Layer Feedforward Networks
- Multilayer Feedforward Networks
- Recurrent Networks
- Spiking Neural Networks (脉冲神经网络)

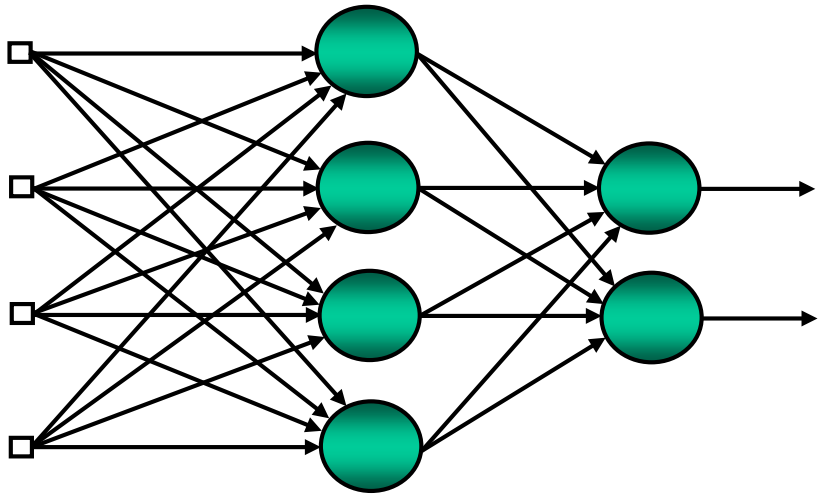


Input layer

Output layer



Multilayer Feedforward Networks

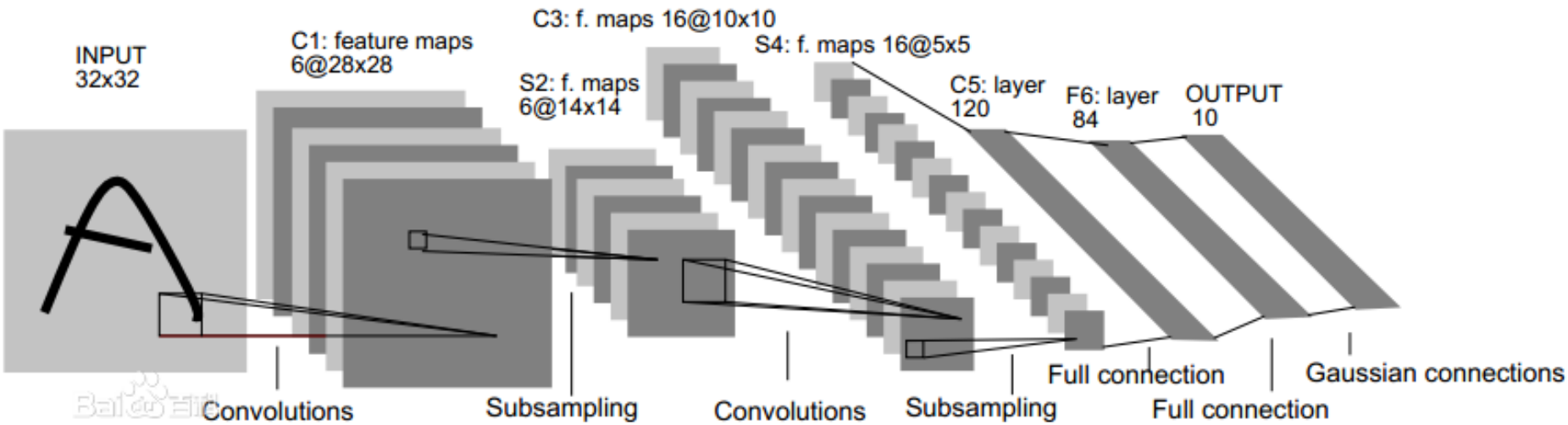


Input layer

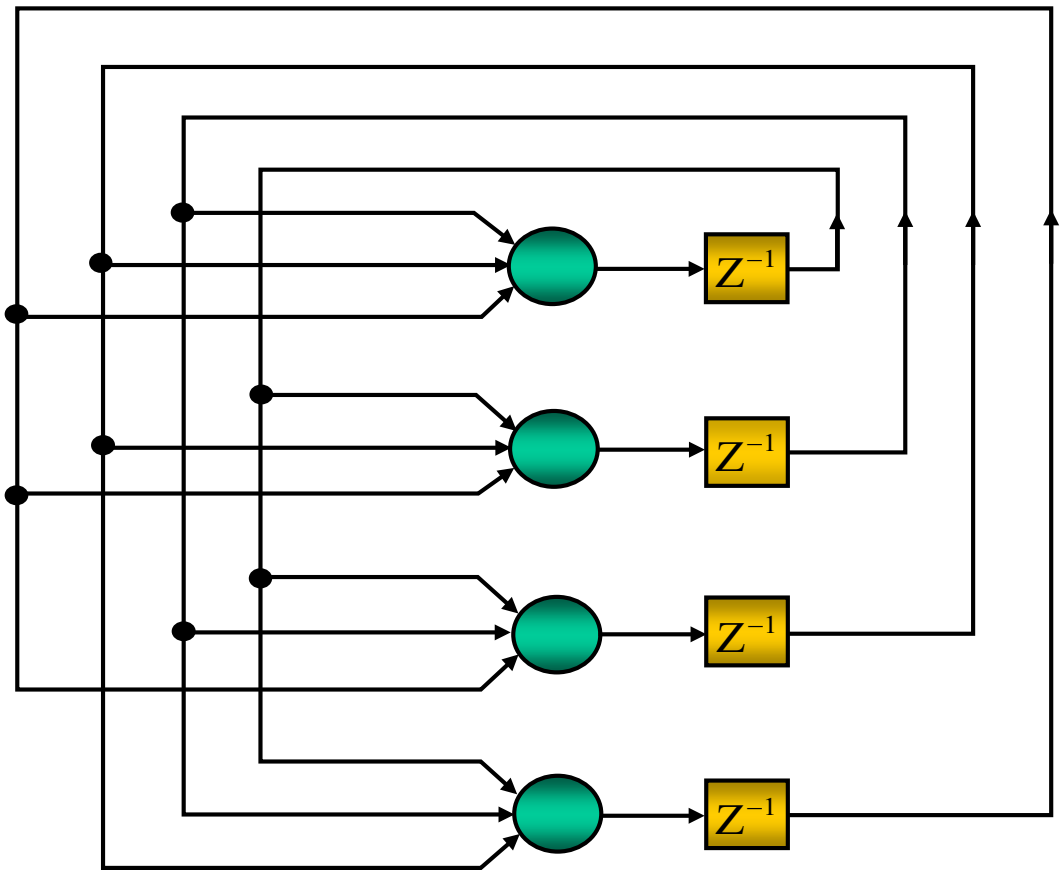
Hidden layer

Output layer

Deep Learning Structure



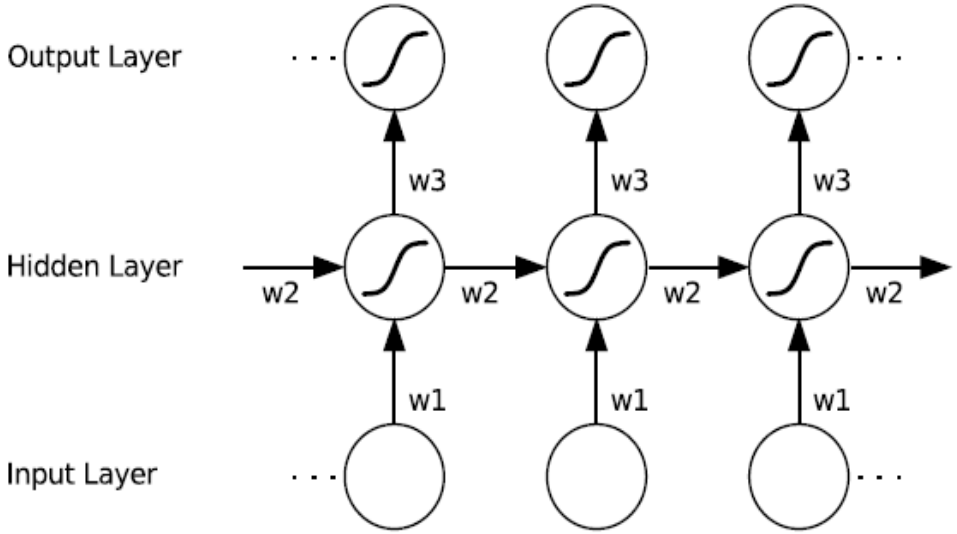
Recurrent Networks

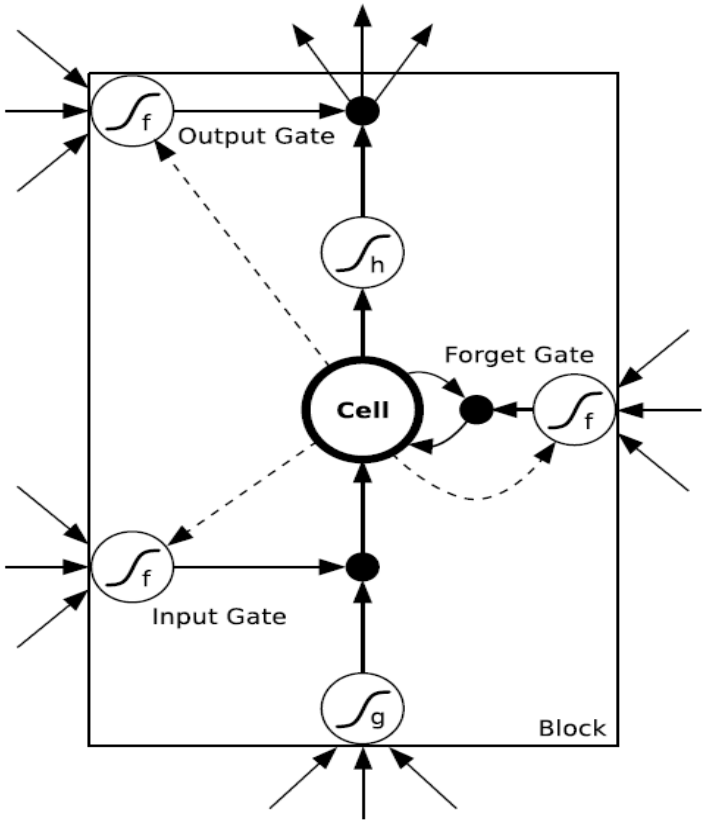


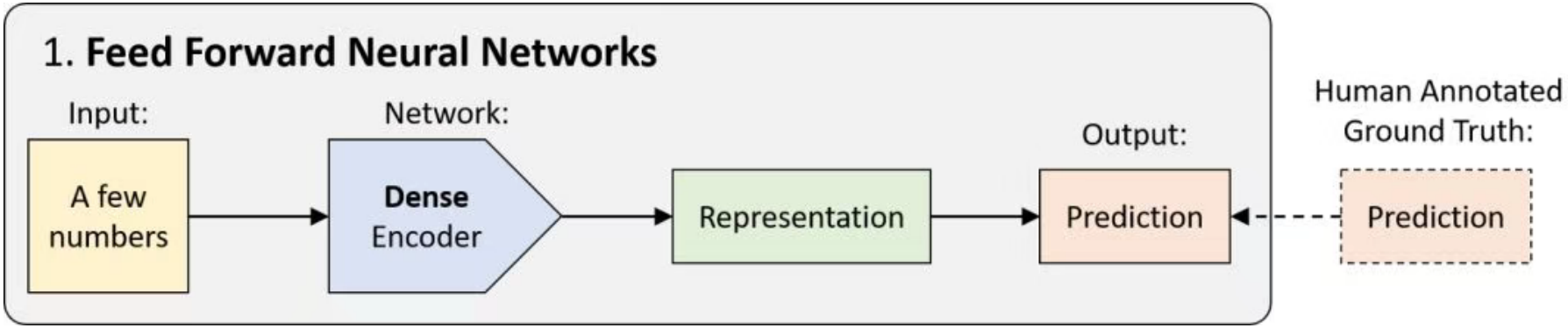
Neurons Unit-delay Operators

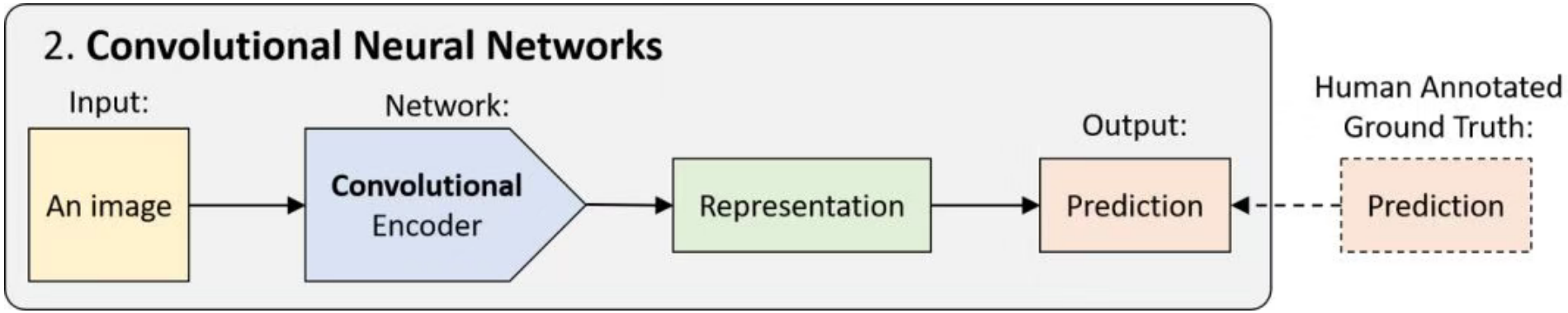
LSTM Neural Network

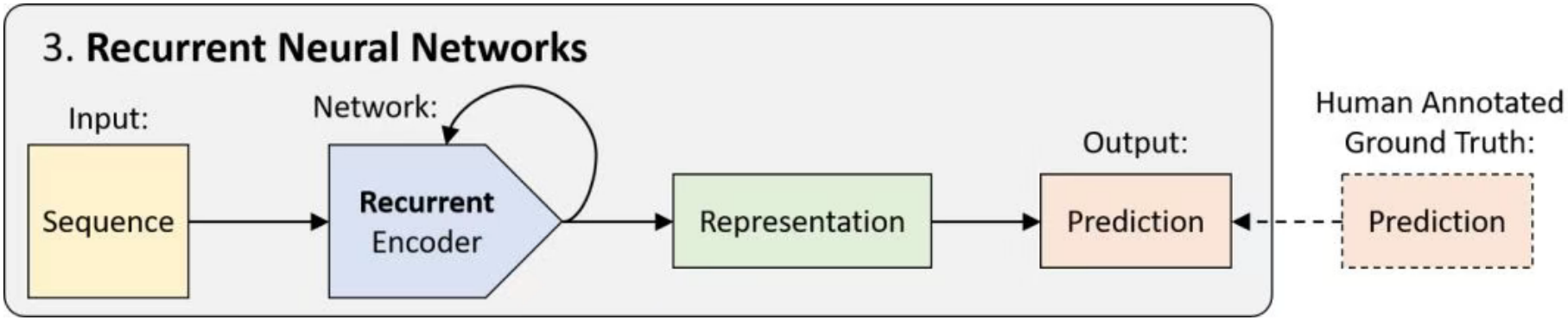
- Long Short Time Memory (LSTM) is one kind of recurrent neural network which can store states over a long period of time.

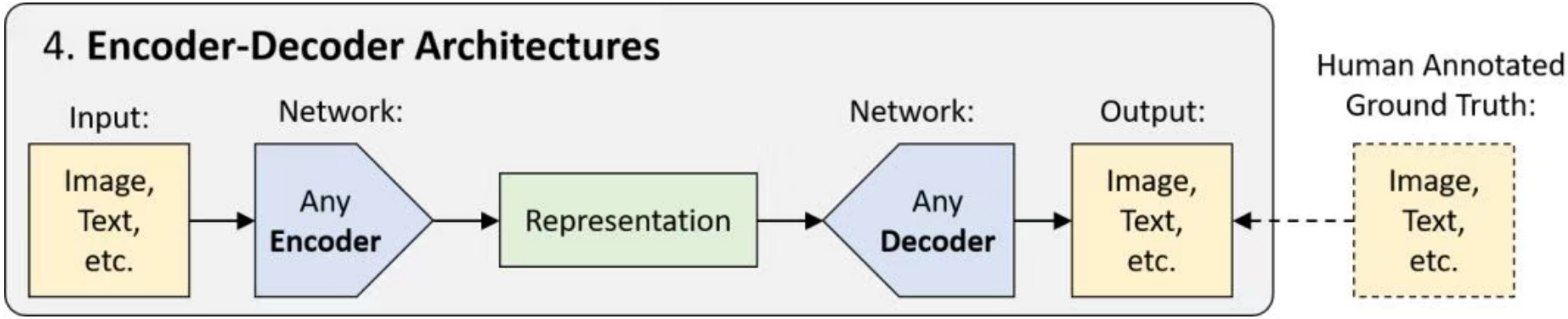


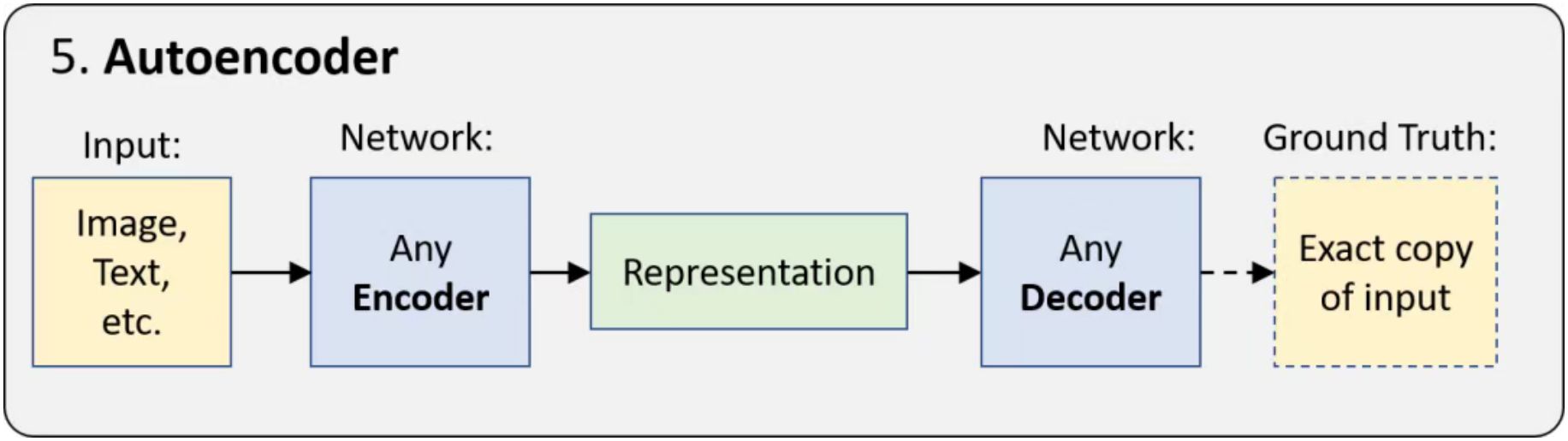


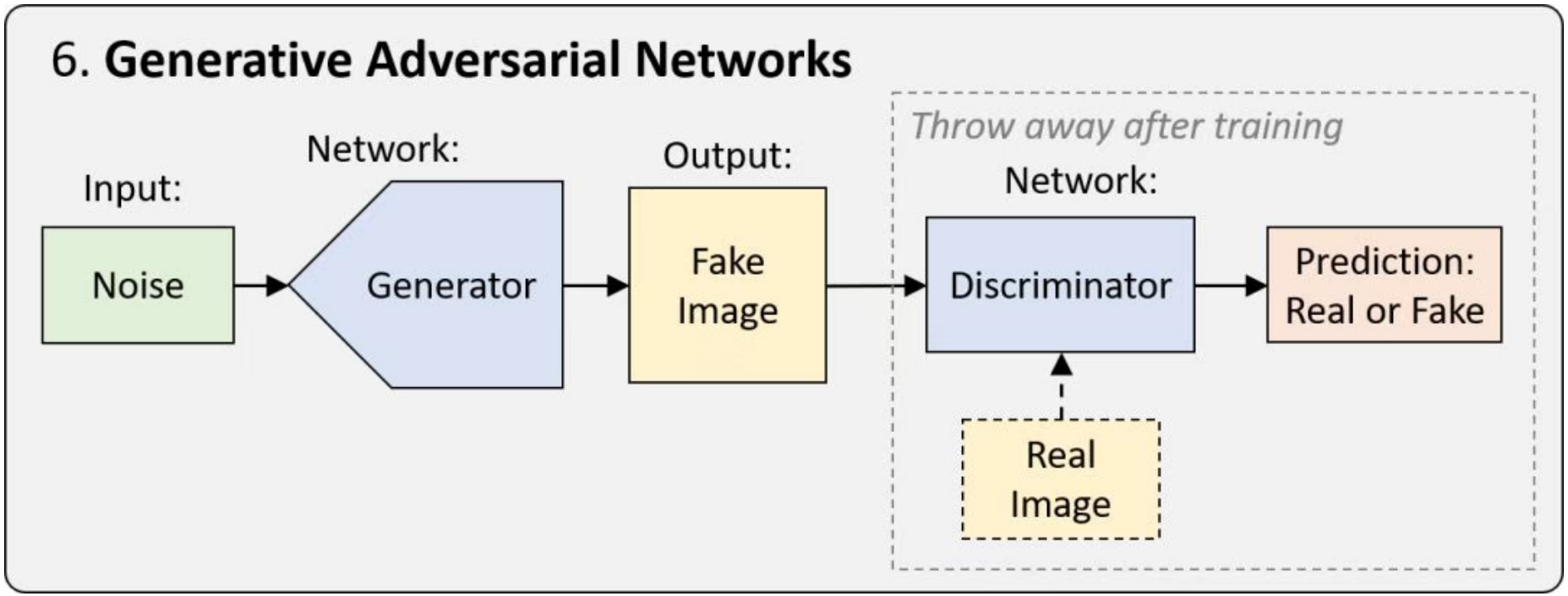

1. Feed Forward Neural Networks
Input:
A few numbers
Network:
Dense Encoder
Representation
Output:
Prediction
Human Annotated Ground Truth:
Prediction

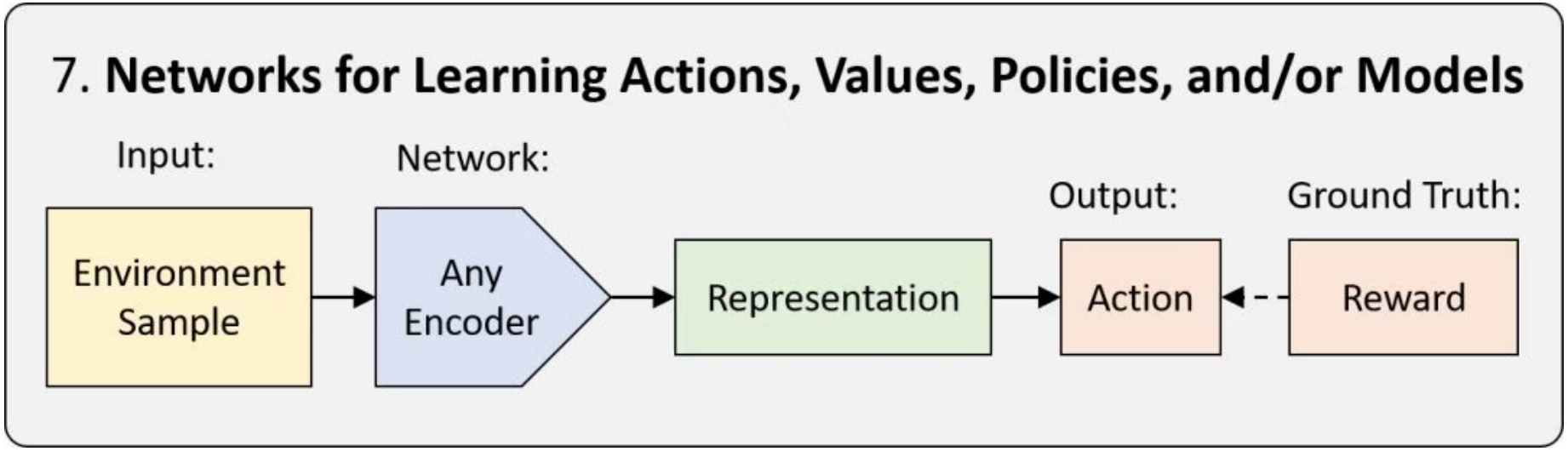

2. Convolutional Neural Networks
Input:
An image
Network:
Convolutional
Encoder
Representation
Output:
Prediction
Human Annotated
Ground Truth:
Prediction


3. Recurrent Neural Networks
Input:
Sequence
Network:
Recurrent
Encoder
Representation
Output:
Prediction
Human Annotated
Ground Truth:
Prediction


4. Encoder-Decoder Architectures
Input:
Image, Text, etc.
Network:
Any Encoder
Representation
Network:
Any Decoder
Output:
Image, Text, etc.
Human Annotated Ground Truth:
Image, Text, etc.


