《神经网络理论与应用》第一讲

Neural Network Theory and Applications

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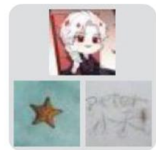
课程微信群



群聊: 2025神经网络理论与
应用课程群

该二维码7天内(2月21日前)有效，重新进入将更新

上课时间安排

- 2月17日-6月2日，共16周
- 每周一晚：18：00-20：20
  - 18：00-18：45 上课
  - 18：45-18：55 课间休息
  - 18：55-20：20 上课
- 特邀报告2次：第11-12周（待定）
- 大作业：第13-16周；期间无课堂教学
- 助教答疑：提前发邮件，电信学院3号楼214（有变化会提前通知）
- 上课前提前在CANVAS上发布上课PPT

平时作业和课程大作业

- 平时