5. Autoencoder
Input:
Image, Text, etc.
Network:
Any Encoder
Representation
Network:
Any Decoder
Ground Truth:
Exact copy of input

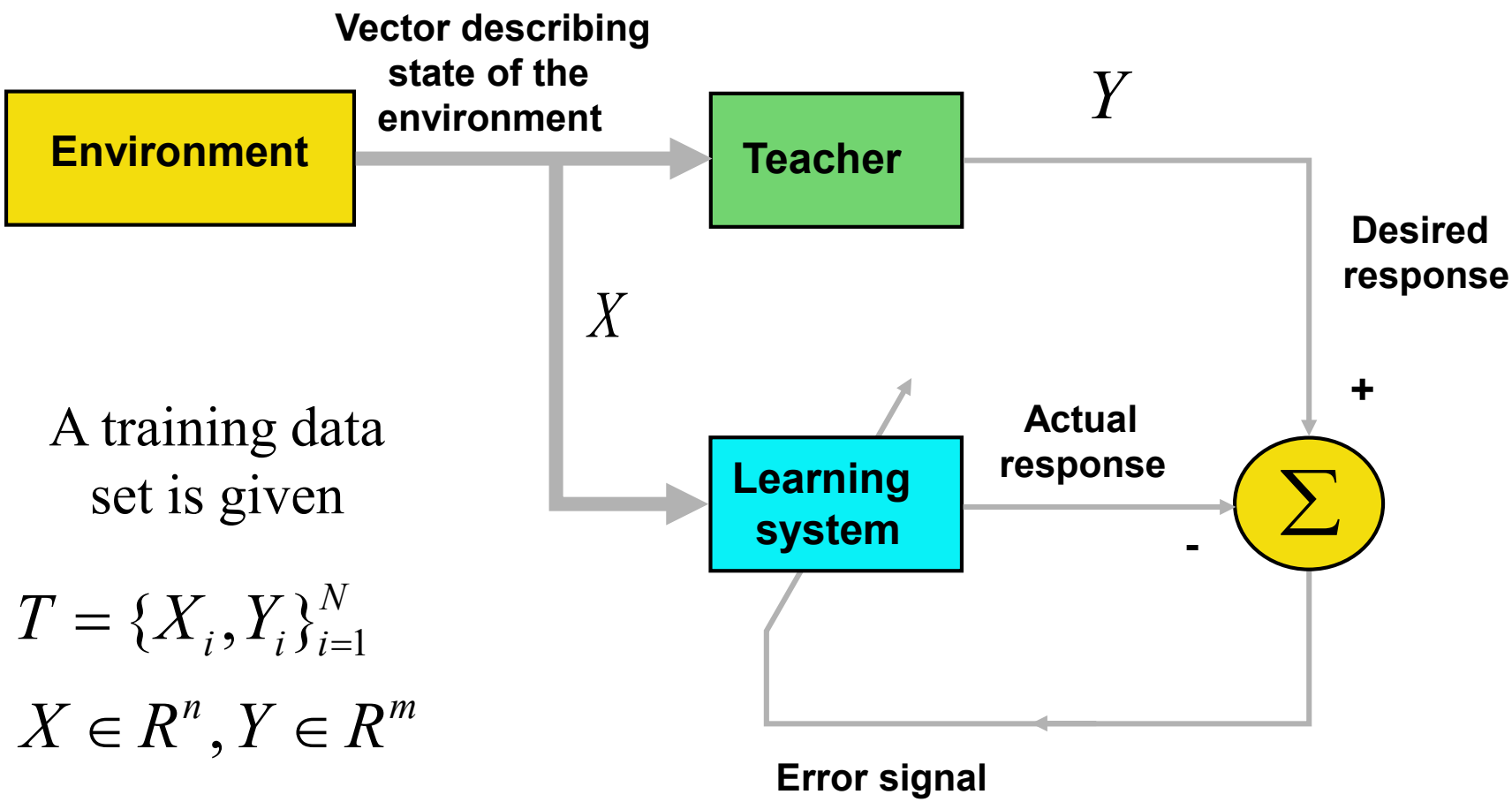

6. Generative Adversarial Networks
Input:
Noise
Network:
Generator
Output:
Fake Image
Throw away after training
Network:
Discriminator
Prediction: Real or Fake
Real Image


7. Networks for Learning Actions, Values, Policies, and/or Models
Input:
Network:
Output:
Ground Truth:
Environment Sample
Any Encoder
Representation
Action
Reward

Learning Paradigms

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

Supervised Learning



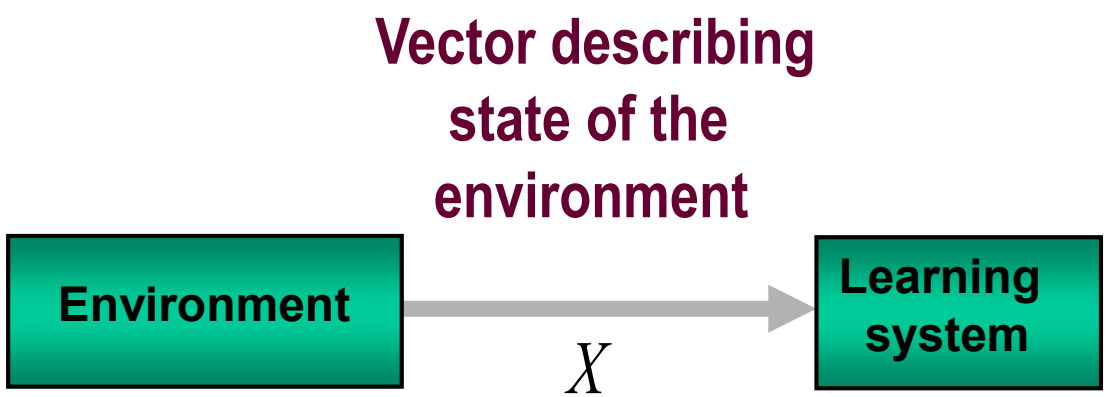
A training data set is given

$$T = \{X_i, Y_i\}_{i=1}^{N}$$

$$X \in R^n, Y \in R^m$$

Unsupervised Learning

Unsupervised Learning:
No labeled training examples are now available

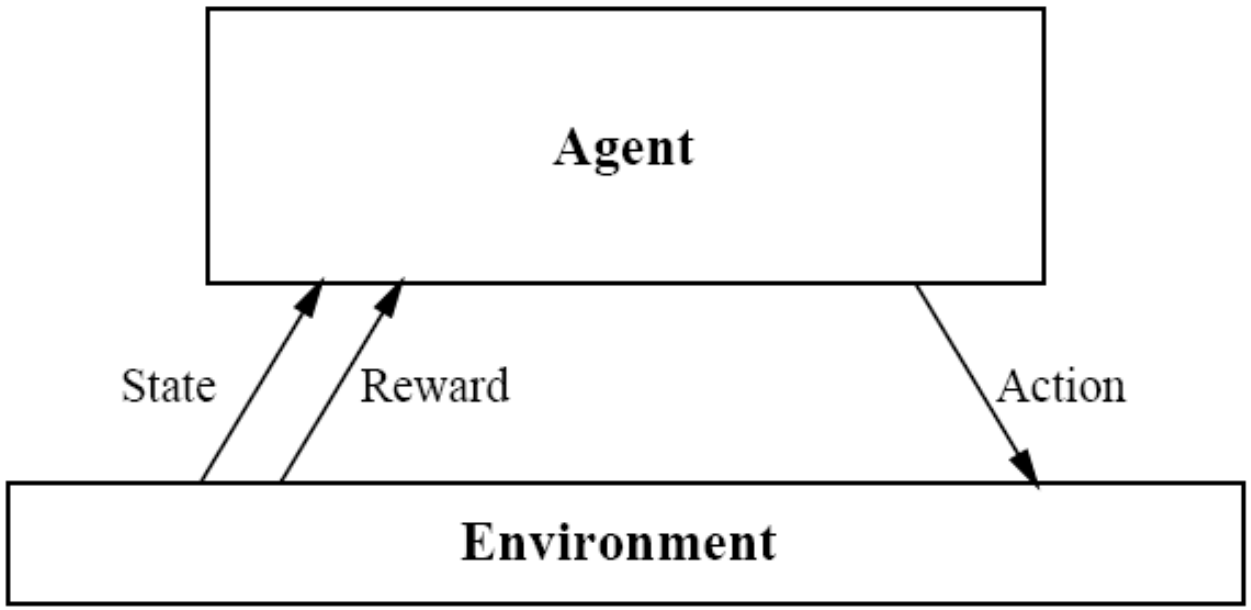


A training set without label is given

$$T = \{X_i\}_{i=1}^{N}$$

$$X \in R^n$$

Reinforcement Learning



$$s_0 \xrightarrow[r_0]{a_0} s_1 \xrightarrow[r_1]{a_1} s_2 \xrightarrow[r_2]{a_2} \ldots$$

Goal: Learn to choose actions that maximize

$$r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots \text{ , where } 0 \leq \gamma < 1$$

Reinforcement Learning: The Agent View

Environment

Reward

Senses

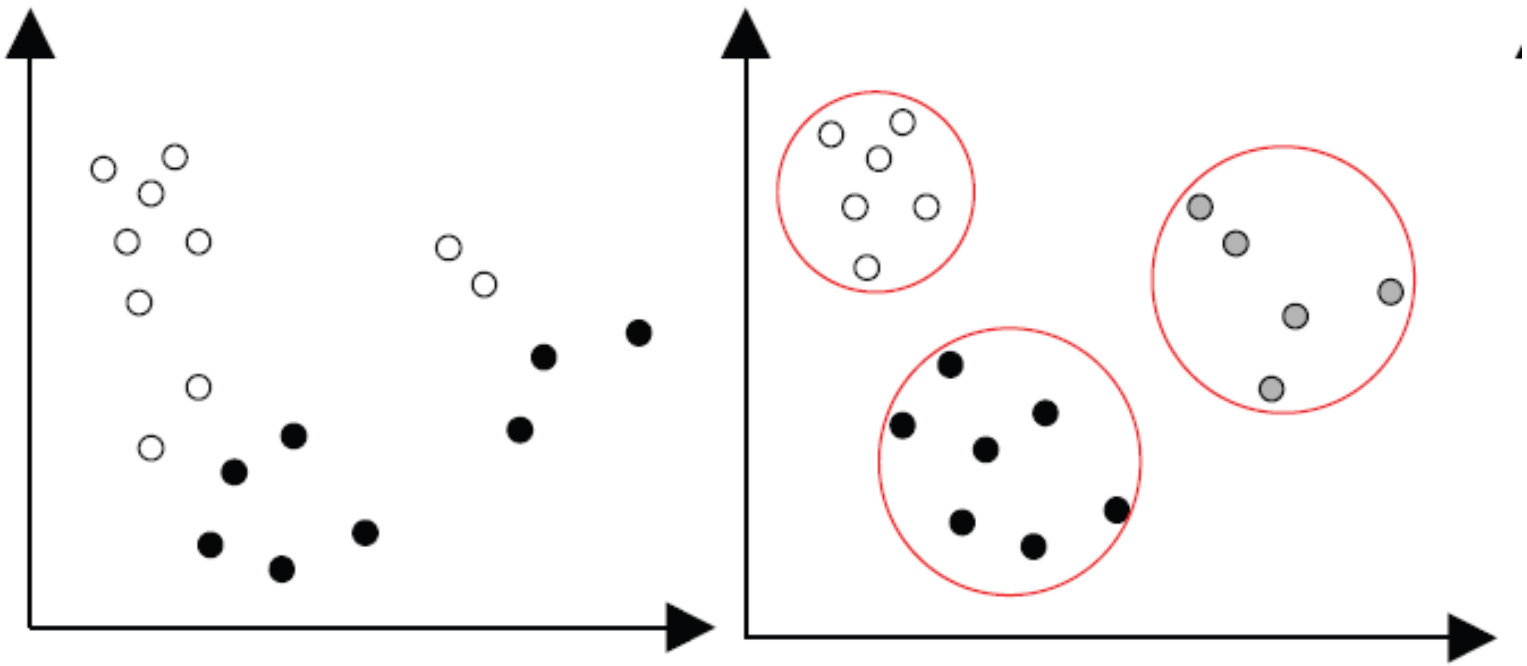
Actions

Agent

Learning Paradigms

- Semi-supervised Learning
- Semi-supervised clustering
- Supervised clustering
- Transfer learning
- Multitask learning ……

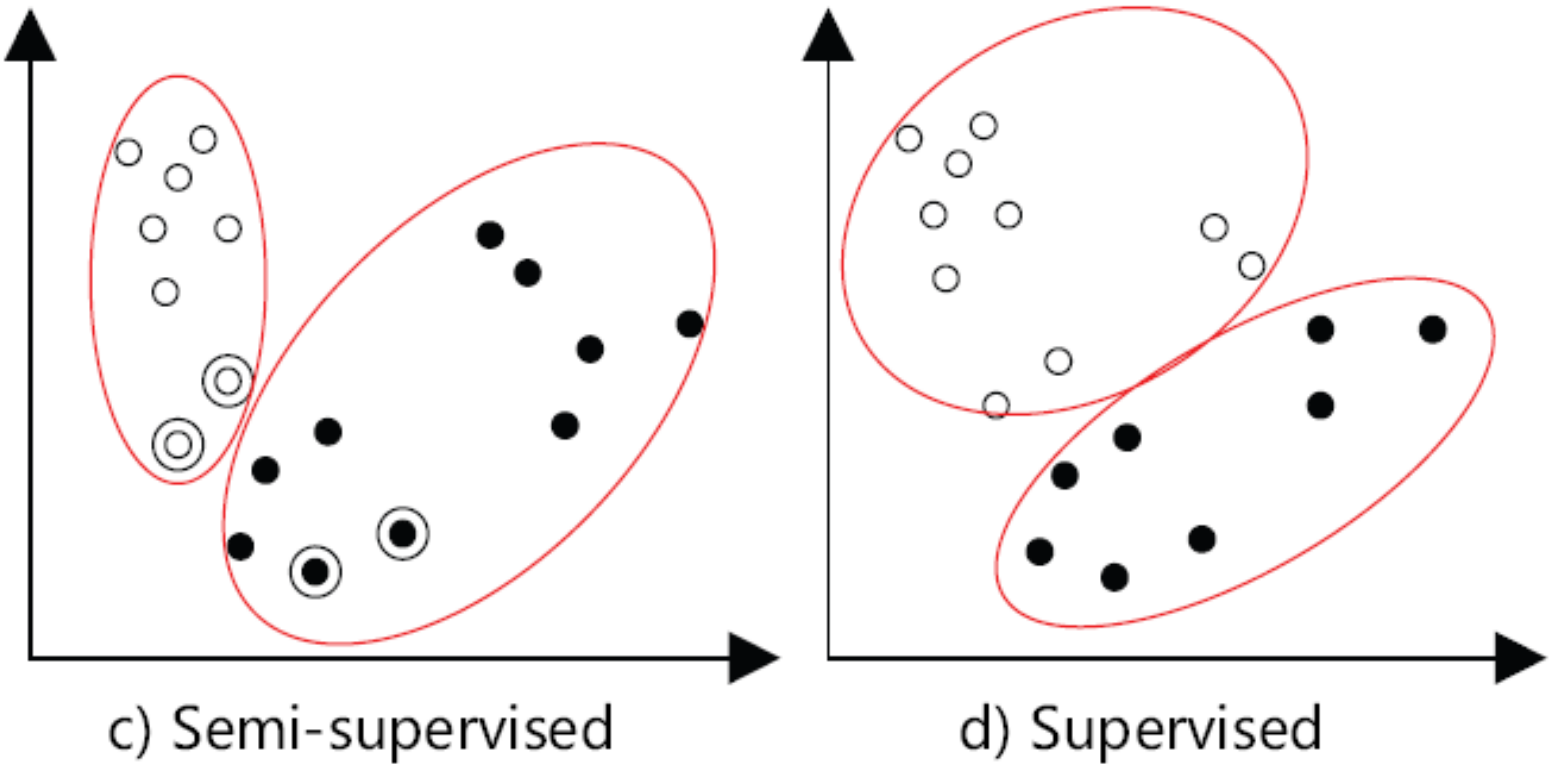
Unsupervised Clustering



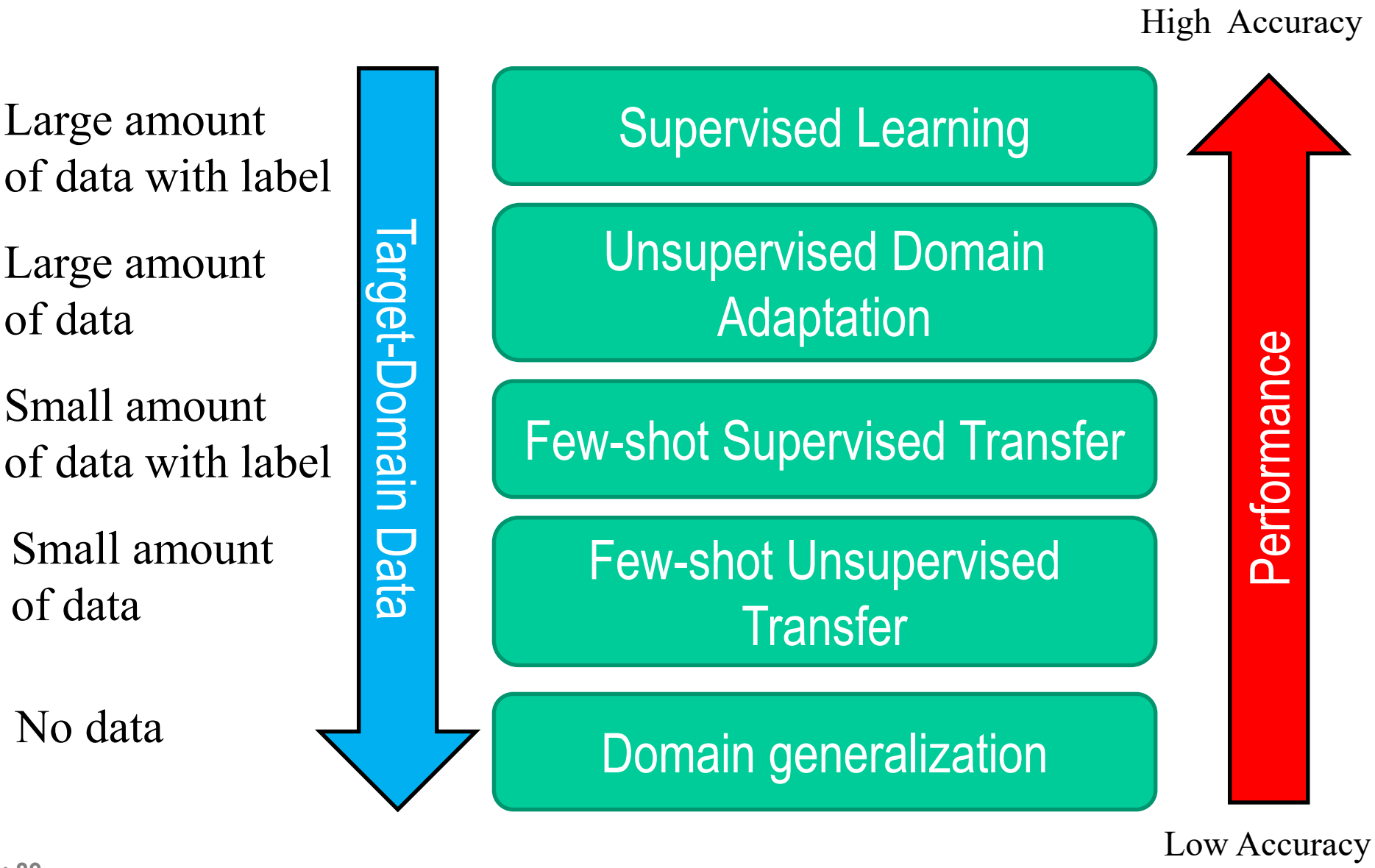
a) Given Dataset

b) Unsupervised

Semi-supervised vs Supervised



Supervised Learning versus Transfer Learning



Learning Tasks

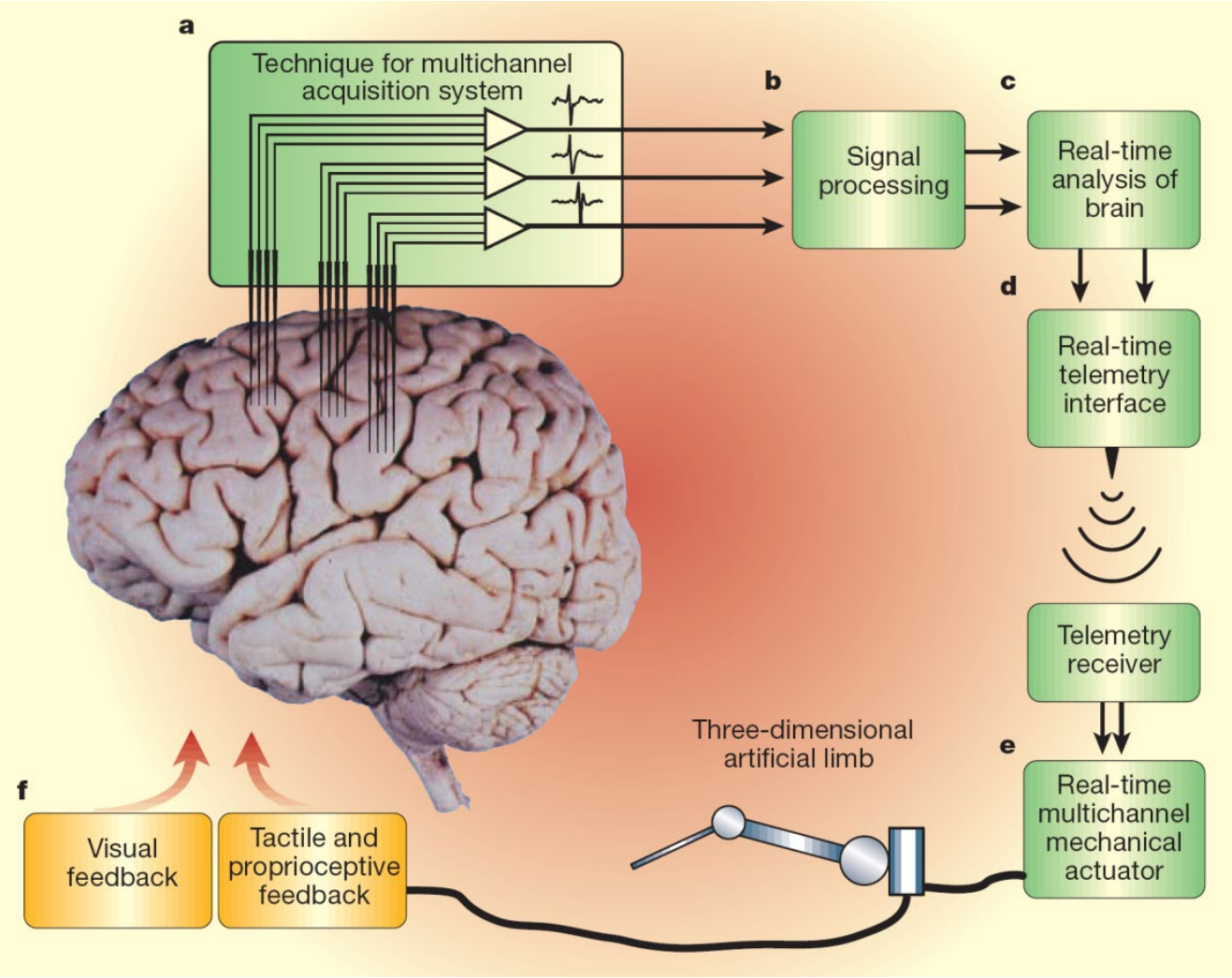
- Pattern Classification（模式分类）
- Regression （回归）or Function Approximation （函数逼近）
- Clustering (聚类）

Applications in my Lab

- Driving fatigue detection
- Emotion recognition

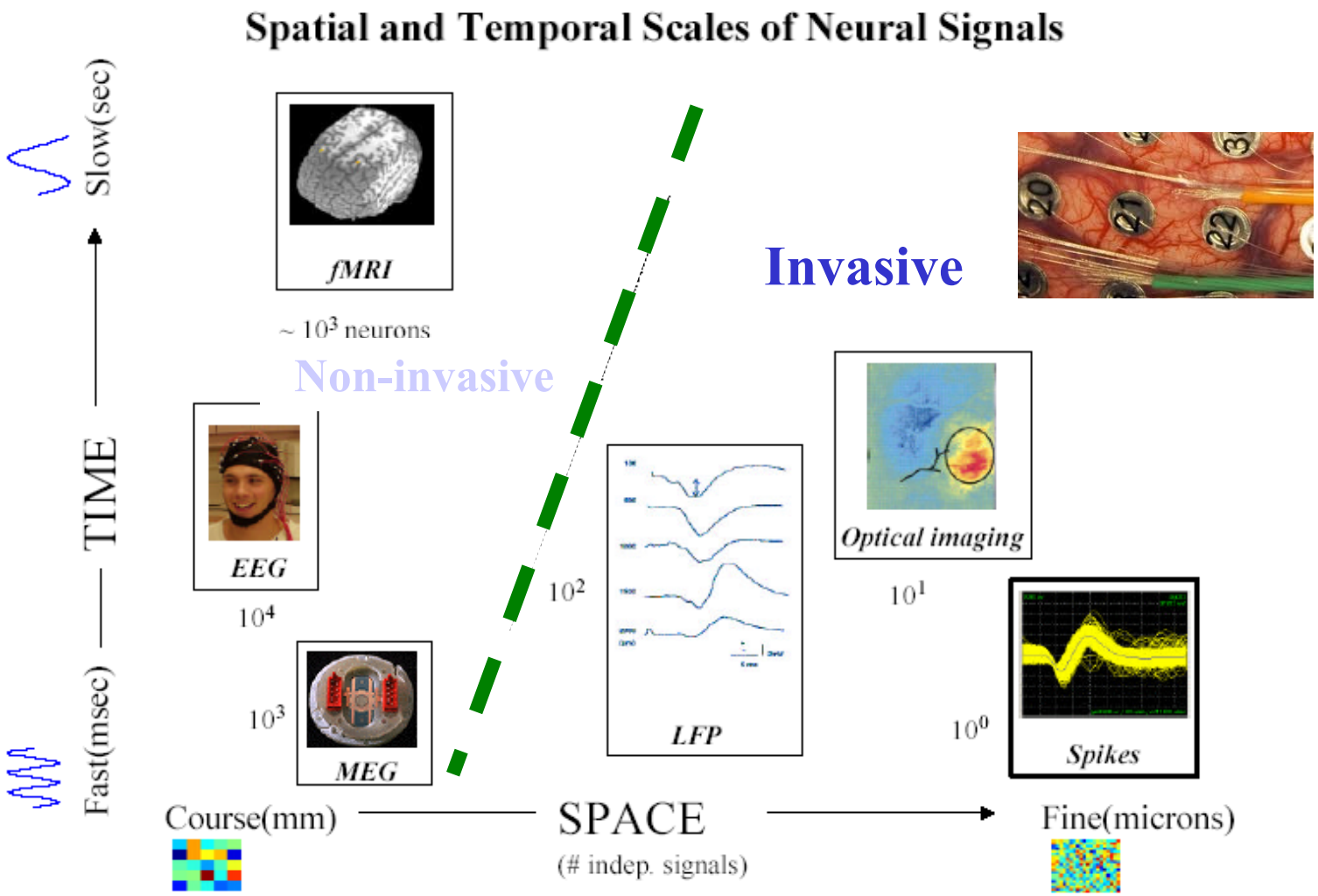
Brain-Computer Interface (Neural Engineering)

Brain-Computer/Machine Interface, BCI, BMI



脑-机接口是是在人或动物脑与外部设备间创建的直接连接通路

BCIs: Invasive vs. Non-invasive



《科学》2012年度十大科学突破

BRAIN-MACHINE INTERFACES START TO GET A GRIP

This week researchers in Pennsylvania reported that a 53-year-old woman paralyzed from the neck down by a genetic neurodegenerative condition had learned to manipulate a robotic arm with her thoughts. Surgeons had implanted two 4×4-millimeter grids of hair-thin electrodes in her brain to capture signals from an area involved in planning hand movements. A computer translated those signals into commands to move the robotic arm, which was engineered to have nearly all the same movement capabilities as the real thing. In videos, the woman uses the arm to grasp and move various objects, removing plastic cones stacked on a base and restacking them one by one on another base, for example. The demonstrations represent the most complex movements yet performed by a paralyzed human patient using a brain-machine interface (BMI), as such sophisticated prosthetics are often called.

RUNNER-UP

By demonstrating more fluid and natural movements, this case study improves on another impressive report earlier this year. In that study—the first published demonstration that paralyzed human patients can use a BMI to execute complex movements in three dimensions—a 58-year-old woman who had been unable to speak or move her limbs for 15 years manipulated a robotic arm with her thoughts, reaching out to grasp a bottle and take a sip of coffee. A tetraplegic man, 66, also learned to touch and grasp objects.

All of this work builds on more than a decade of research with monkeys and other animals. And that work continues to advance. In 2011, researchers described a prosthetic system that provides tactile feedback by stimulating the somatosensory cortex, the brain region responsible for the perception of touch. And in April of this year, a team used signals from electrodes implanted in the motor cortex of the brain to stimulate muscles in the temporarily paralyzed arms of two monkeys, enabling the animals to pick up rubber balls and place them in a chute. Such

CREDIT: KAROL NASS, CFEL

1530 21 DECEMBER 2012 VOL 338 SCIENCE www.sciencemag.org
Published by AAAS

9. 脑-机接口：曾经用大脑神经记录移动电脑荧幕上光标的同一个研究团队在2012年向人们展示，瘫痪的病人能够用他们的思想来移动一个机械臂并从事复杂的三维运动。该技术虽然仍处于试验阶段且极端昂贵，但科学家希望更先进的计算程序可改善这种神经性假体以帮助因中风、脊髓损伤及其他疾病导致瘫痪的病人。

PVAMC
MGH

疲劳驾驶自动监测迫在眉睫！

- 据统计，在2006-2010年内，中国交通事故引起的死亡人数每年超过7.5万。
- 对酒后驾驶 、超速、超载、超员已经很好的技术。但目前还没有可靠的疲劳驾驶检测的技术
- 疲劳驾驶检测的困难
  - 疲劳驾驶是一个过程，不像酒后驾驶是一个时间点
  - 对于疲劳级别的判断，还没有很好的方法
- 限制驾驶时间的法规及弊端
  - 连续驾驶时间不得超过4小时，连续行车4小时，必须停车休息20分钟以上；
  - 凌晨2点至5点禁止长途客车行驶！
  - 时间和资源的巨大浪费！
- 基于图像的警觉度估计的优点和缺点:
  - 容易记录、非接触并且成本低
  - 难以对疲劳驾驶进行预测
- 结合脑电

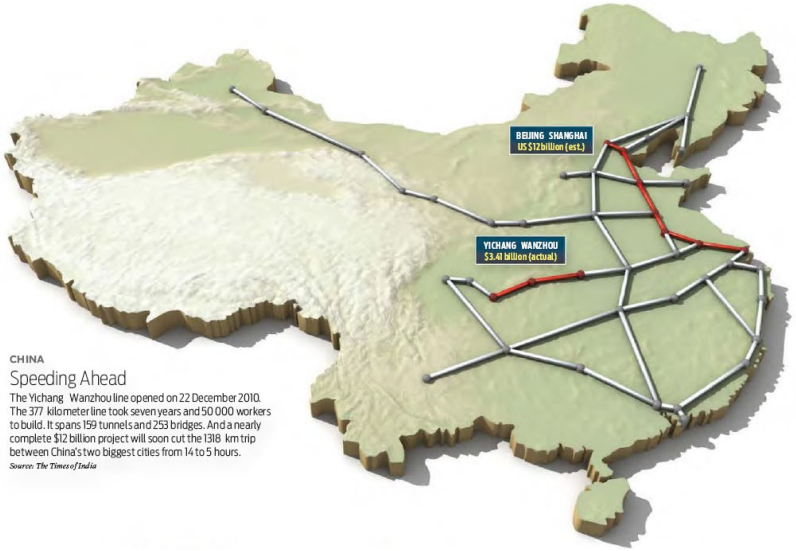
(截止2015年底中国高速公路开通12.3万公里)

Asleep at the wheel of a high-speed train

- The driver of a high-speed train in Taiwan fell asleep while going 190 miles per hour with hundreds of passengers on board on 10 May, 2010.
- Using the train's automatic systems, the train controllers managed to take control of the train for about 13 minutes until it glided safely into Taichung station.
- There was no casualty in this accident.

High-speed railways in China

- 20380 kms in use. It is about half the world's supply
- 16775 kms are developing
- 30000 kms will be finished by 2020
- Active safety and mental state monitoring technologies become very important
  - Check sleep quality before work
  - Predict drowsy driving during work
  - Monitor mental state before work, during work, and after work



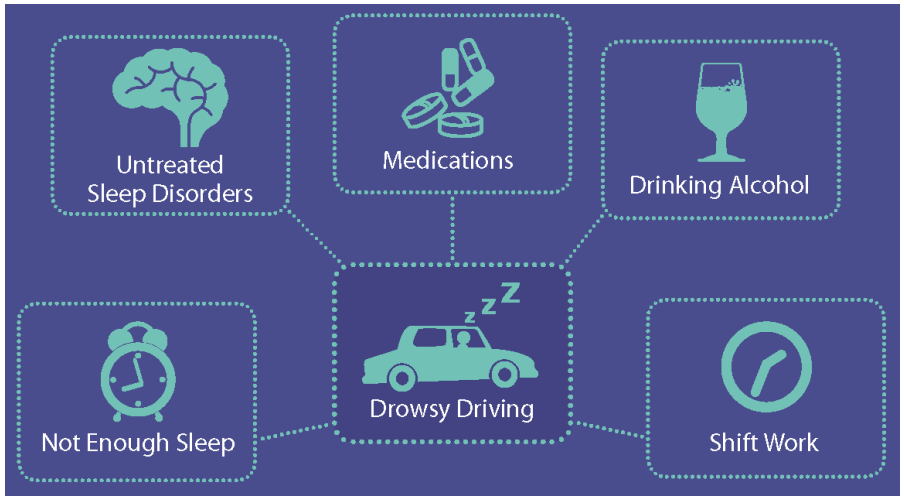
High demand for detecting driving fatigue

- In China, the number of traffic accident deaths is more than 75 thousands each year during 2006-2010.
- We have good technologies for detecting
  - **drunk driving**
  - **Over speed**
  - **Over load**
  - **Over persons**

- Unfortunately, we have no reliable methods for monitoring drowsy/fatigue driving
- Difficulties of detecting drowsy/fatigue driving
  - **Drowsy/fatigue is a process, instead of a time point as checking drunk driving**
  - **There is no good measure to judge drowsy/fatigue level**

What is driving fatigue?

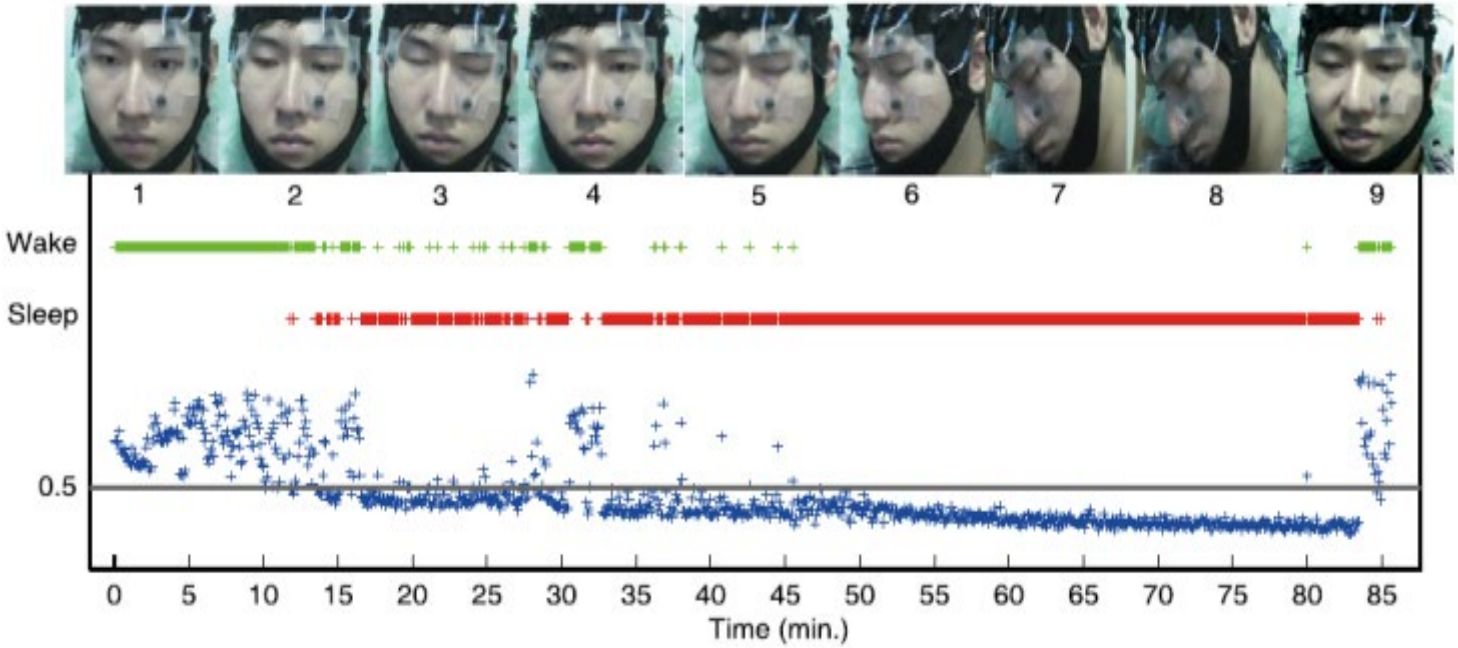
- Driving fatigue is the dangerous combination of driving and sleepiness or fatigue. This can happen to a driver for several reasons:



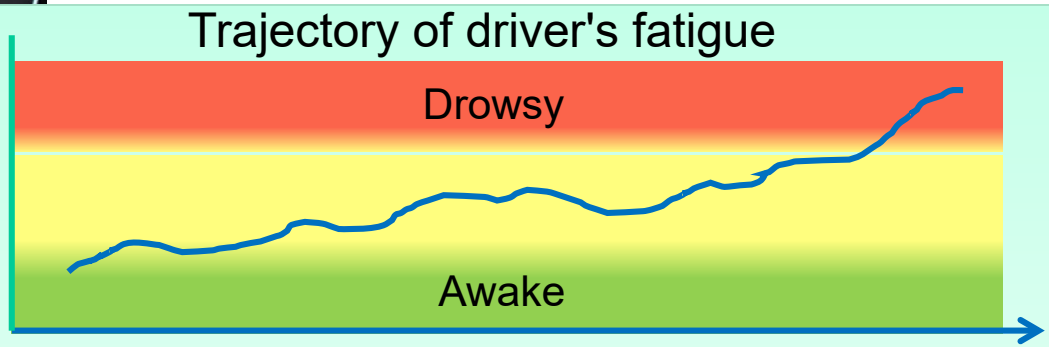
- The driving fatigue problem
  - Makes drivers less able to pay attention to the road
  - Slows reaction time if you have to brake or steer suddenly
  - Affects a driver's ability to make good decisions
  - Up to 6000 fatal crashes each year may be caused by drowsy drivers in USA

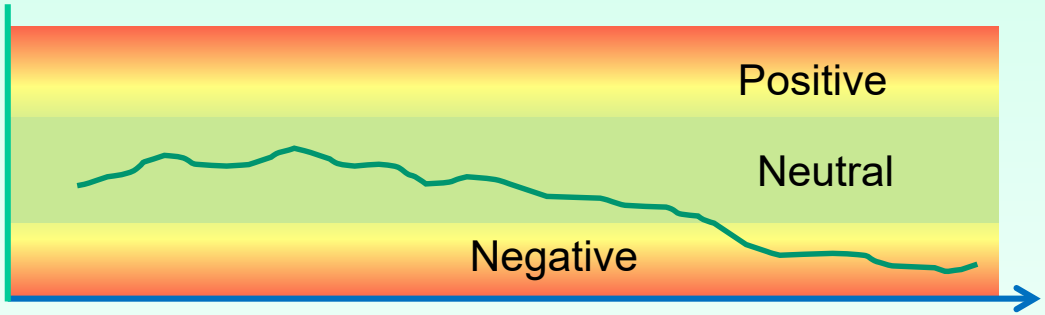
Challenges for Driving Fatigue Detection

- Lack of measures for determining driving fatigue
- Lack of grading standard for evaluating driving fatigue
- Lack of reliable techniques (hardware and software) for predicting driving fatigue



Our goal: Monitor driver's drowsy and emotion





Related work: image based approach

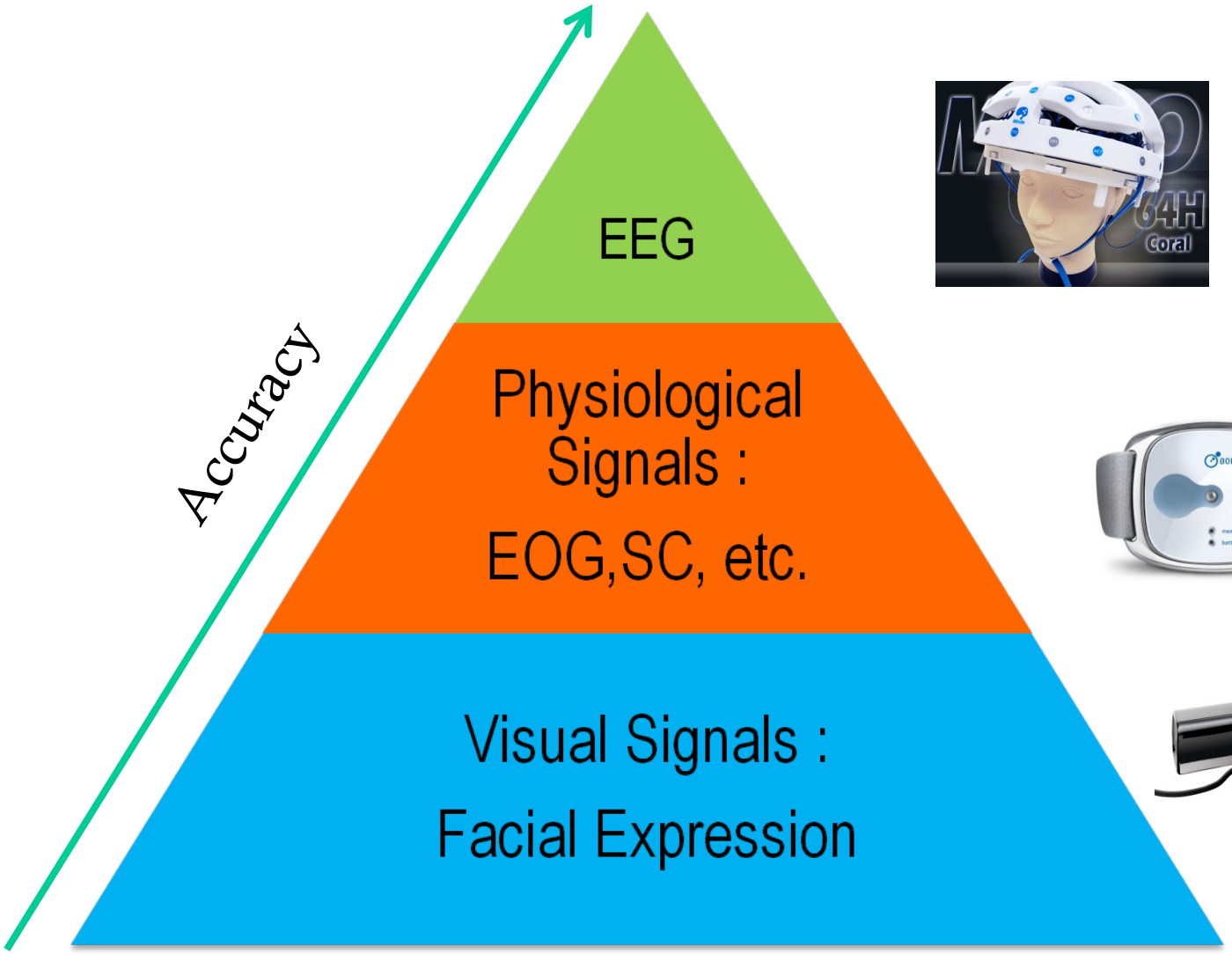
PERCLOS is used as a measure for detecting driver fatigue

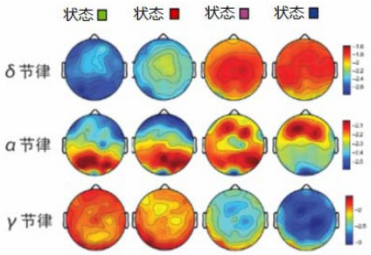
PERCLOS is the percentage of eyelid closure over the pupil over time and reflects slow eyelid closures rather than blinks.

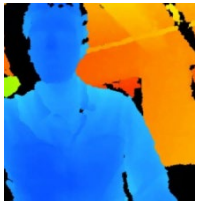
Merits and demerits of image based vigilance estimation:

- Easy to be record
- Non-contact and lower cost
- Hard to predict drowsy driving
- Can't be used to disabled persons

Multiple sensors vs. detection accuracy

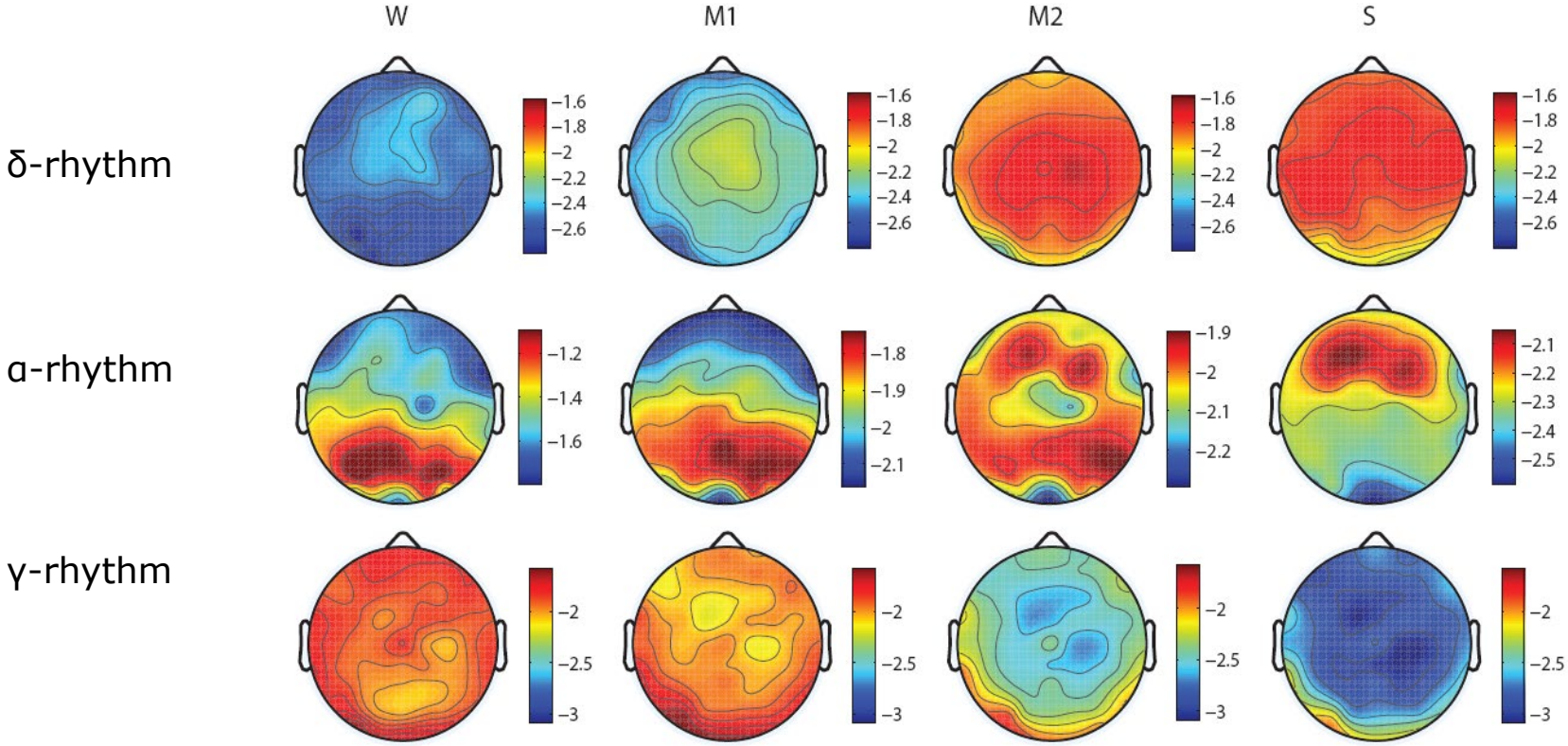






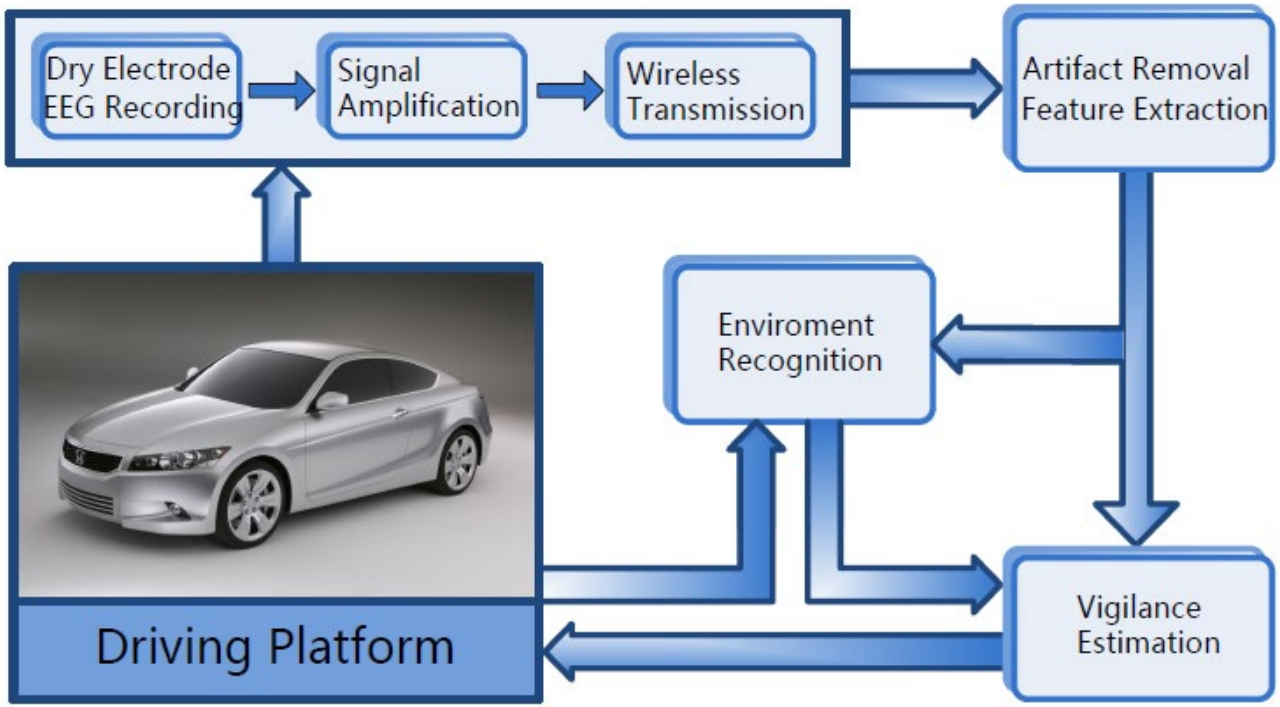
Why choosing EEG for driving fatigue detection?

- Various physiological signals are used for analyzing vigilance. Among them, EEG has been proved very effective and stably related to vigilance.



Driving fatigue detection using physiological signals

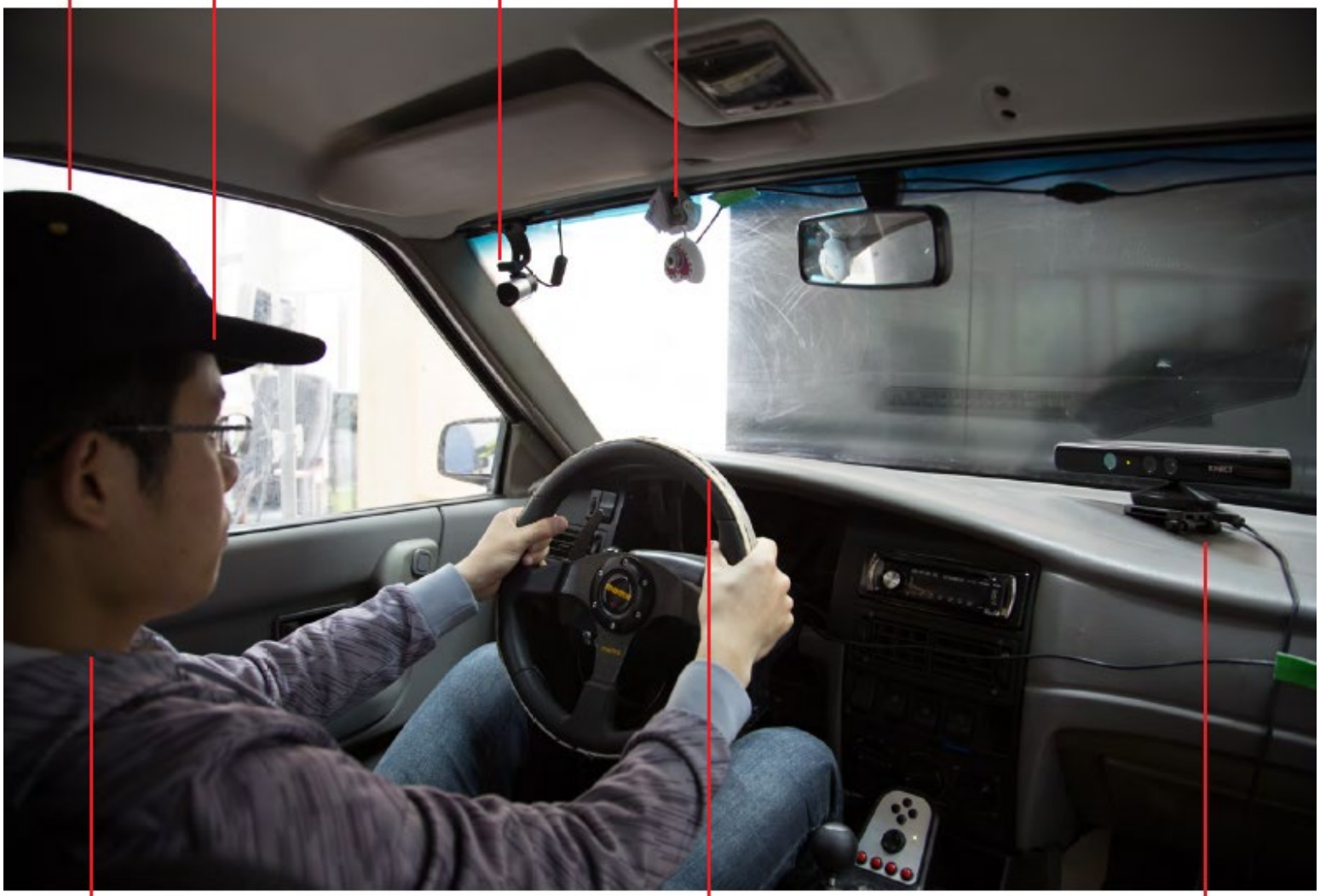
- Wearable dry-electrode EEG cap
- Low-power consumption amplifier VLSI chip
- Measure and grading standars for detecting drowsy driving
- Predicting drowsy driving with physiological signals such as EEG



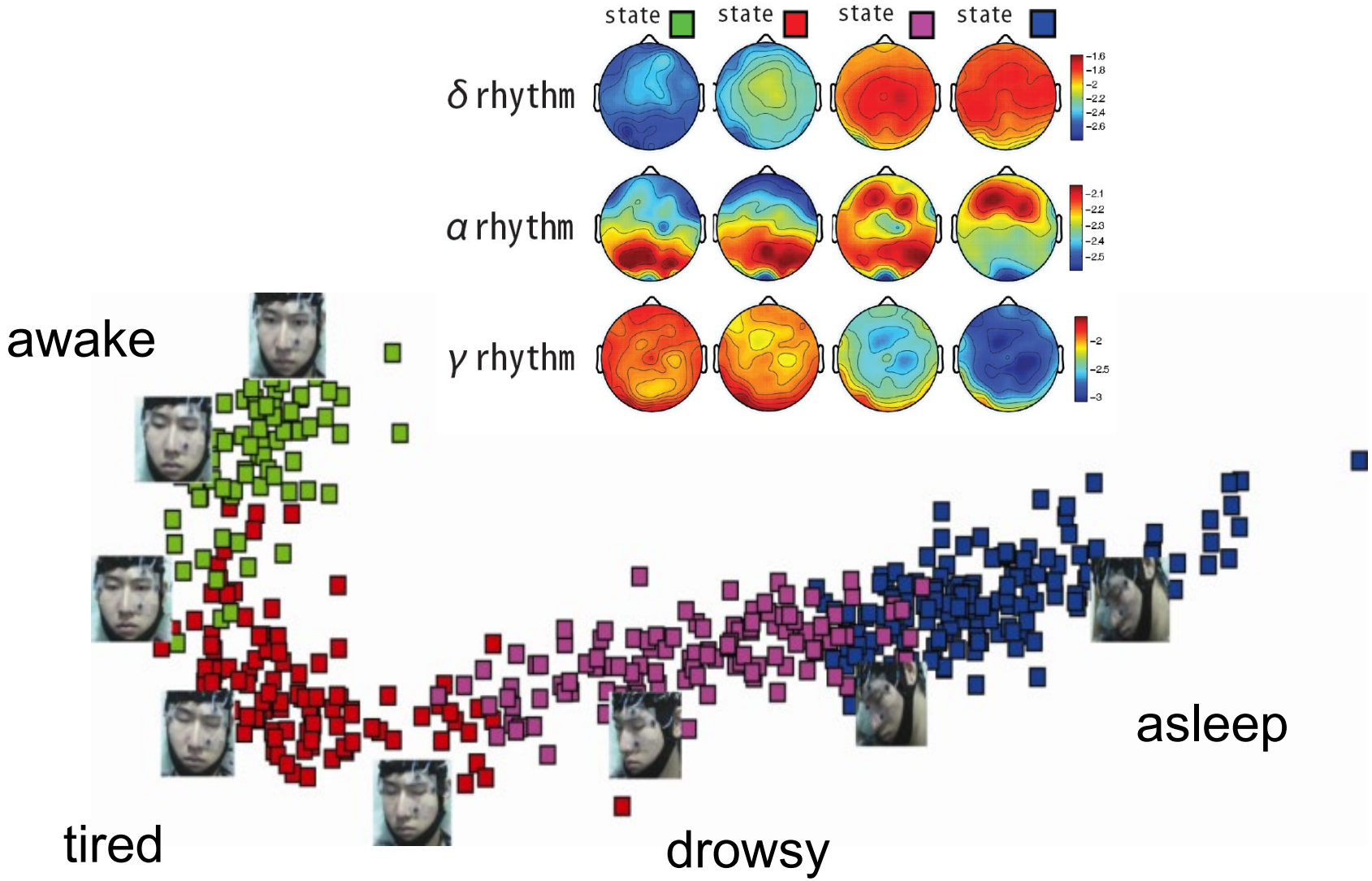
(Supported by NSFC, 973 Projects, and Science and Technology Commission of Shanghai Municipality since 2008)

Driving simulation system in our lab

Multiple sensors at driving simulation system



EEG feature and estimated vigilance states

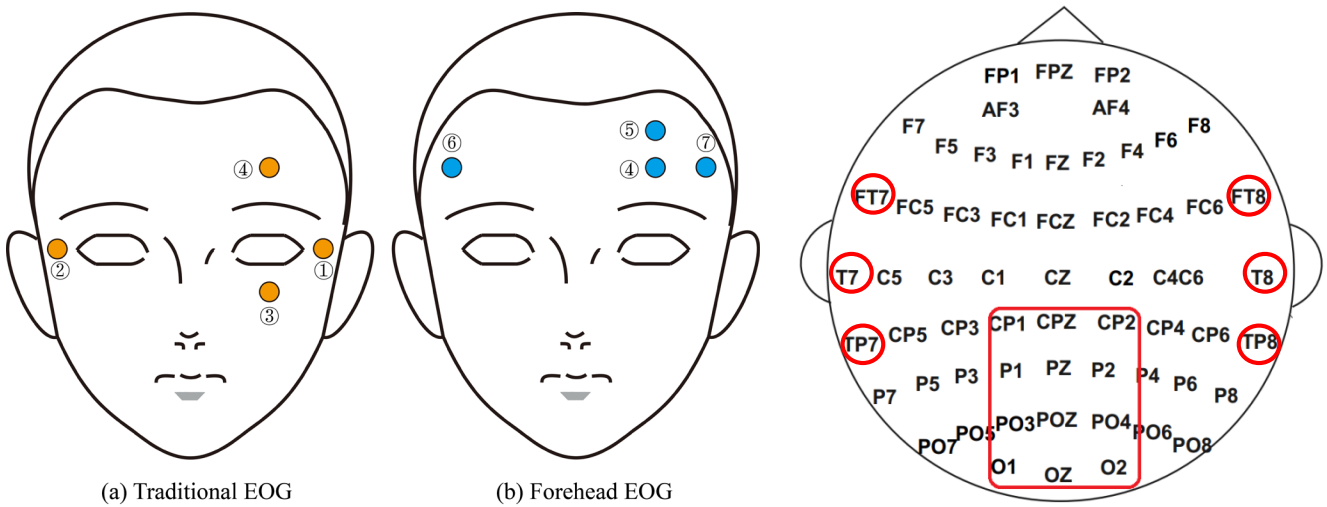


A Multimodal Approach to Estimating Vigilance Using EEG and Forehead EOG

Wei-Long Zheng and Bao-Liang Lu, A Multimodal Approach to Estimating Vigilance Using EEG and Forehead EOG, Journal of Neural Engineering, 2017

Experimental Setup and Vigilance Annotations

- Electrode placements of EEG and EOG



(a) Traditional EOG (b) Forehead EOG

- Vigilance Annotations

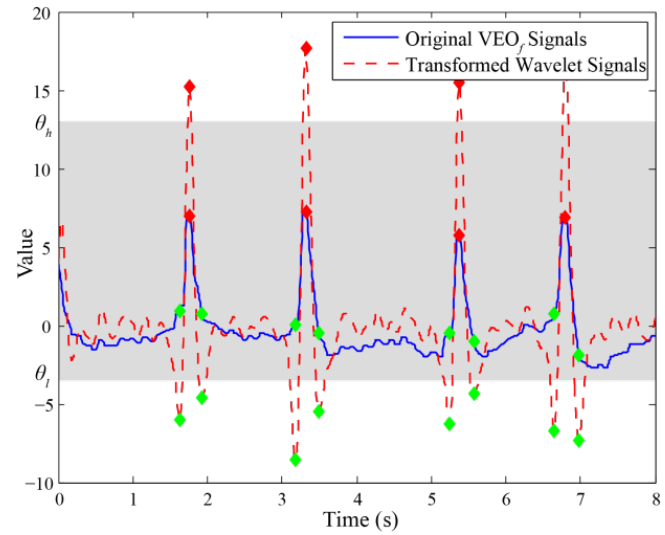
$$PERCLOS_{ETG} = \frac{blink + CLOS}{interval} \quad (1)$$

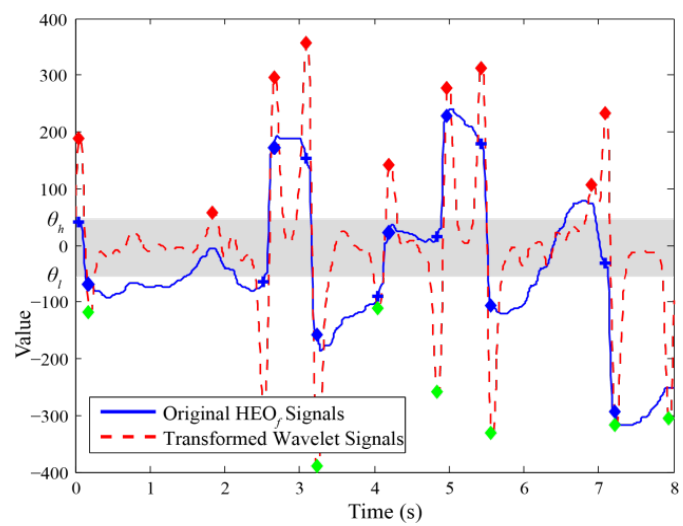
$$interval = blink + fixation + saccade + CLOS \quad (2)$$

Feature Extraction for EOG

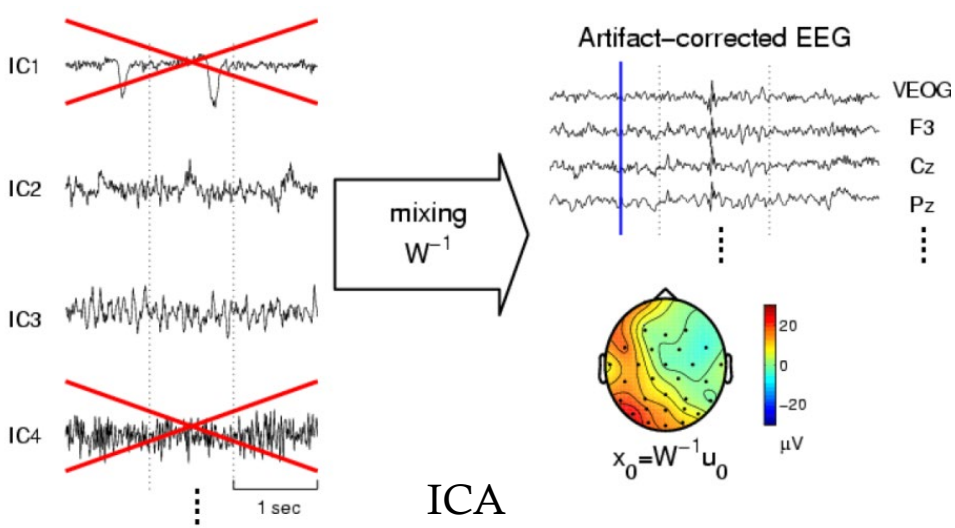
- Blink and saccade detection using continuous wavelet transform

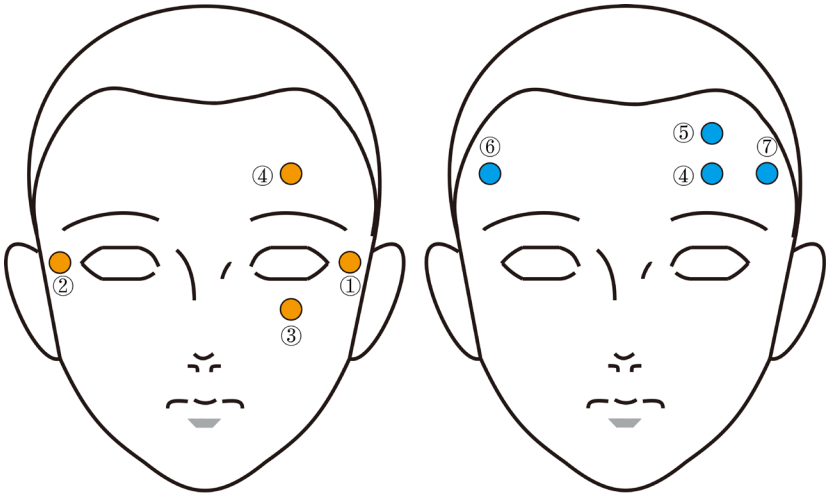
Group	Extracted Features
Blink	maximum/mean/sum of blink rate maximum/minimum/mean of blink amplitude, mean/maximum of blink rate variance and amplitude variance power/mean power of blink amplitude blink numbers
Saccade	maximum/minimum/mean of saccade rate and saccade amplitude, maximum/mean of saccade rate variance and amplitude variance, power/mean power of saccade amplitude, saccade numbers
Fixation	mean/maximum of blink duration variance and saccade duration variance maximum/minimum/mean of blink duration and saccade duration.



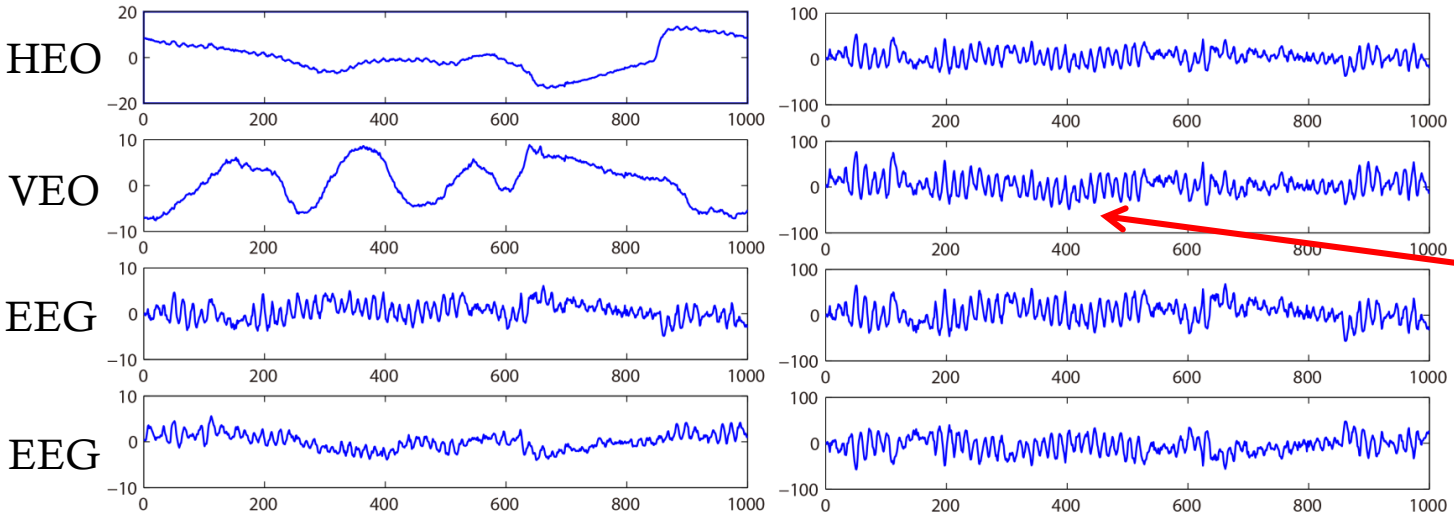


Extracting EEG from Forehead Electrodes





(a) Traditional EOG (b) Forehead EOG



(a) Decomposed ICA Components (b) Reconstructed Forehead EEG

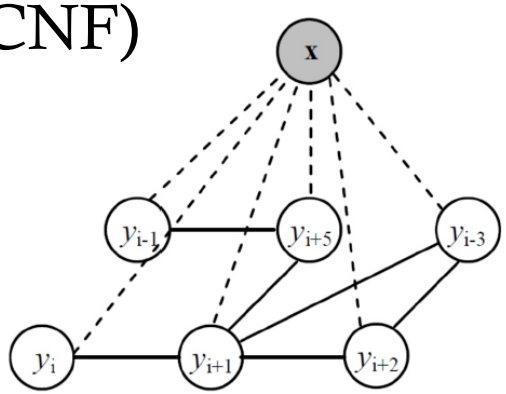
Strong Alpha activities are verified under eye closure conditions.

Incorporating Temporal Dependency

- Vigilance is a dynamic changing process because the intrinsic mental states of users involve temporal evolution.
- Continuous conditional random field (CCRF)
- Continuous conditional neural field (CCNF)

$$P(\mathbf{y}|\mathbf{x}) = \frac{exp(\Psi)}{\int_{-\infty}^{\infty} exp(\Psi) d\mathbf{y}},$$

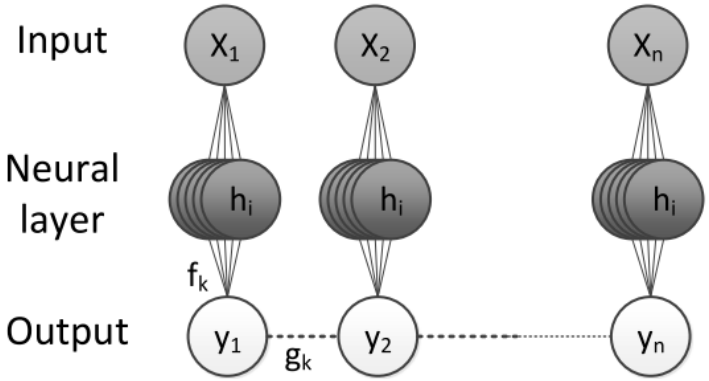
$$\Psi = \sum_i \sum_{k=1}^{K_1} \alpha_k f_k(y_i, \mathbf{x}_i, \boldsymbol{\theta}_k) + \sum_{i,j} \sum_{k=1}^{K_2} \beta_k g_k(y_i, y_j)$$



$$f_k(y_i, \boldsymbol{x}_i, \boldsymbol{\theta}_k) = -(y_i - h(\boldsymbol{\theta}_k, \boldsymbol{x}_i))^2, and$$

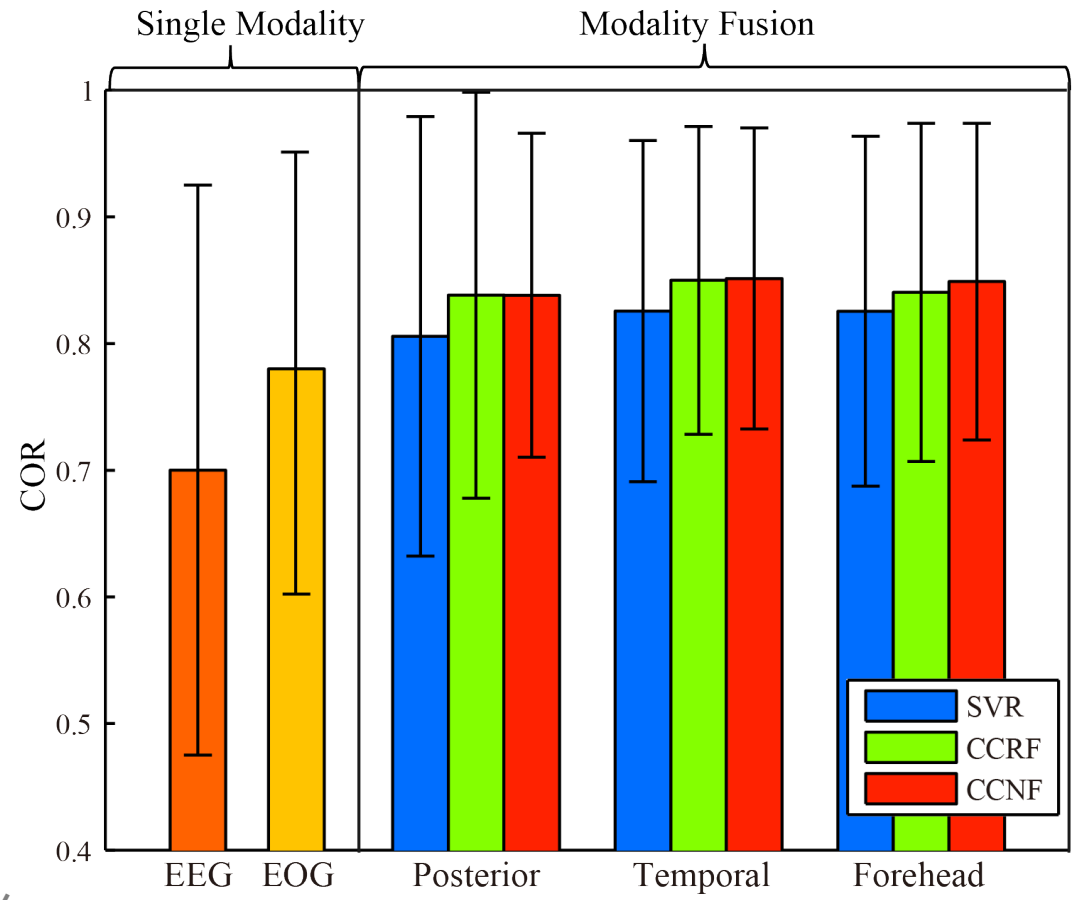
$$h(\boldsymbol{\theta}, \boldsymbol{x}_i) = \frac{1}{1 + e^{-\boldsymbol{\theta}^T \boldsymbol{x}_i}},$$

$$g_k(y_i, y_j) = -\frac{1}{2} S_{i,j}^{(k)} (y_i - y_j)^2$$



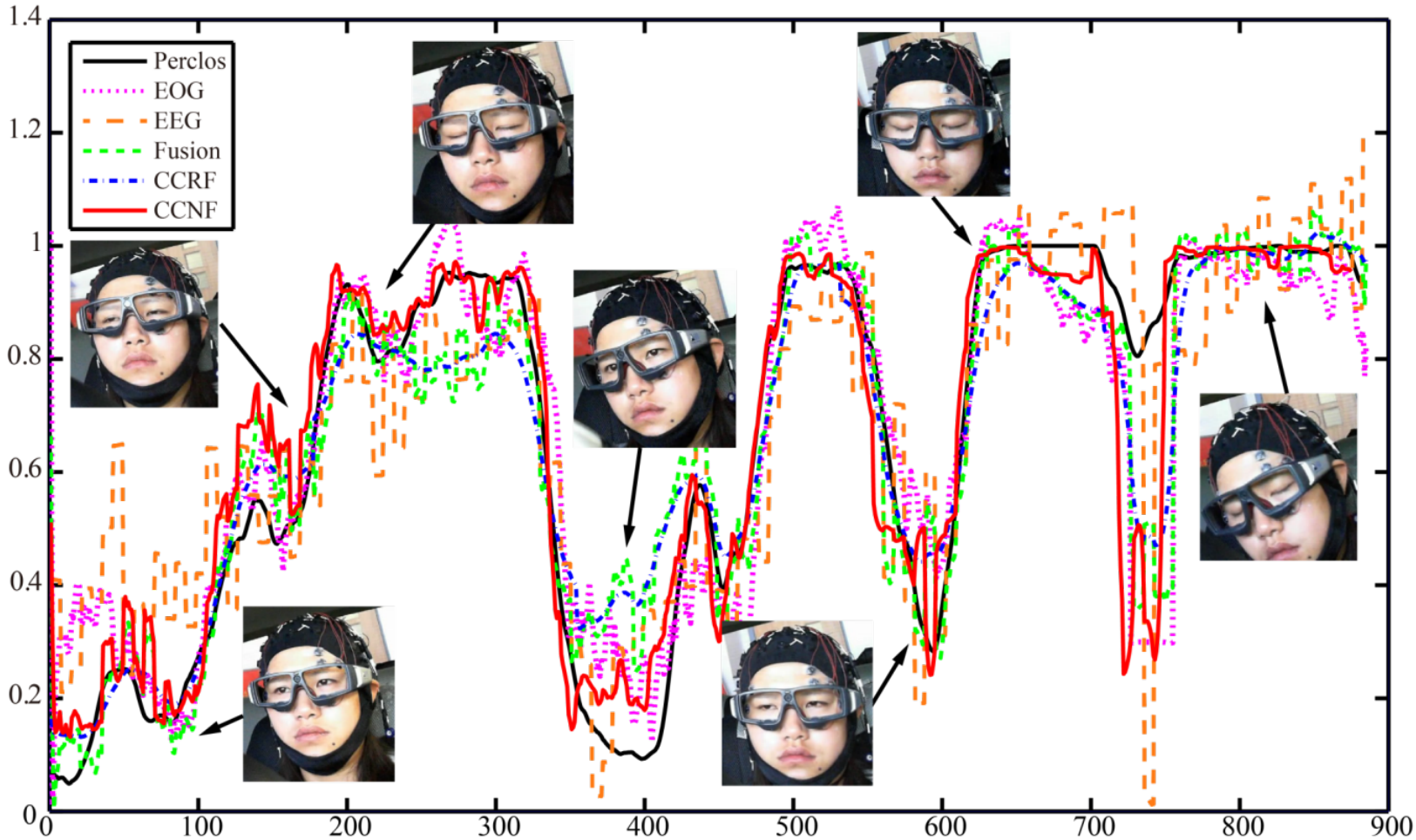
Experimental Results

- For the forehead setup, the mean COR/RMSE of SVR, CCRF, and CCNF are 0.83/0.10, 0.84/0.10, and **0.85/0.09,** respectively. The CCNF achieves the best performance with higher accuracies and lower standard deviations.



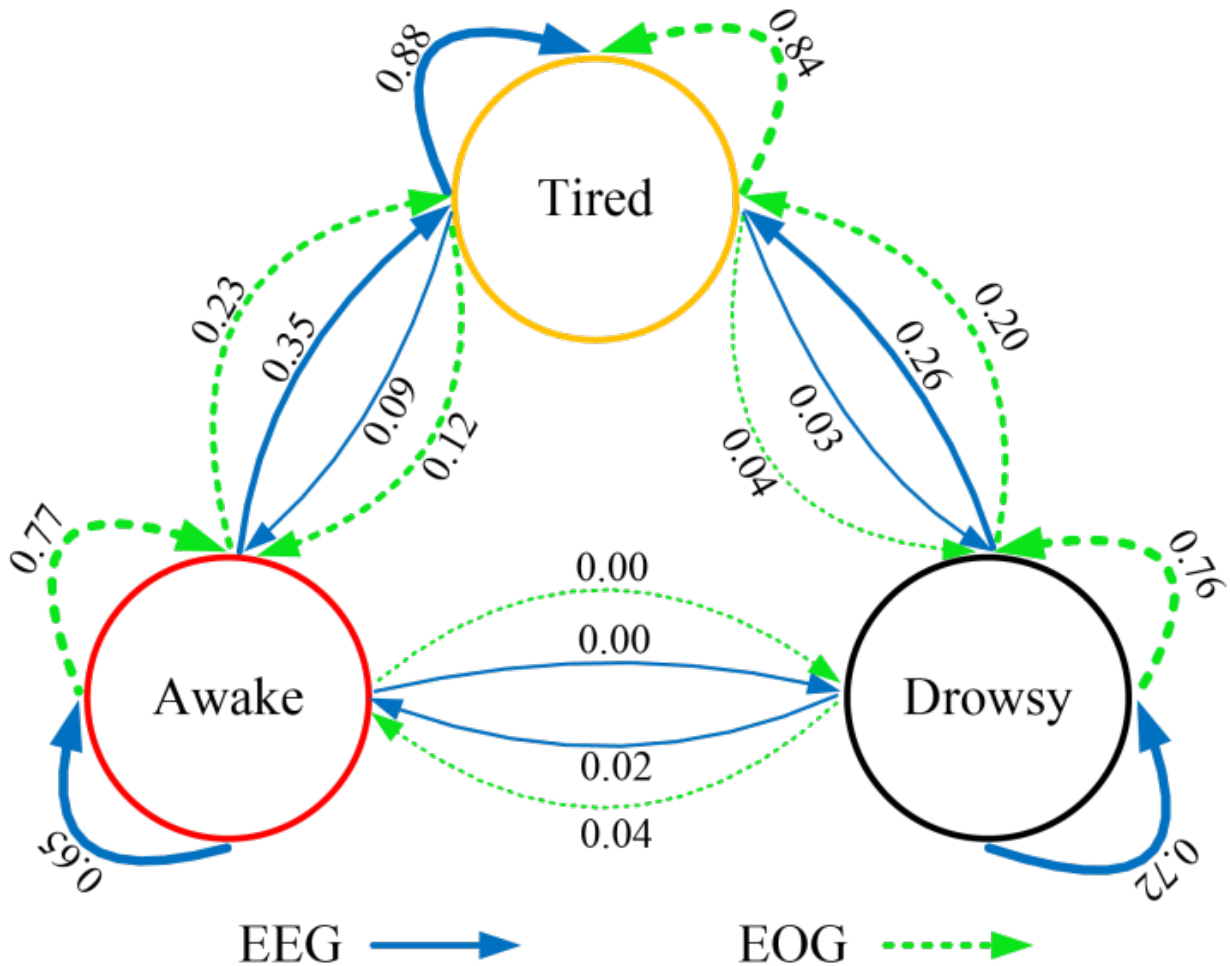
Experimental Results (2)

- The predictions from our proposed approaches are almost consistent with the true subjects' behaviors and cognitive states.



Experimental Results (3)

- Complementary characteristics of EOG and EEG for vigilance estimation.



Germanwings Flight 9525

- On 24 March 2015, the aircraft, an Airbus A320211, crashed 100 kilometres northwest of Nice in the French Alps. All 144 passengers and six crew members were killed!
- The crash was deliberately caused by the copilot, Andreas Lubitz, who had previously been treated for suicidal tendencies and been declared "unfit to work" by a doctor.
- The European Federation of Psychologists' Associations (EFPA) issued a statement supporting psychological testing in the selection of pilots.

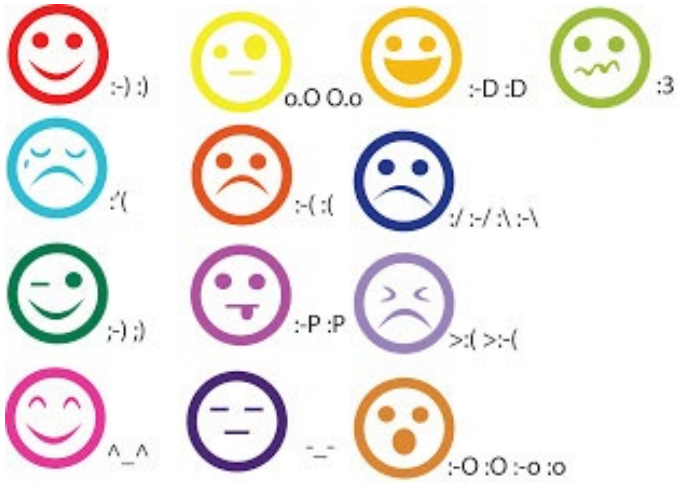
Emotion Recognition

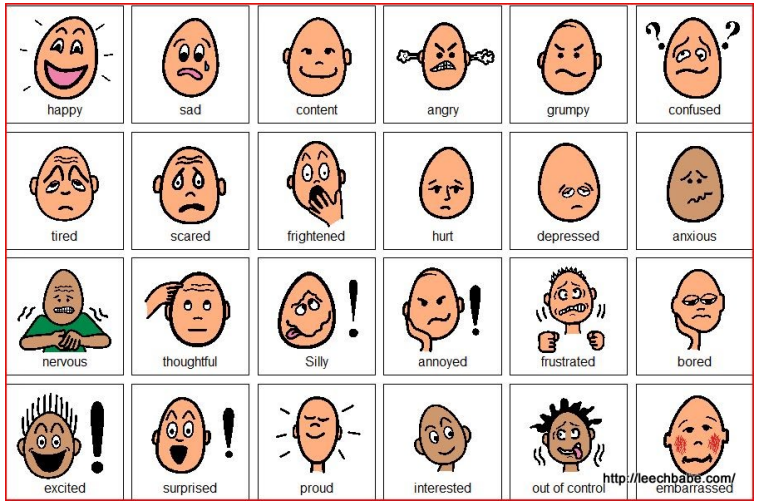
- Traditional methods for emotion recognition
  - facial expression, voice, gesture
  - advantage: easy to obtain signals
  - disadvantage: not reliable to detect emotions; cannot be used for people with disabilities
- EEG-based method for emotion recognition
  - advantage: reliable to detect emotions; wide applications
  - disadvantage: need special equipment to get EEG signals

What is emotion?

- No rigorous definition
- An informal definition:
  Emotion is a set of complex interactions between subjects and objects, which is regulated by nervous system and hormone. These interactions can trigger some emotional feelings (e.g. happiness/ sadness) or produce some cognition.

William James (1884)



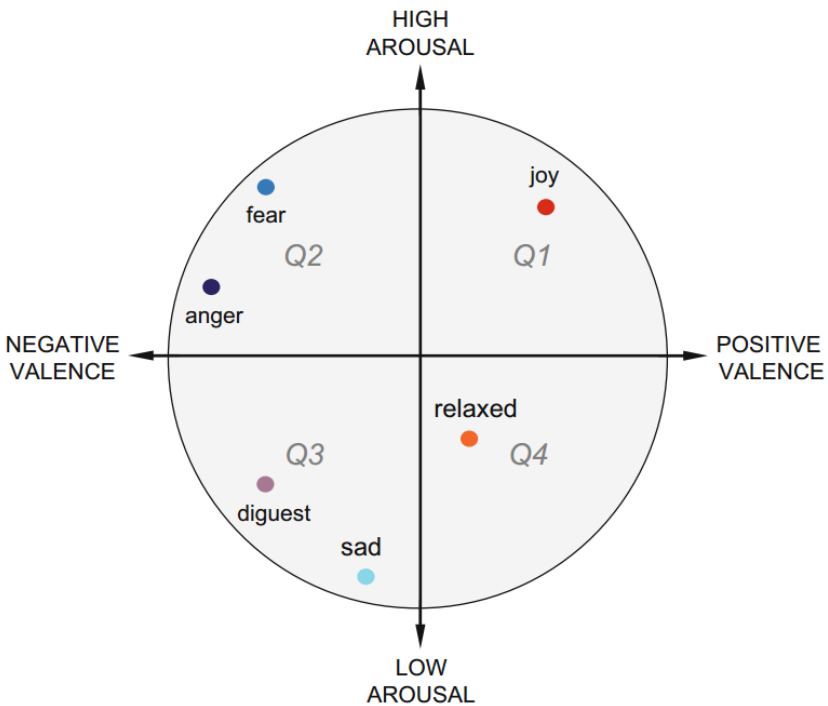


Emotion model and representation

- Classic model:

  The classic model divides emotions into a group of different and discrete emotion state sets, such as anger, fear, sadness, happiness, surprise, etc.

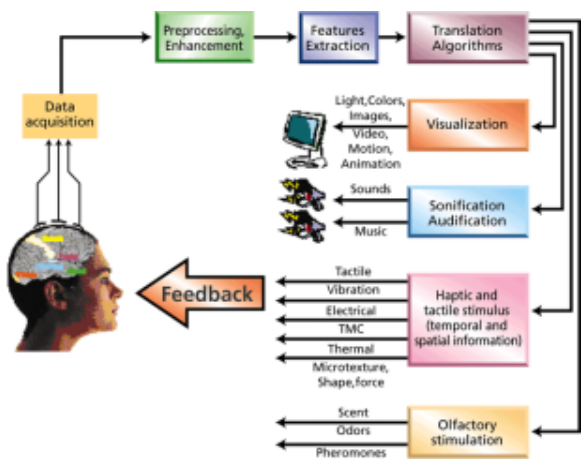
- Dimension Model
  - Arousal refers to the quantitative activation level ranging from calm to excited;
  - Valence represents the quality of an emotion ranging from unpleasant to pleasant;

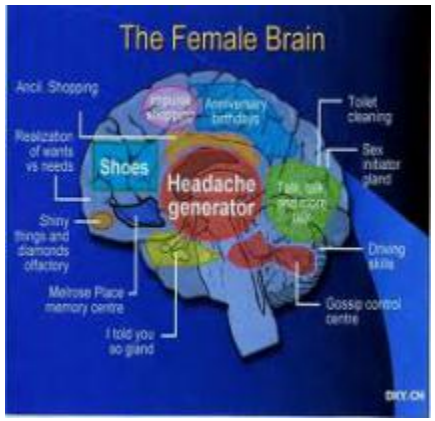


Land's Model: Two-dimensional emotion model

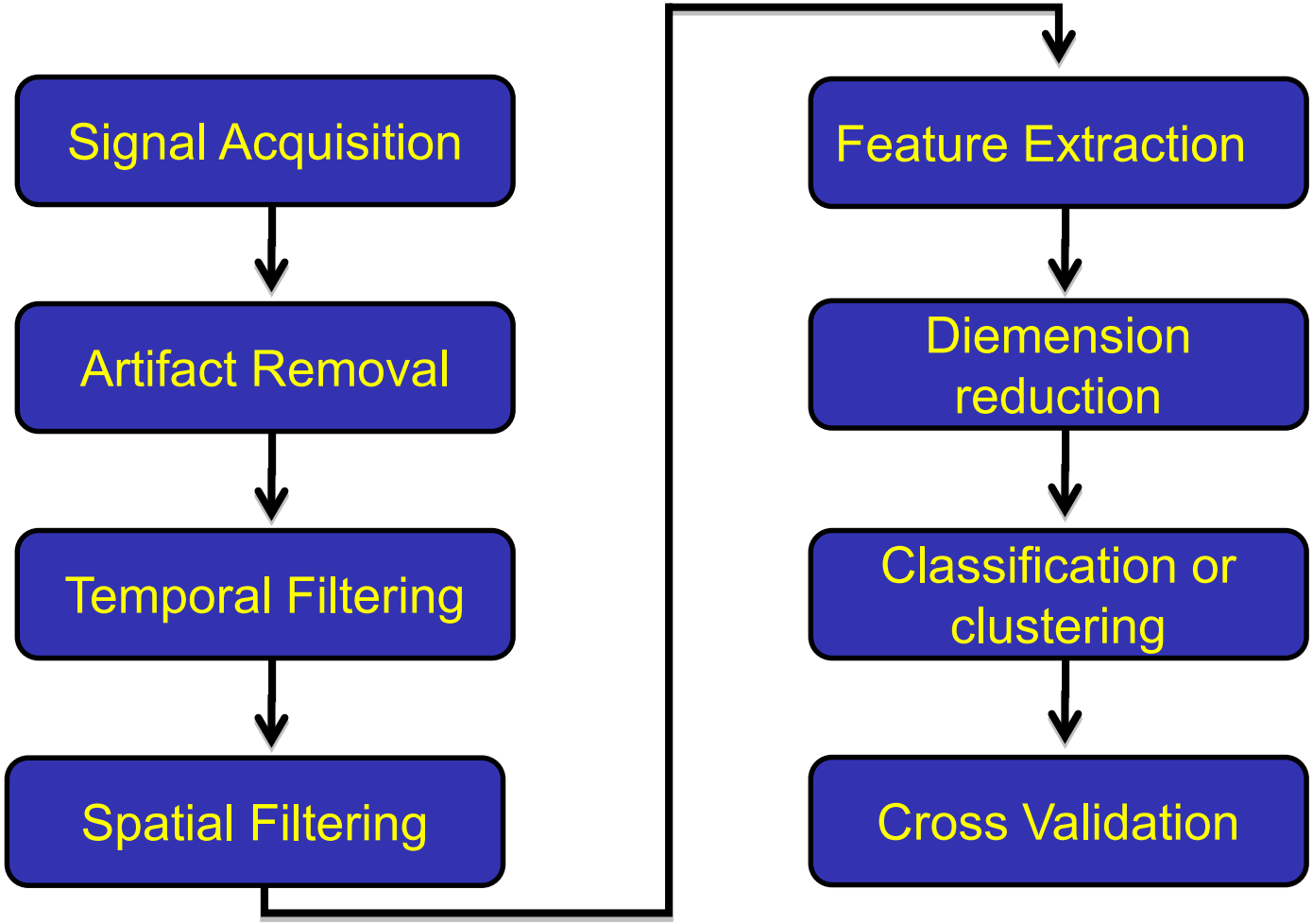
Problems of EEG-based emotion recognition

- Are there subject-independent features for discriminating different emotions?
- Are there critical bands and channels for discriminating different emotions?
- How to tackle the variability of subject to subject?
- Whether multiple modalities are useful?





Framework of EEG-based emotion recognition



Emotion stimuli and film clip selections

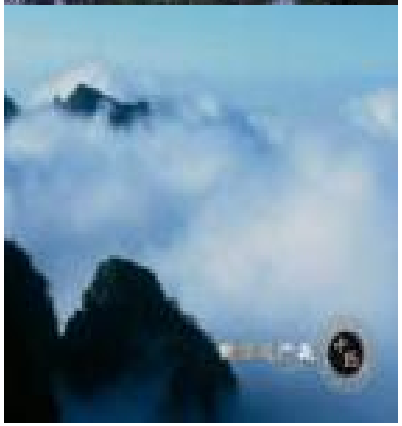
- The reliability of film clips for eliciting emotions has been studied in the literature [Schaefer et al. (2010), Koelstra et al. (2012)].
- Total 168 film clips for four emotions (happy, sad, fear and neutral).
- No. participants: 37 (19 females)
- Feedback: keywords and ratings of seven points for valence and arousal.
- Finally, 72 film clips with time length of about 2mins are chosen with highest ratings from the participants.

- Koelstra, S., et al. (2012). "Deap: A database for emotion analysis; using physiological signals." IEEE Transactions on Affective Computing, 3(1): 18-31.
- Schaefer, A., et al. (2010). "Assessing the effectiveness of a large database of emotion-eliciting films: A new tool for emotion researchers." Cognition and Emotion 24(7): 1153-1172.

The selected films as emotion stimuli

Happy

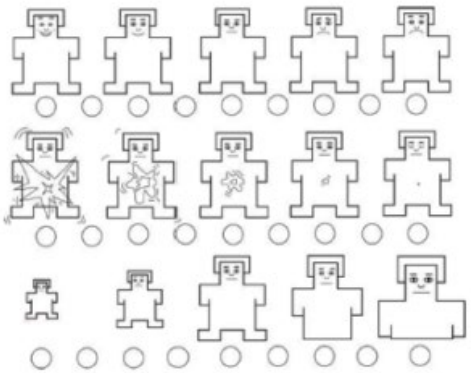
Neutral



Sad

Fear

Process of the experiment



positive or negative movie clip

Hint of Start
- 5sec

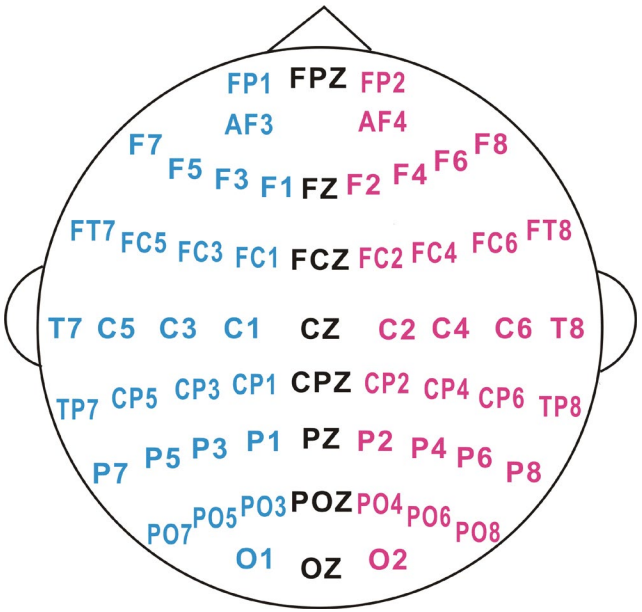
Movie clip
- 4min

Self-assessment
- 45sec

Rest
- 15sec

Session 1 → Session 2 → Session 3 → … → Session N

Feature extraction: differential entropy



Feature	Delta	Theta	Alpha	Beta	Gamma	Total
ES	62	62	62	62	62	310
DE	62	62	62	62	62	310
DASM	27	27	27	27	27	135
RASM	27	27	27	27	27	135
ASM	54	54	54	54	54	270

- ES: energy spectrum
- DE: differential entropy:

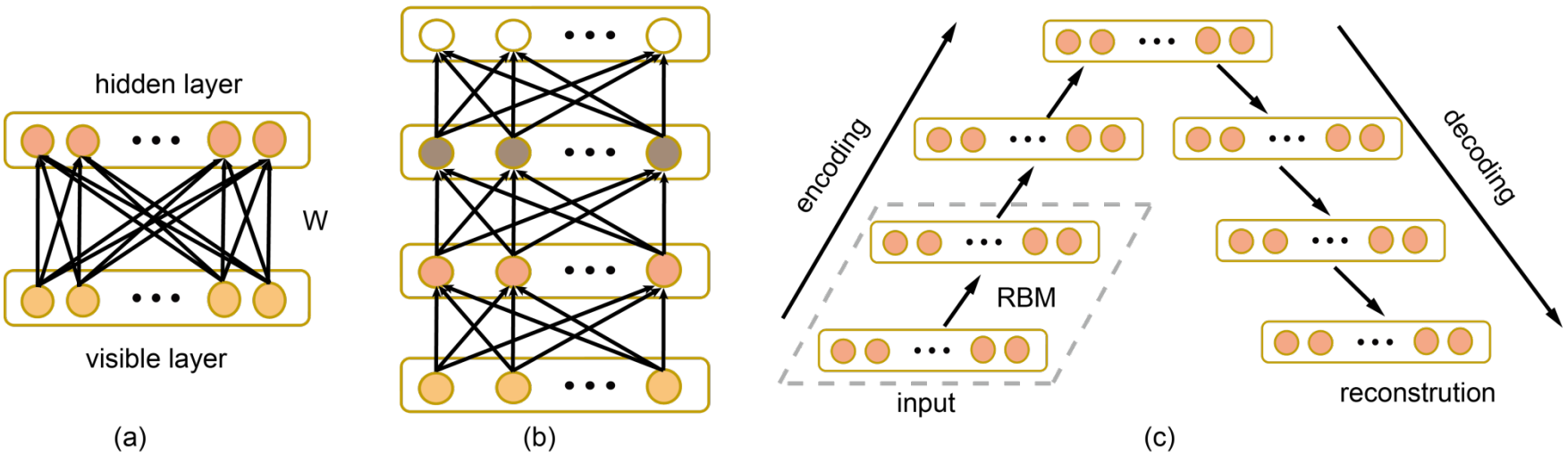
$$h(X) = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) dx = \frac{1}{2}\log(2\pi e\sigma^2),$$

- RASM: rational asymmetry: RASM = DE_{left} / DE_{right}
- DASM: differential asymmetry: DASM = DE_{left} – DE_{right}
- ASM: combination of DASM and RASM

(L. C. Shi, Y. Y. Jiao and B. L. Lu, Differential Entropy Feature for EEG-based Vigilance Estimation, EMBC2013)

Deep belief networks

- Deep Belief Networks (DBN) is a probabilistic generative model with deep architecture.
- A DBN is constructed by stacking a predefined number of restricted Boltzmann machines (RBMs).

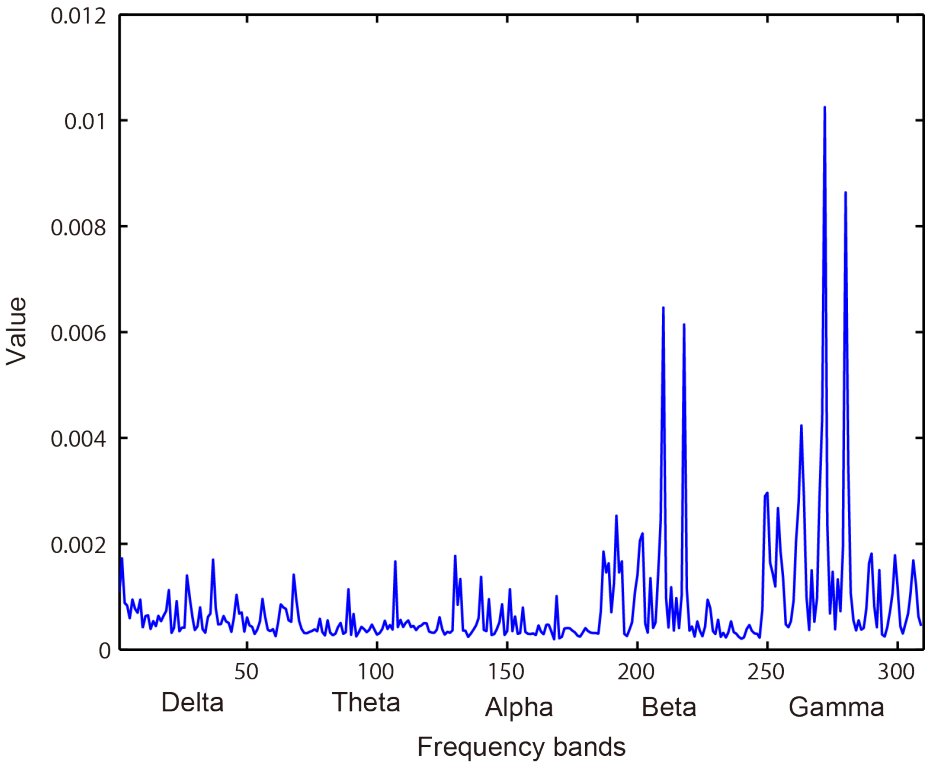


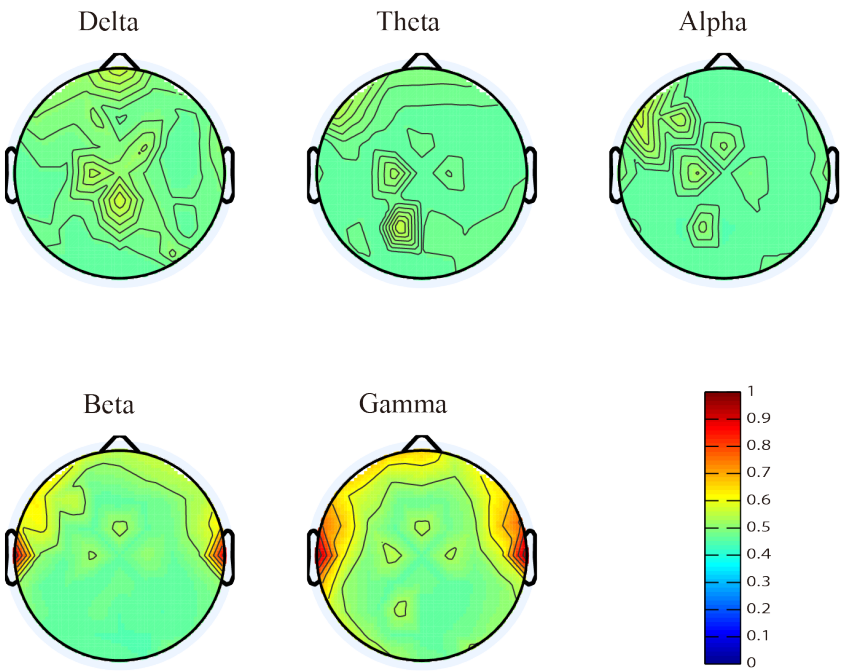
(Wei-Long Zheng, Jia-Yi Zhu and Bao-Liang Lu, Multimodal Emotion Analysis in Response to Multimedia, Proc. of IEEE International Conference on Multimedia and Expo (IEEE ICME2014).

Comparison of SVM and DBN

Feature	Classifier	Delta	Theta	Alpha	Beta	Gamma	Total
PSD	SVM	58.03/15.39	57.26/15.09	59.04/15.75	**73.34/15.20**	71.24/16.38	59.60/15.93
	DNN	60.05/16.66	55.03/13.88	52.79/15.38	60.68/21.31	**63.42/19.66**	61.90/16.65
DE	SVM	60.50/14.14	60.95/10.20	66.64/14.41	80.76/11.56	79.56/11.38	**83.99/09.72**
	DNN	64.32/12.45	60.77/10.42	64.01/15.97	78.92/12.48	79.19/14.58	**86.08/08.34**
DASM	SVM	48.87/10.49	53.02/12.76	59.81/14.67	**75.03/15.72**	73.59/16.57	72.81/16.57
	DNN	48.79/09.62	51.59/13.98	54.03/17.05	69.51/15.22	70.06/18.14	**72.73/15.93**
RASM	SVM	47.75/10.59	51.40/12.53	60.71/14.57	74.59/16.18	74.61/15.57	**74.74/14.79**
	DNN	48.05/10.37	50.62/14.02	56.15/15.28	70.31/15.62	68.22/18.09	**71.30/16.16**
DCAU	SVM	55.92/14.62	57.16/10.77	61.37/15.97	75.17/15.58	76.44/15.41	**77.38/11.98**
	DNN	54.58/12.81	56.94/12.54	57.62/13.58	70.70/16.33	72.27/16.12	**77.20/14.24**

Critical channels and bands



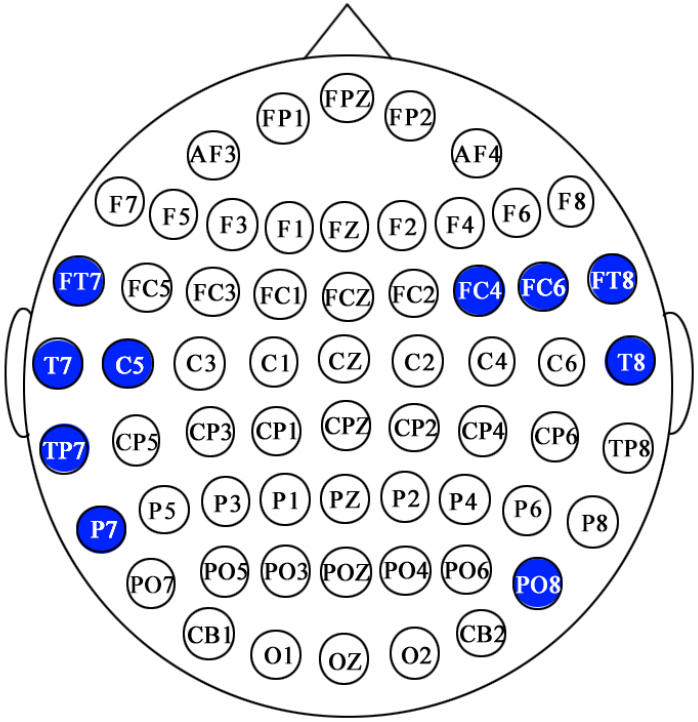


The mean absolute weight distribution of the trained DBNs in first layer.

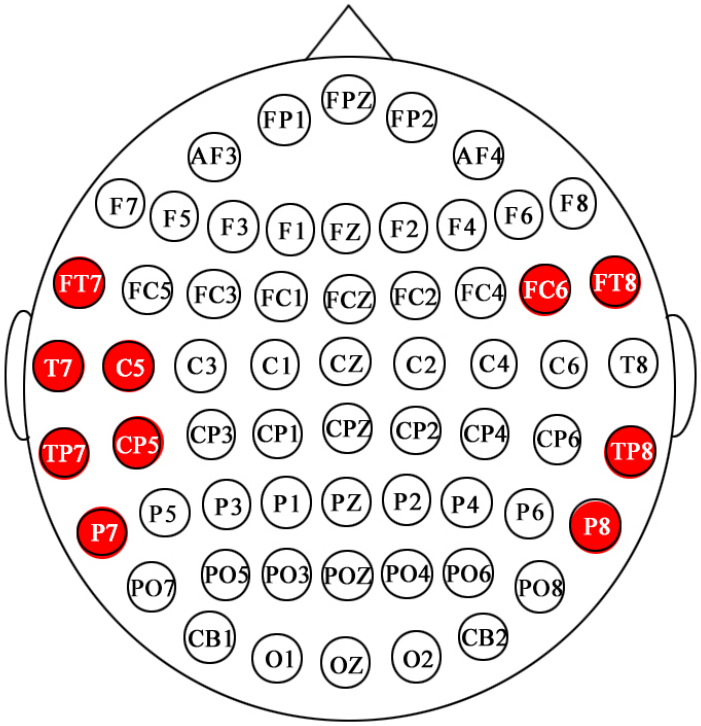
The weight distribution of different brain regions in five frequency bands.

(Mu Li and Bao-Liang Lu, “Emotion Classification Based on Gamma-band EEG”, in Proc. IEEE EMBC, pp. 1323-1326, Mineapolis, USA, 2009)

Subject-independent features



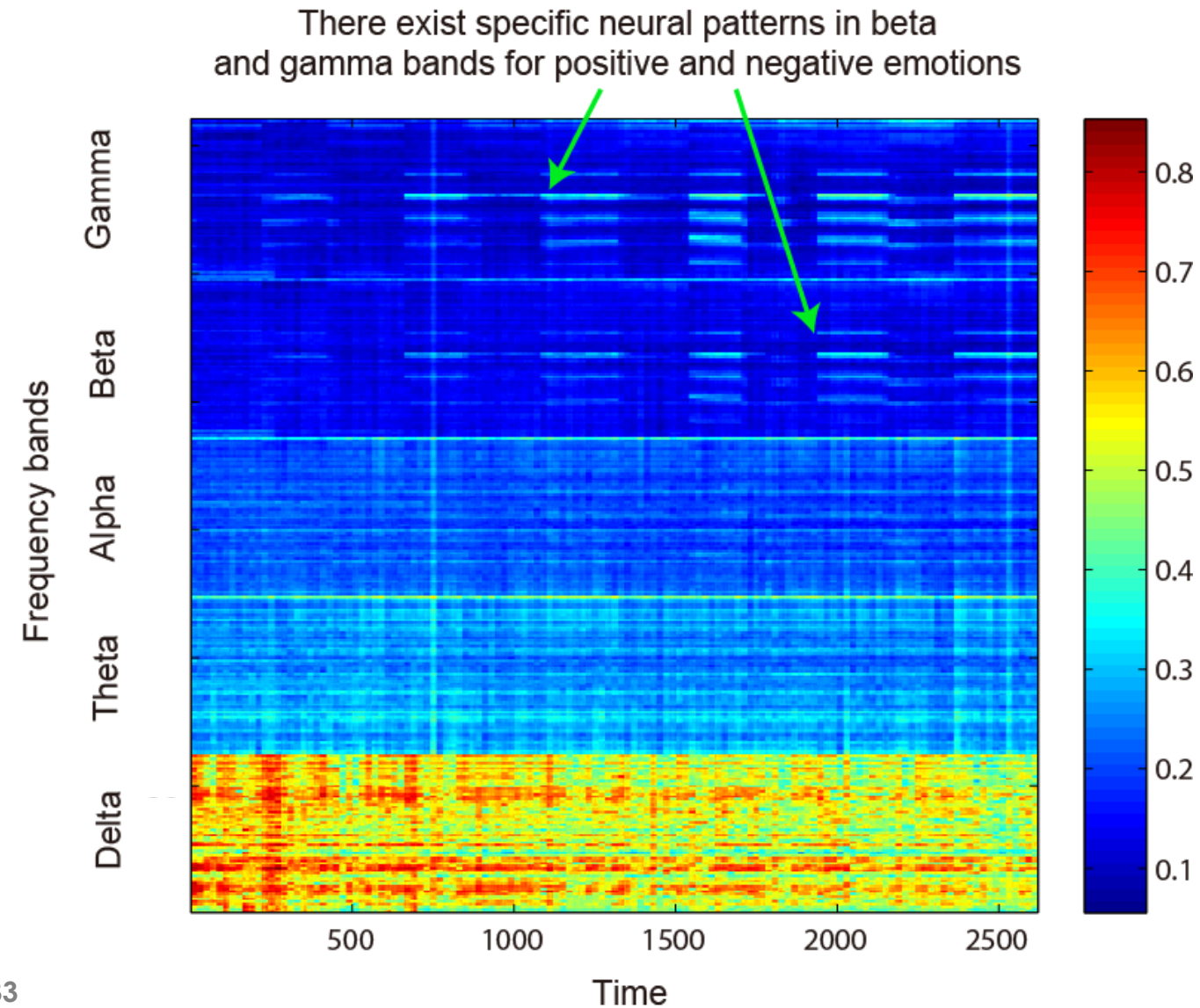
Beta band



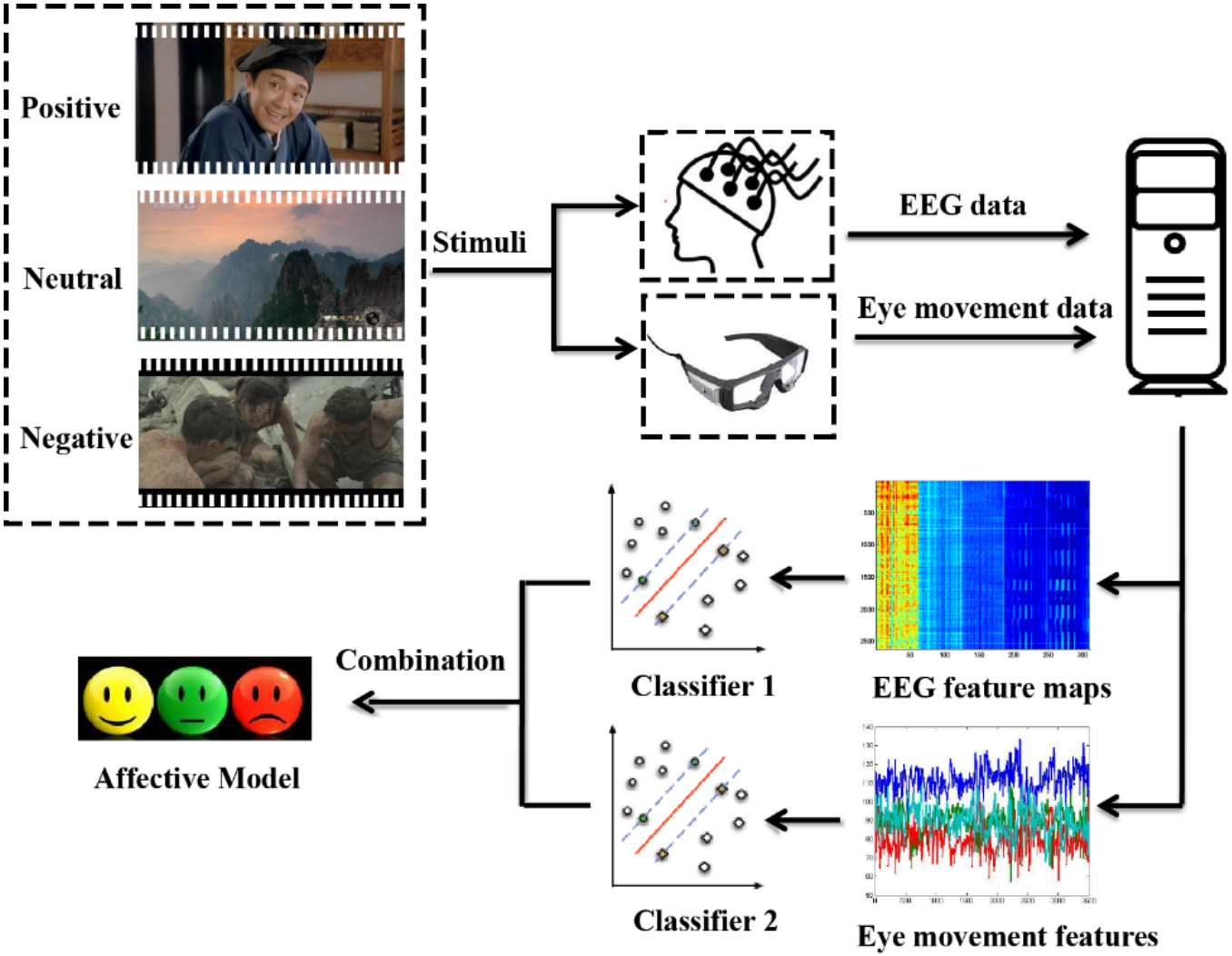
Gamma band

Using correlation coefficients, we can get 20 subject-independent features which are most relevant to emotion recognition. They are all in temporal lobes.

Neural patterns in beta and gamma bands



Combining EEG and eye movement data



(Zheng, Dong & Lu, Multimodal Emotion Recognition Using EEG and Eye Tracking Data, Proc. of IEEE EMBC2014)

Feature and classifier

- Perform PCA to remove the light reflex of same video clips on the pupil diameters of all the subjects.
- We extract 15 eye movement features in total.
  - Pupil diameter, dispersion, fixation duration, blink duration, saccade duration, saccade amplitude, event statistics (blink frequency, fixation frequency, etc.).
- Differential entropy (DE) is extracted as EEG features for 5 frequency bands [Duan et al., 2013].

$$h(X) = -\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \log\left(\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}\right) dx = \frac{1}{2}\log(2\pi e\sigma^2),$$

- Modality Fusion Strategies
  - Feature level fusion (FLF): concatenating two feature vectors
  - Decision level fusion (DLF): maximal rule, sum rule, fuzzy integral
- SVMs with linear kernel are used as classifiers

Classification accuracies

- **Eye movement features**

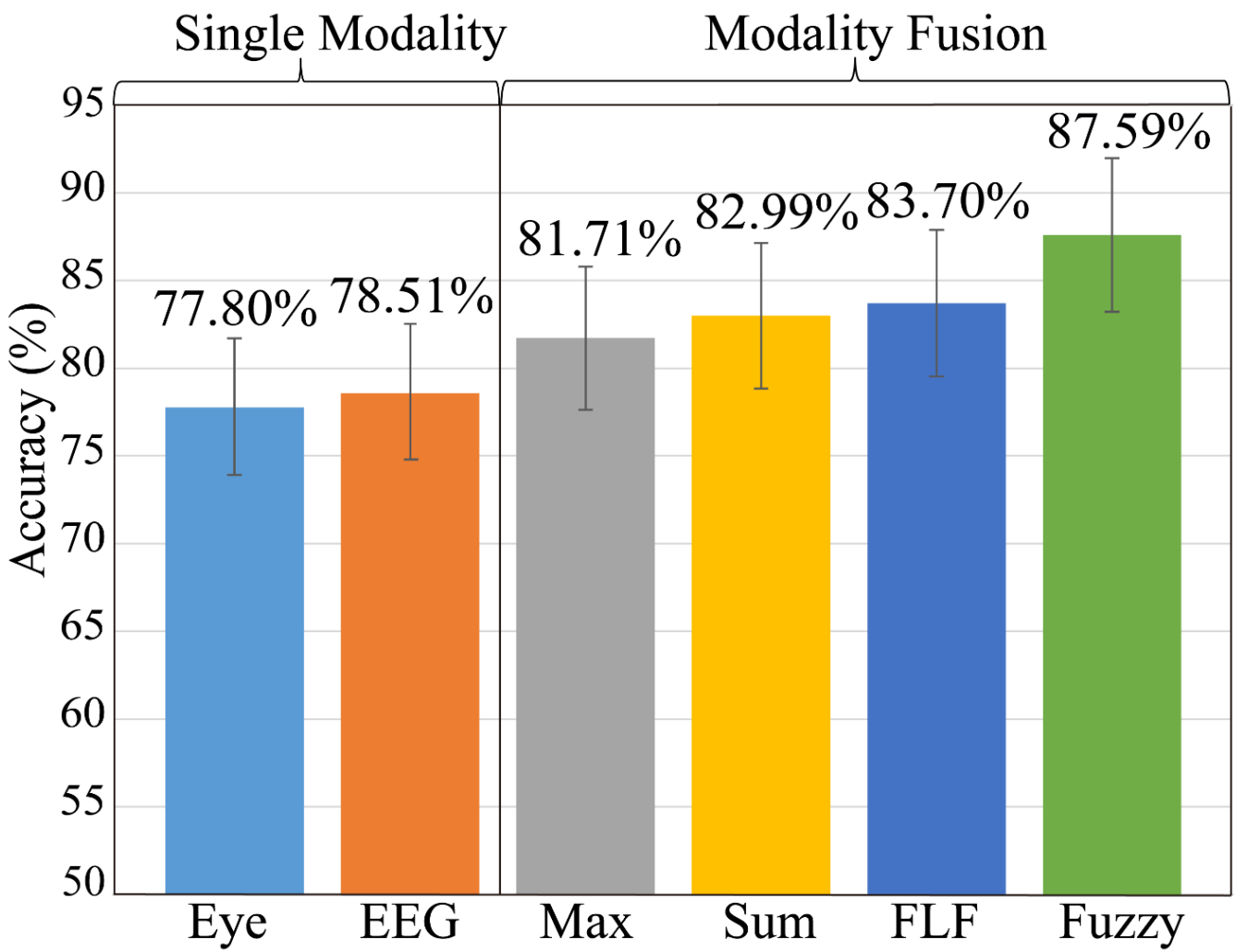
	PD	Dispersion	Fixation	Saccade	Event	FLF
Ave.	57.40	50.17	47.32	57.95	62.26	**77.80**
Std.	17.92	16.99	16.79	21.51	23.82	**14.61**

（FLF： Feature Level Fusion)

- **EEG features**

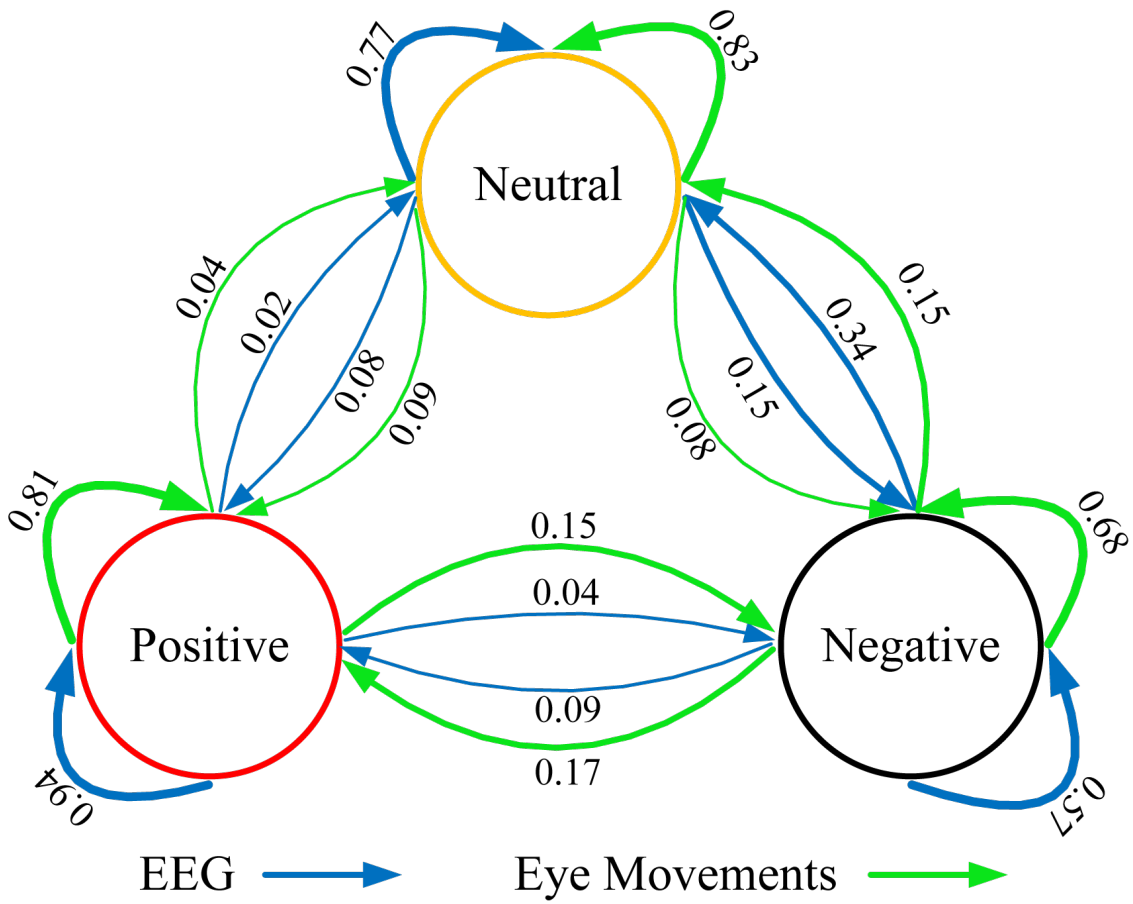
	δ	θ	α	β	γ	FLF
Ave.	69.14	63.39	68.07	78.33	77.48	78.51
Std.	14.45	16.94	16.94	13.11	16.60	14.32

Performance of modality fusion strategies



（Yifei Lu, Wei-Long Zhen, Binbin Li, Bao-Liang Lu: Combining Eye Movements and EEG to Enhance Emotion Recognition. IJCAI 2015)

Confusion graph for three emotions



- Eye movement modality is not so good at classifying positive state as EEG modality.
- Neutral and negative states can be recognized with higher accuracy in eye movement modality than in EEG modality.
- EEG signals and eye movement data have complementary property for emotion recognition

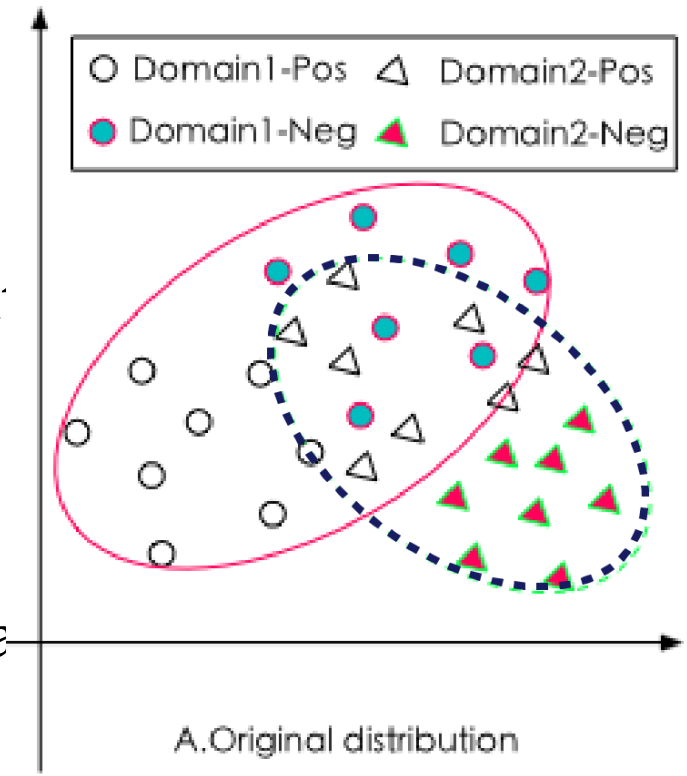
Personalizing EEG-based Affective Models with Transfer Learning

Wei-Long Zheng and Bao-Liang Lu, Personalizing EEG-based Affective Models with Transfer Learning, Proc. of the 25th International Joint Conference on Artificial Intelligence (IJCAI-16).

Challeges of Subject Transfer

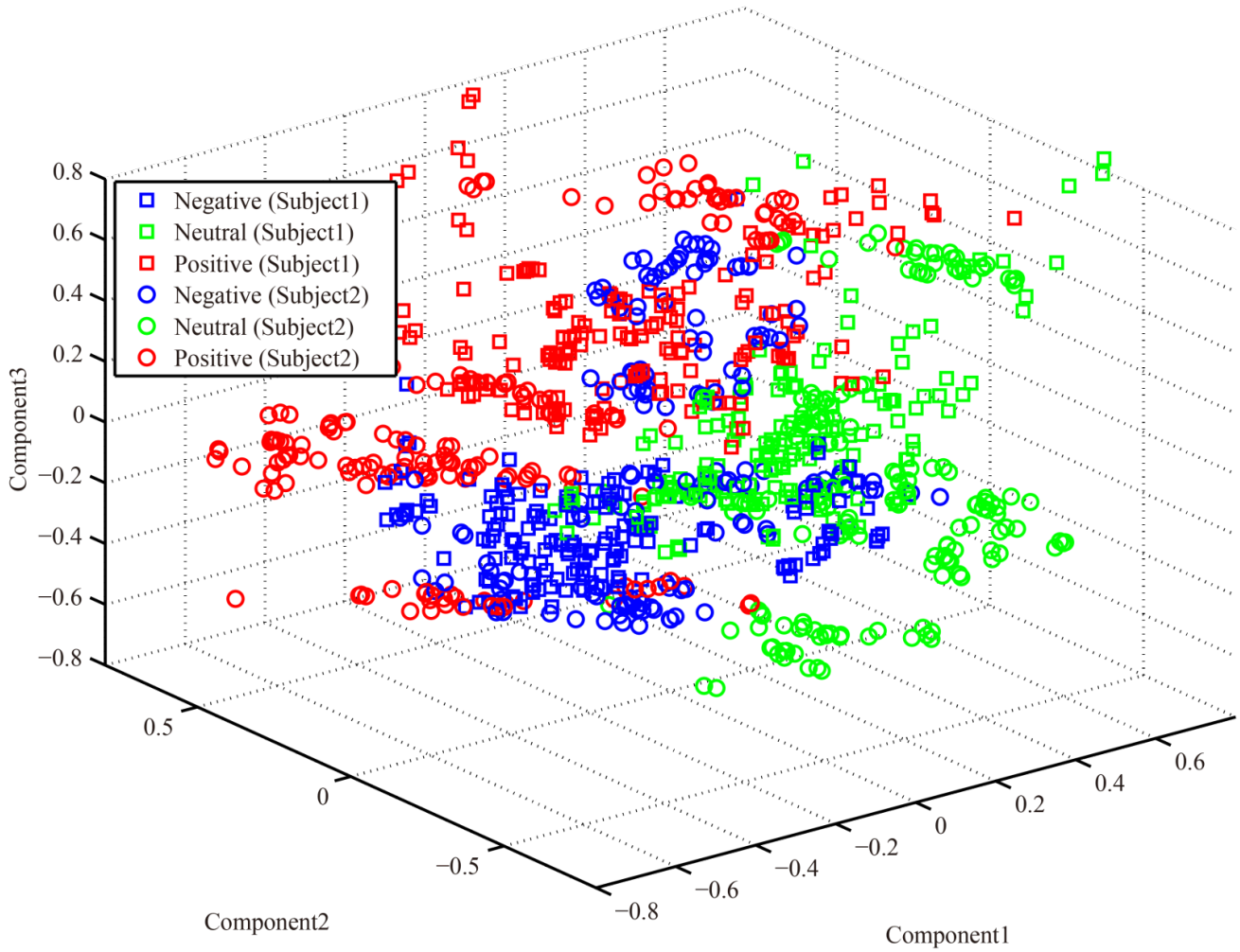
The feature distributions of EEG data of source subjects and target subjects are not independently and identically distributed (i.i.d.) due to:

- The structural and functional variabili between subjects
- The non-stationary nature of EEG signals
- The inherent changes of environmenta variables

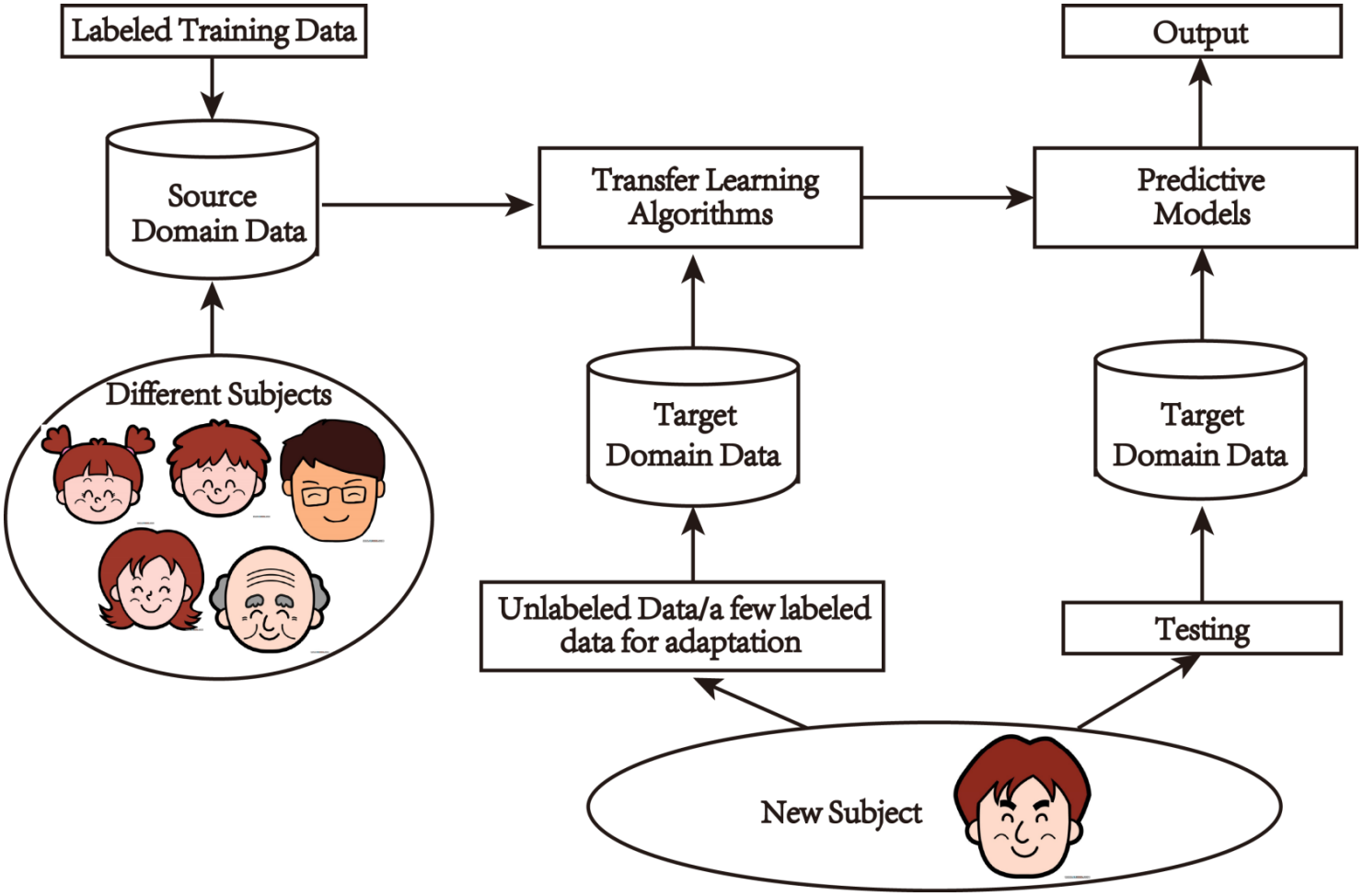


Covariate Shift Challenges

- Individual Differences Across Subjects and Sessions
- Non-stationary Characteristics of EEG



Transfer learning framework



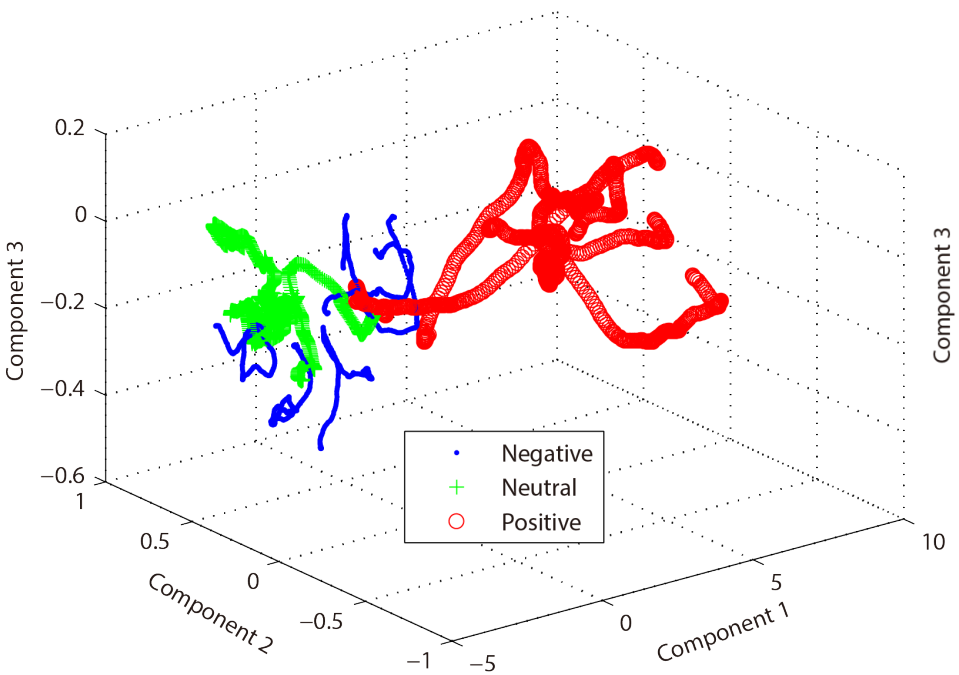
Transfer Component Analysis

Although the distributions of source domain and target domain in high dimensional space are different, we may find a low dimensional manifold space where the distributions of both domains are similar.

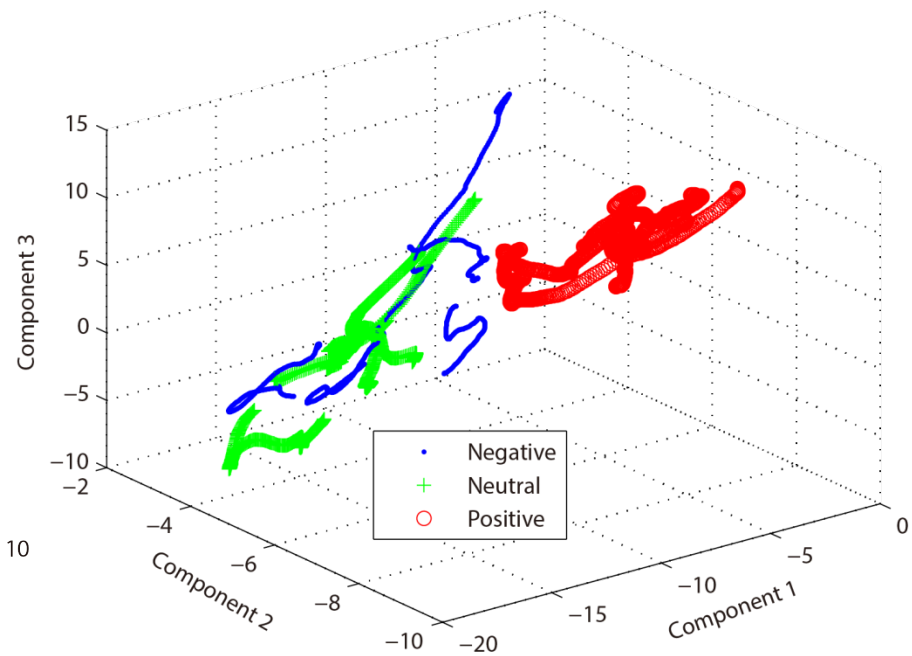
TCA and KPCA try to learn a set of common transfer components underlying both the source domain and the target domain. When projected to this subspace, the difference of feature distributions of both domains can be reduced.

$$P(\phi(X_S)) \approx P(\phi(X_T))$$
$$P(Y_S|\phi(X_S)) \approx P(Y_T|\phi(X_T))$$

Feature visualization in 3D latent space



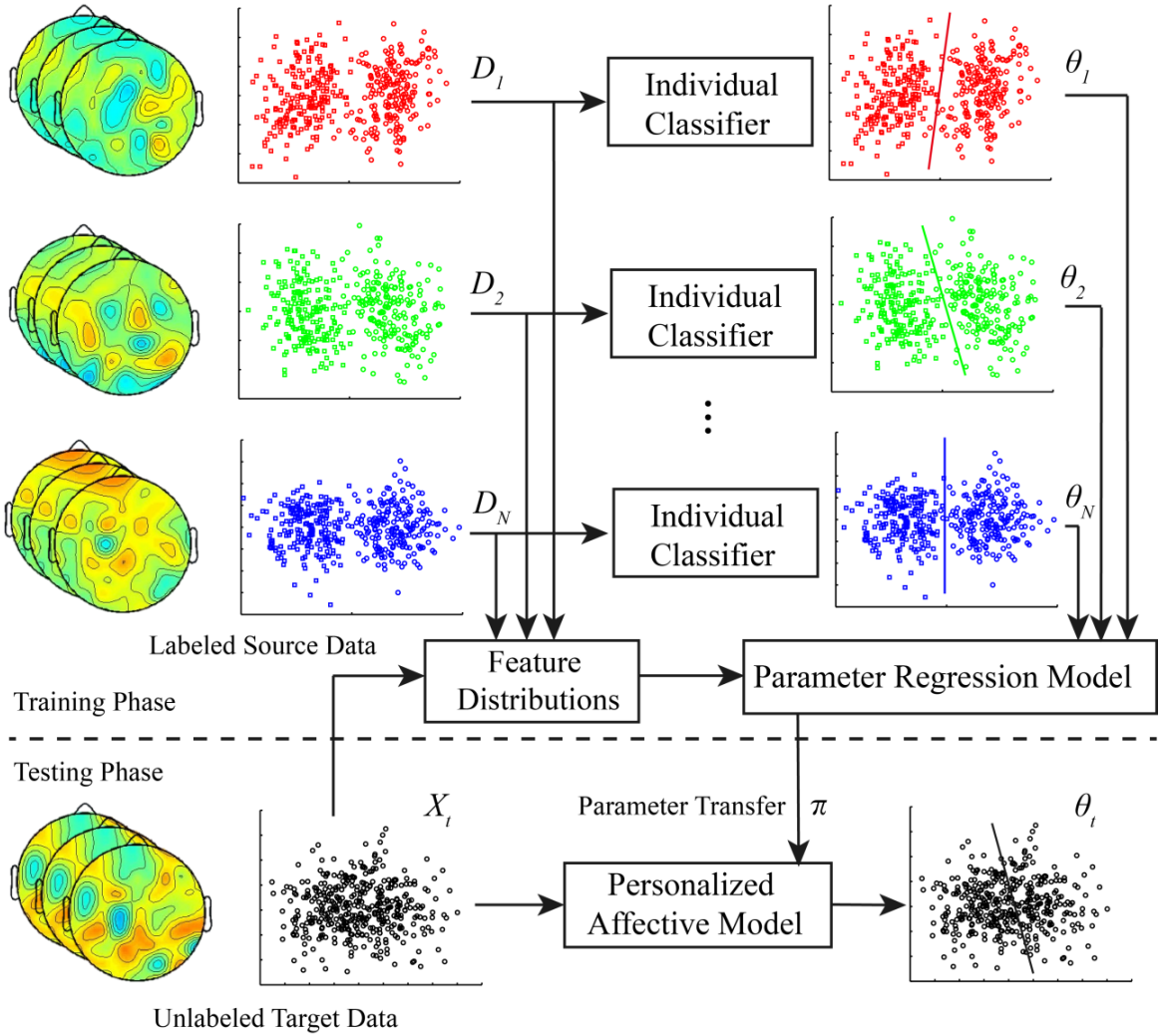
TCA



KPCA

The neural patterns of neutral and negative emotions are more similar to each other and it is easier to recognize positive emotions among these three emotions.

Transductive Parameter Transfer



Enver Sangineto, Gloria Zen, Elisa Ricci, and Nicu Sebe. We are not all equal: Personalizing models for facial expression analysis with transductive parameter transfer. In ACM International Conference on Multimedia, pages 357–366. ACM, 2014.

Transductive Parameter Transfer

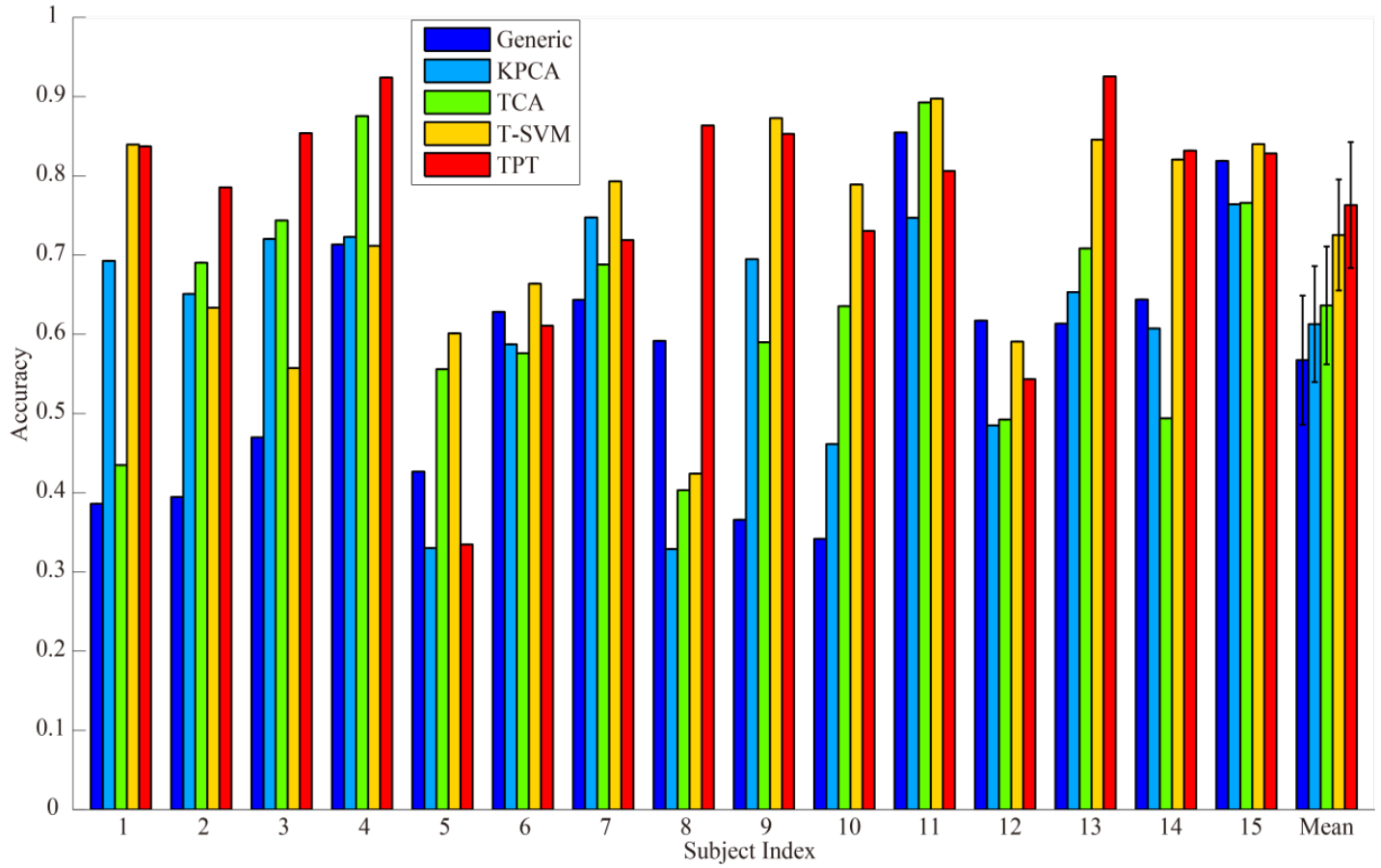
- Multiple individual classifiers are learned on each training dataset
- A regression function is trained to learn the relation between the data distributions and classifiers' parameter vectors.
- Finally, the target classifier is obtained using the target feature distribution and the distribution-to-classifier mapping.

Algorithm 3 TPT-based Subject Transfer

input : Source domain data sets $\mathcal{D}_1^s, ..., \mathcal{D}_N^s$, target domain data set X^t, and some regularization parameters for SVMs.
output : The parameter vector of target classifier: $\boldsymbol{w}_t$, b_t.

1: Construct individual classifiers: $\{\boldsymbol{\theta_i} = (\boldsymbol{w}_i, b_i)\}_{i=1}^N$.
2: Create a training set $\mathcal{T} = \{X_i^s, \boldsymbol{\theta_i}\}_{i=1}^N$.
3: Compute the kernel matrix $\boldsymbol{K}$, $\boldsymbol{K}_{ij} = \kappa(X_i^s, X_j^s)$.
4: Given K and $\mathcal{T}$, learn $f(\cdot)$ using multioutput support vector regression.
5: Compute $(\boldsymbol{w}_t, b_t) = f(X^t)$
6: **Return** $\boldsymbol{w}_t, b_t$.

Evaluation Results



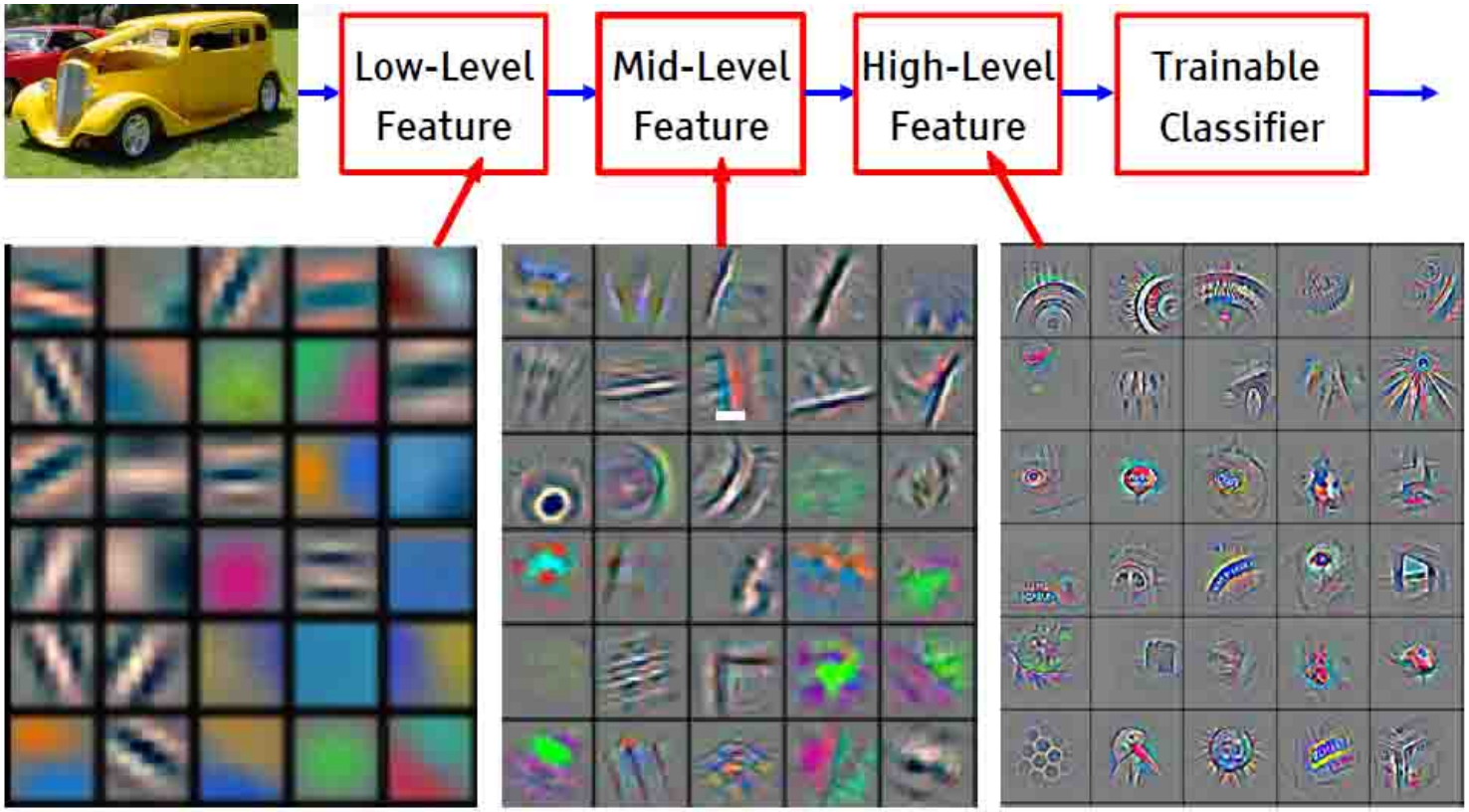
Stats.	Generic	KPCA	TCA	T-SVM	TPT
Mean	0.5673	0.6128	0.6364	0.7253	**0.7631**
Std.	0.1629	0.1462	0.1488	**0.1400**	0.1589

Multimodal deep learning for emotion recognition

Wei Liu, Wei-Long Zheng, and Bao-Liang Lu. Emotion recognition using multimodal deep learning. Proc. of ICONIP2016

Deep learning

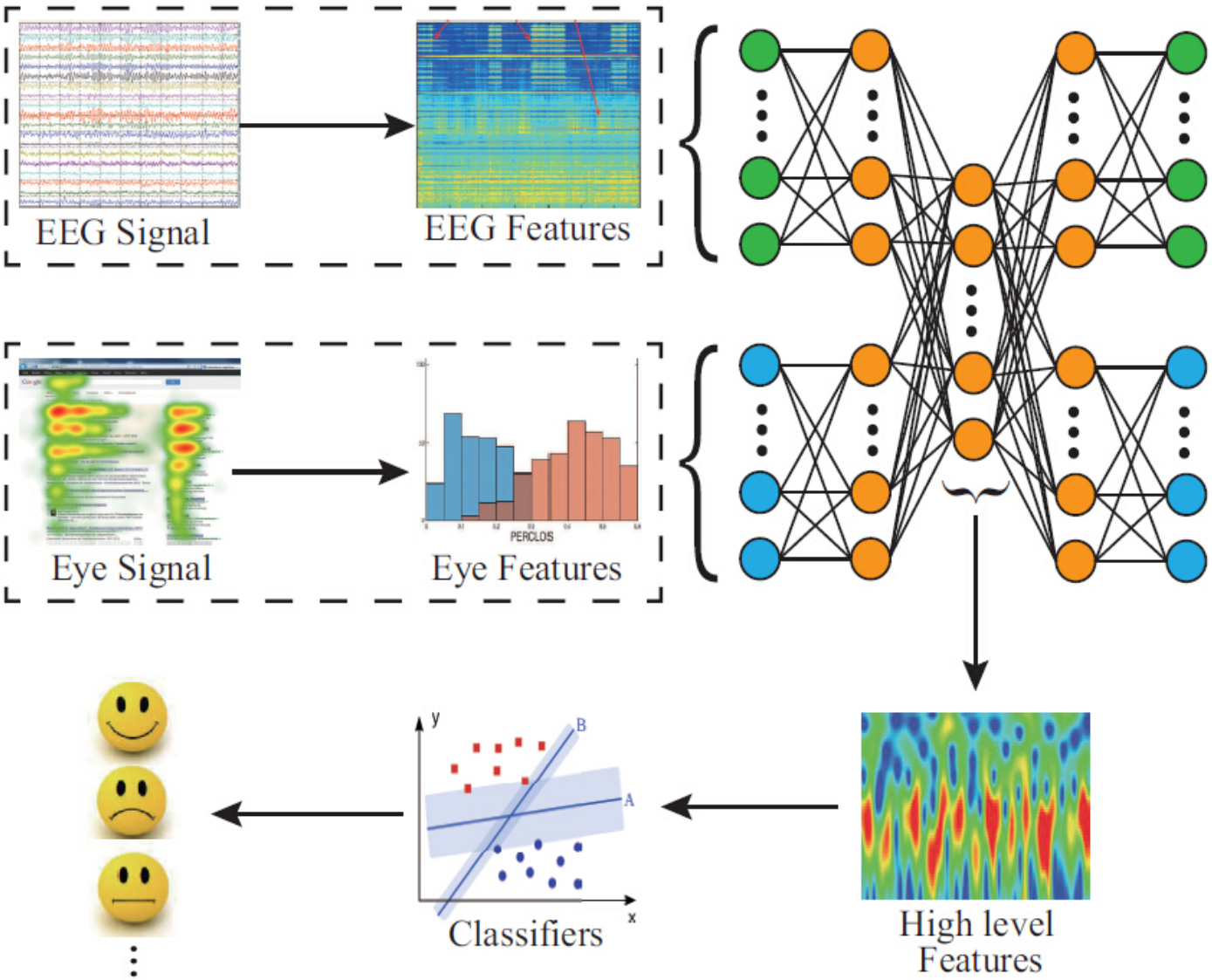
Deep learning = automatically hierarchical feature learning



Multimodal Emotion Recognition

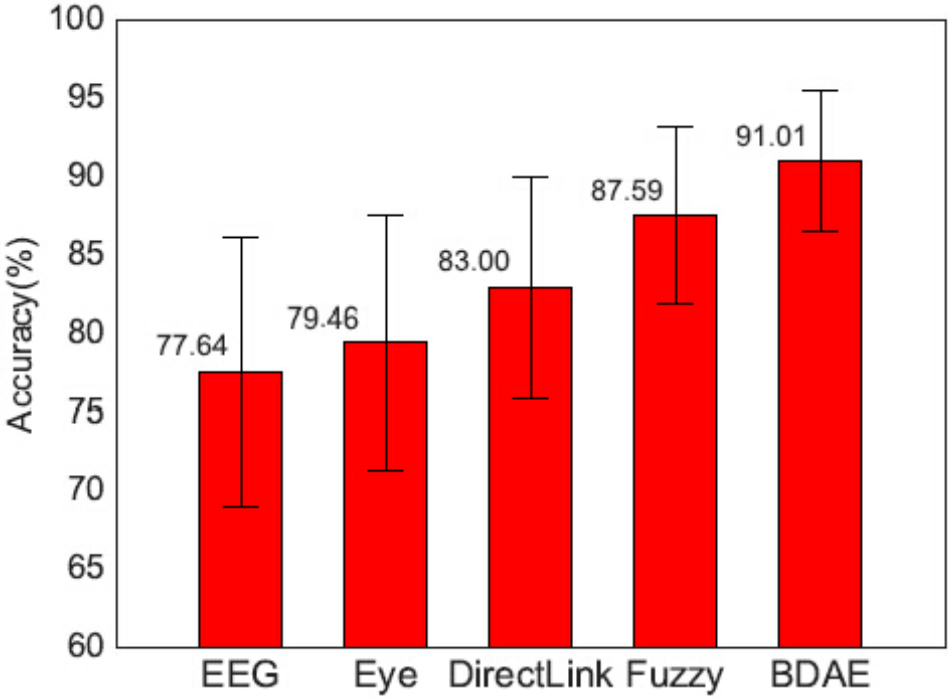
	Feature Learning	Supervised Learning	Testing
Classical Machine Learning	EEG	EEG	EEG
	Eye	Eye	Eye
Multimodal Facilitation	EEG + Eye	EEG + Eye	EEG + Eye
Unimodal Enhancement	EEY + Eye	EEG	EEG
	EEG + Eye	Eye	Eye
Cross-modal Learning	EEG + Eye	EEG	Eye
	EEG + Eye	Eye	EEG

Multimodal Facilitation flowchart



Multimodal Facilitation Results

- EEG-only: 77.64%
- Eye-only: 79.46%
- Concatenating: 83.00%
- Fuzzy integral: 87.59
- BDAE: 91.01%



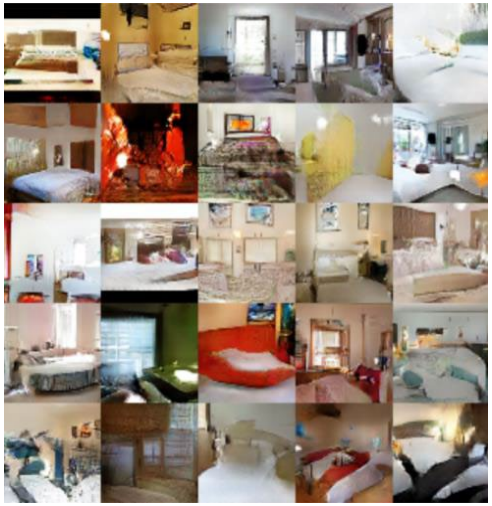
The BDAE framework has the best performance.

EEG Data Augmentation for Emotion Recognition Using a Conditional Wasserstein GAN

Yun Luo, Bao-Liang Lu, EEG Data Augmentation for Emotion Recognition Using a Conditional Wasserstein GAN, appear in **Proc. IEEE EMBC 2018**, Honolulu, 2018.

Data Augmentation and GANs

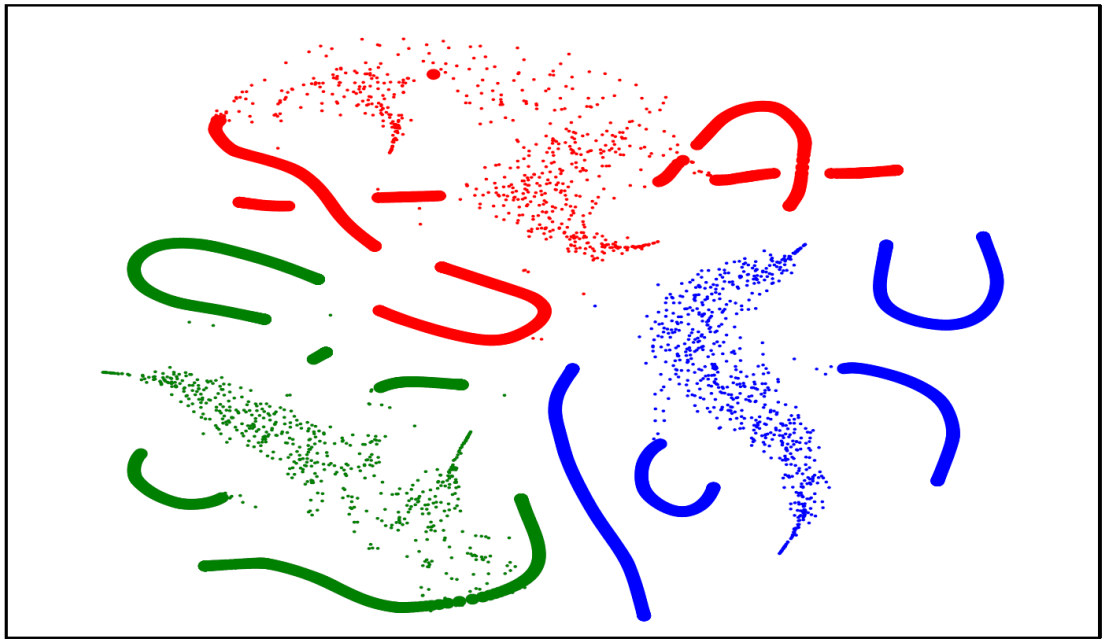
- Unlike geometric transformation, GANs capture the latent distribution of the data by unsupervised learning.
- Data generated by GANs enlarge the data manifold, which leads to a better margin for the classifier.



Pictures generated by GANs

Two-dimensional mapping

- Two-dimensional visualizations of the real and generated DE data of one subject in SEED dataset. Data points with red, green and blue colors represent three emotions of negative, neutral and positive, respectively. The lines represent the real data and the thin points represent the generated data.



Results

- **The experimental results demonstrate that using the EEG data generated by CWGAN significantly improves the accuracies of emotion recognition models.**

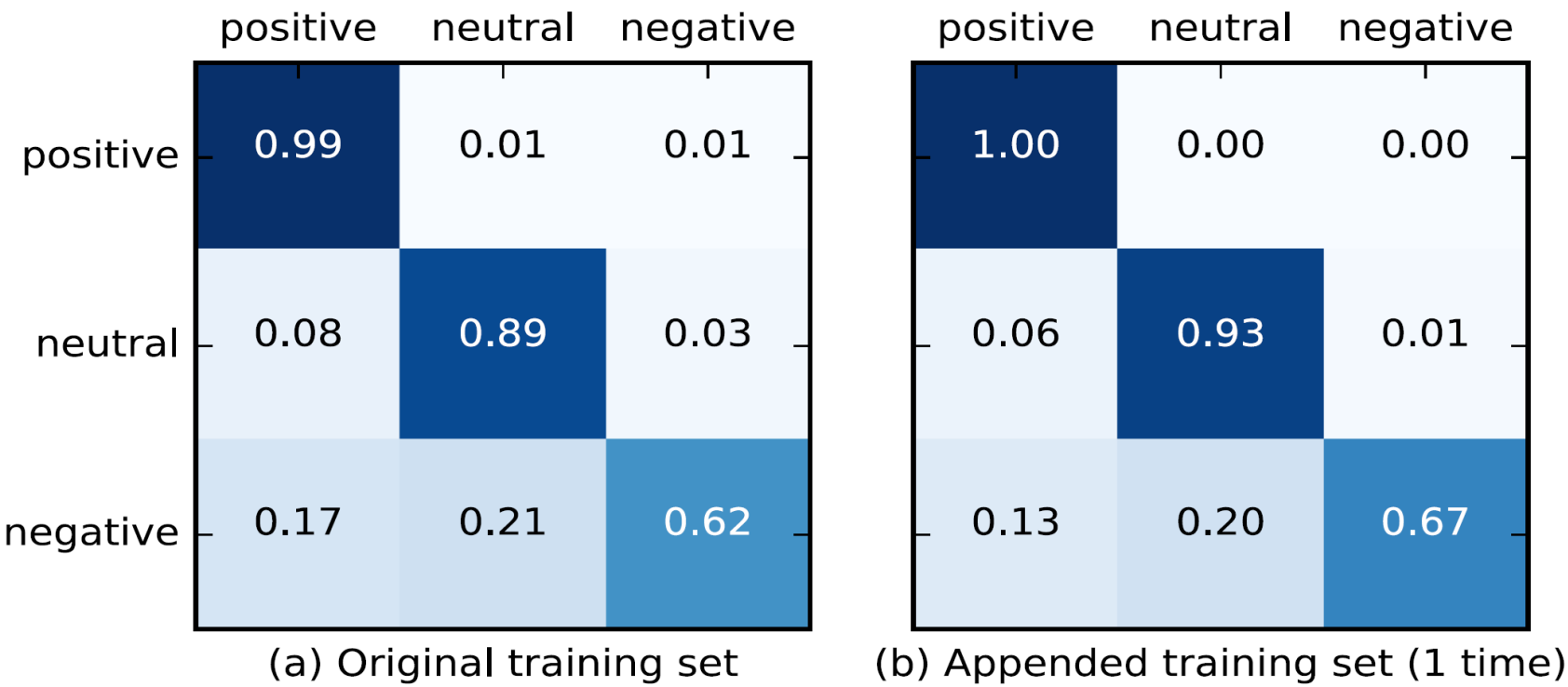
Data Appended	SEED		DEAP-Arousal		DEAP-Valence	
	Mean	Std.	Mean	Std.	Mean	Std.
0×Dataset	0.8399	**0.0972**	0.6902	0.1361	0.5376	0.1308
1×Dataset	**0.8696**	0.1272	**0.7817**	**0.0958**	**0.7389**	**0.1082**
2×Dataset	0.8659	0.1283	0.7437	0.1227	0.6543	0.1506
3×Dataset	0.8638	0.1276	0.7479	0.1133	0.6625	0.1477
4×Dataset	0.8623	0.1275	0.7450	0.1013	0.6496	0.1504
5×Dataset	0.8600	0.1294	0.7434	0.1151	0.6467	0.1372

TABLE I

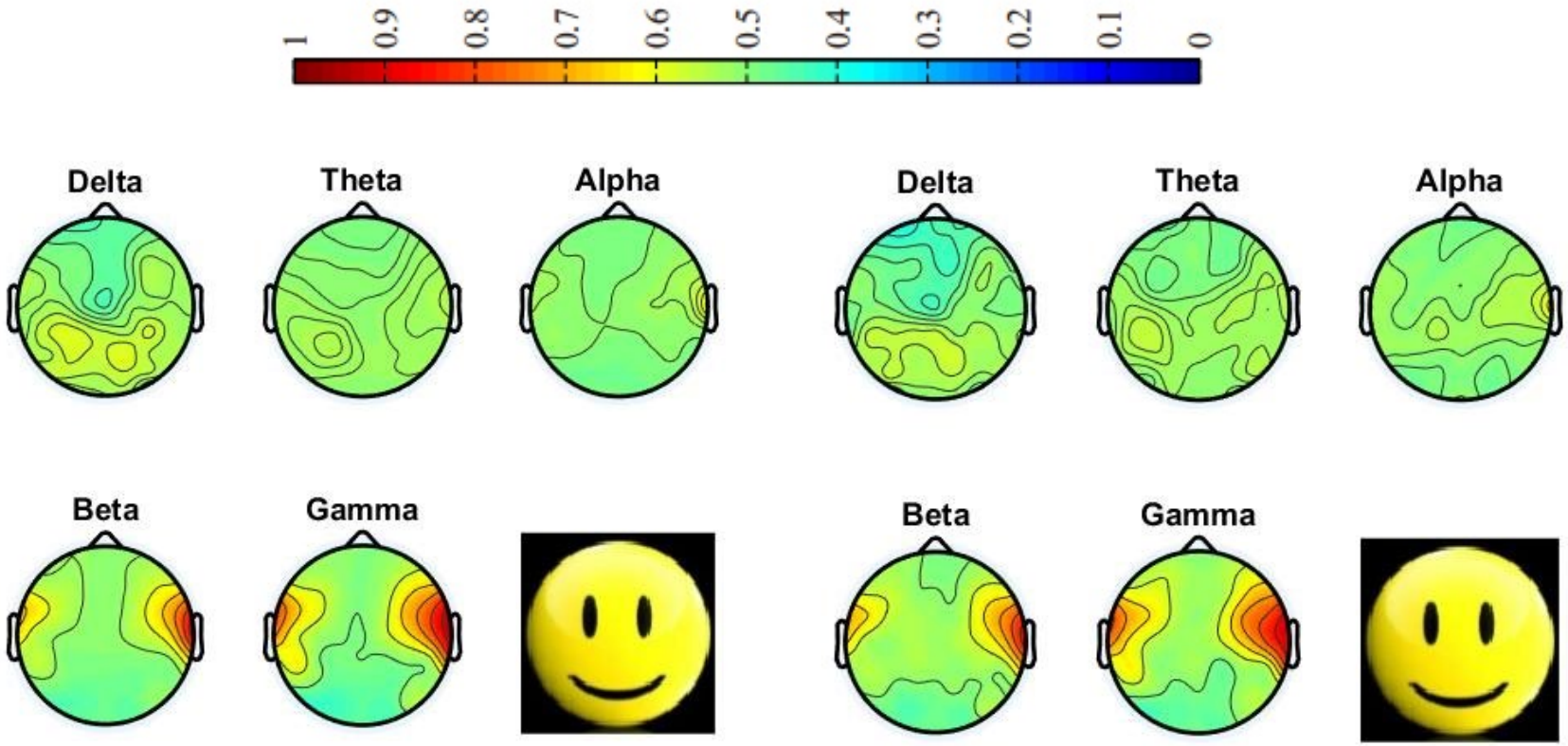
PERFORMANCE OF APPENDING GENERATED EEG DATA

Confusion Matrix

- The confusion matrixes (SEED dataset) trained by (a) original training set and (b) appended training set (1 time).

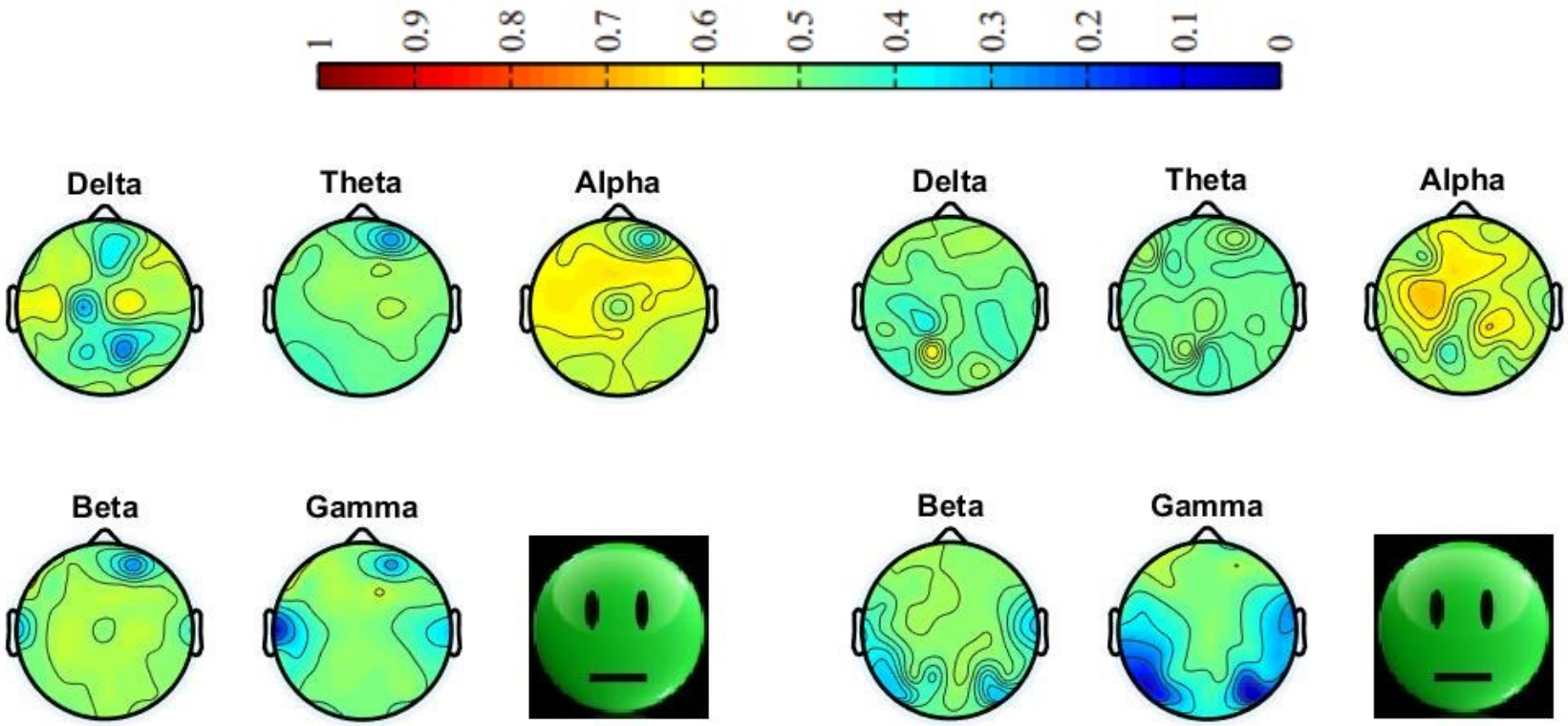


Visualization-Positive



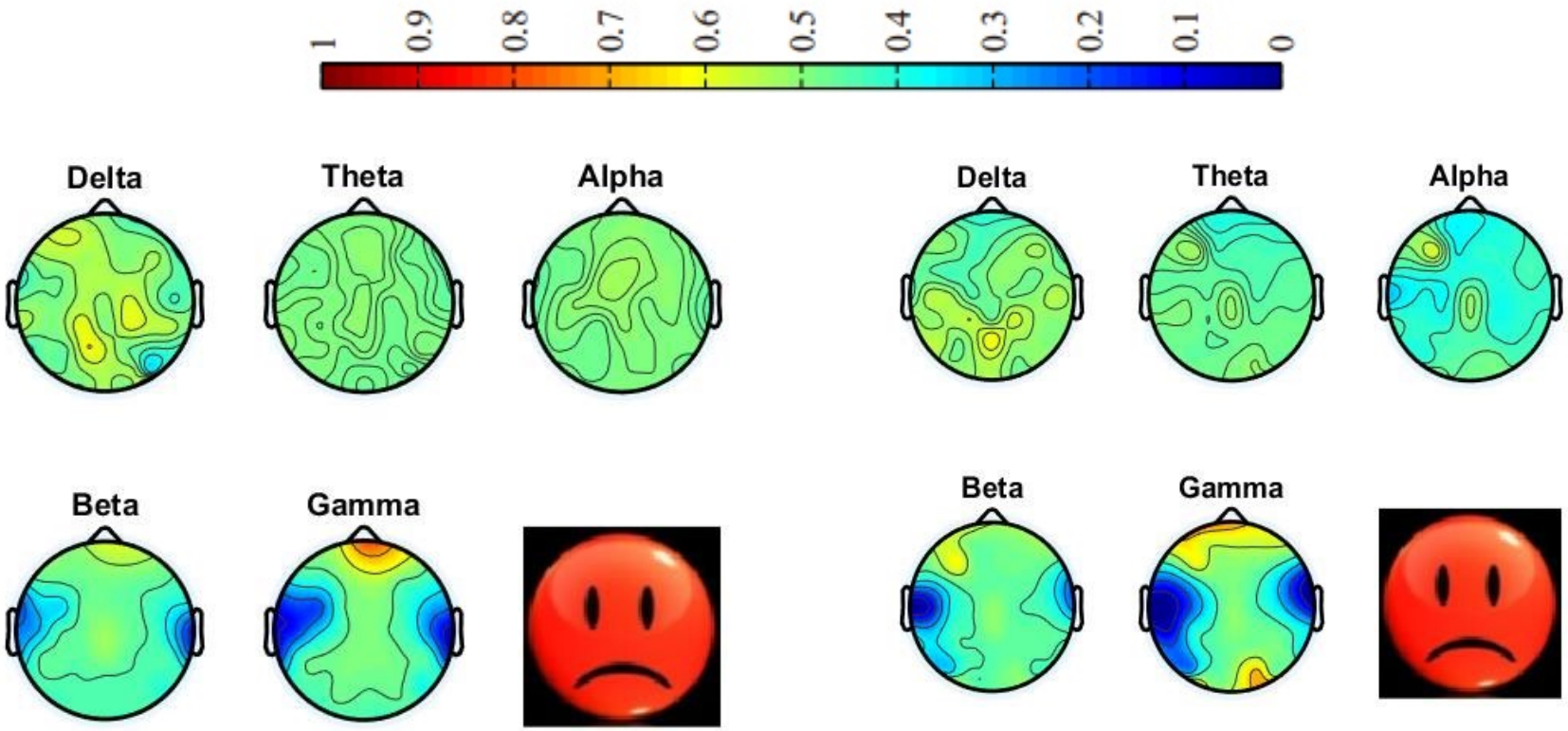
(a) Real Data (b) Generated Data

Visualization-Neutral



(a) Real Data (b) Generated Data

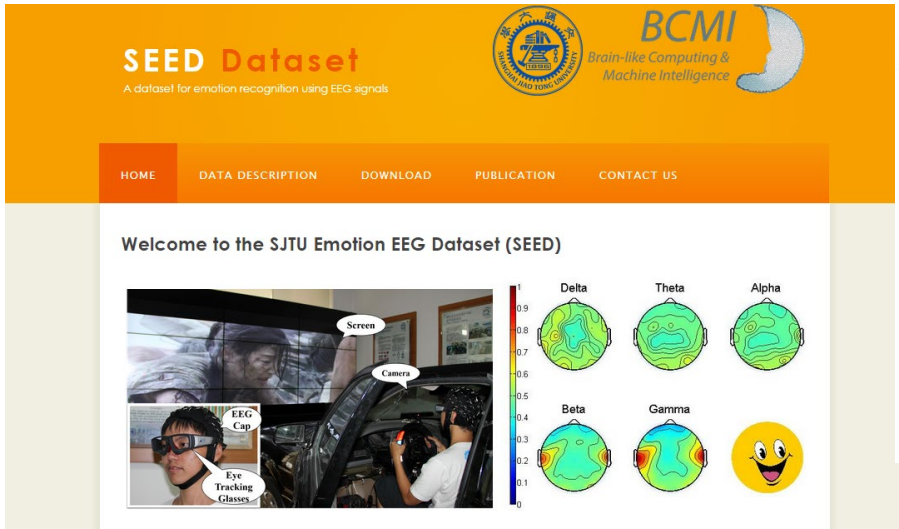
Visualization-Negative

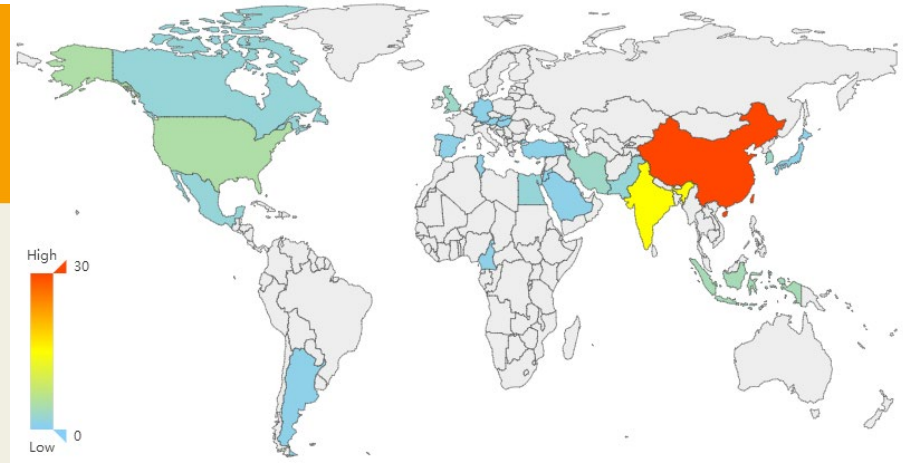


(a) Real Data (b) Generated Data

SJTU Emotion EEG Dataset (SEED)

- Publicly available emotion dataset: EEG and eye tracking data
- No. experiments: 45, No. Channels: 62
- Total number of applications: 422 (Jan. 2019)





http://bcmi.sjtu.edu.cn/~seed/index.html

Wei-Long Zheng, and Bao-Liang Lu, "Investigating Critical Frequency Bands and Channels for EEG-based Emotion Recognition with Deep Neural Networks",, IEEE Transactions on Autonomous Mental Development (IEEE TAMD), 2015

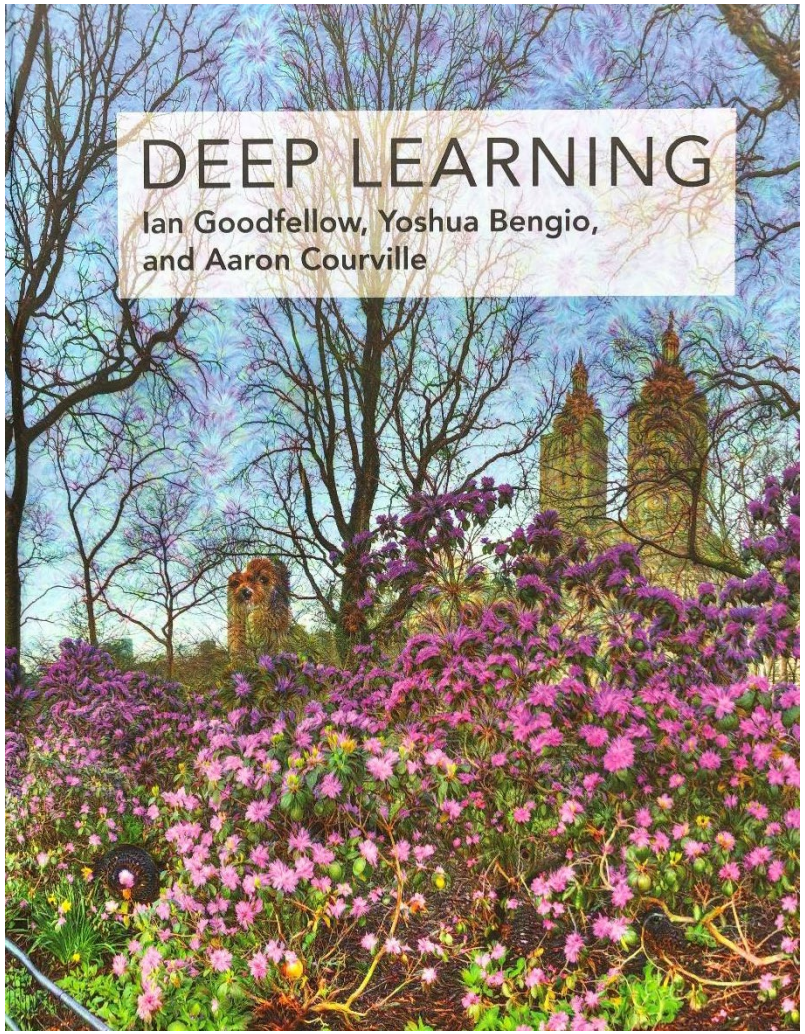
Recommended Textbooks

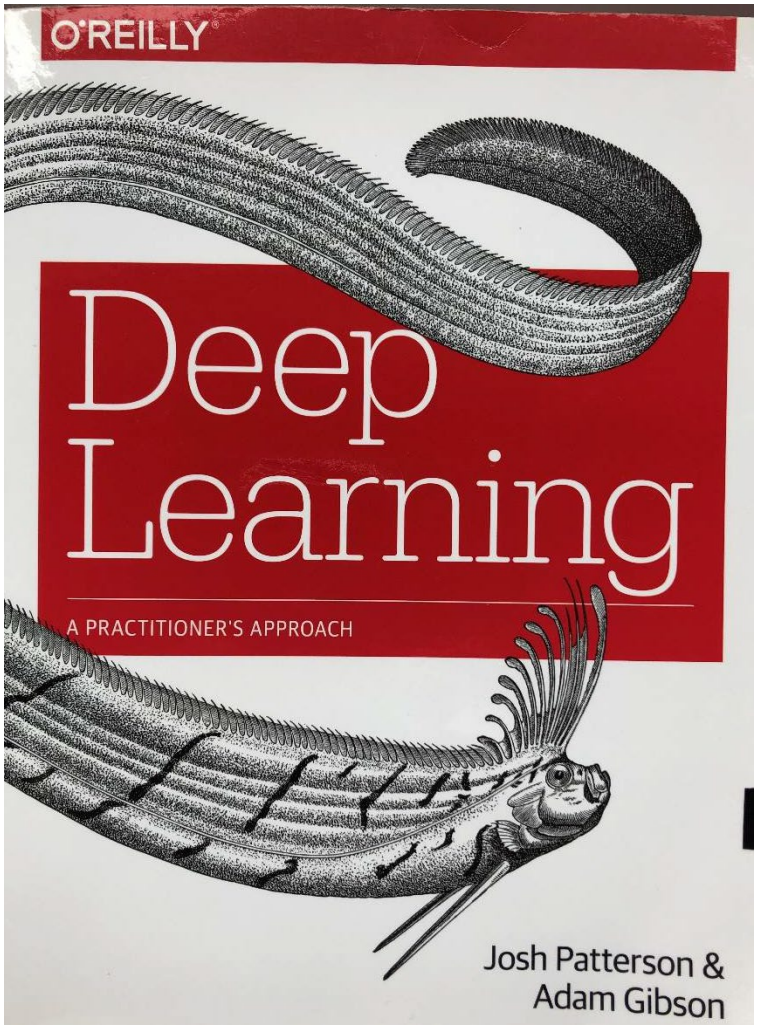
- *Neural Network Design*, 1st ed. Martin T. Hagan, Howard. B. Demuth, and Mark H. Beale, PWS Publ. Company, 1996

  (神经网路设计,机械工业出版社,2002)
- *Neural Networks and Learning Machine*, 3rd ed., Simon Haykin, 2011

  (神经网络与机器学习,机械工业出版社, 2011)
- *Deep Learning,* Ian Goodfellow, Yoshua Bengio, Aaron Courville, 2016, MIT Press
- *Deep Learning, A Prectitioner's Approach*, Josh Patterson & Adam Gibson, OREILLY, 2017
- *Pattern Recognition and Machine Learning*, Christopher M. Bishop,, Springer, 2006

Deep Learning Text Books





Neural Network Journals

- IEEE Trans. Neural Networks and Learning Systems
- Neural Computation
- Neural Networks
- Neurocomputing

- IEEE Trans. Pattern Analysis and Machine Intelligence
- Machine Learning
- Journal of Machine Learning Research

Neural Network Conferences

- Neural Information Processing Systems (NeurIPS)
- IEEE/INNS International Joint Conference on Neural Networks (IJCNN)
- IEEE World Congress on Computational Intelligence （WCCI）
- International Conference on Neural Information Processing (ICONIP)

Deep Learning Frameworks

- With the rapid developments of the deep learning, different deep learning frameworks are developed to make it easy to build deep learning solutions.

  - Tensorflow
  - Keras
  - Caffe
  - Torch
  - PyTorch
  - MXNet
  - …

Instructor and Slides

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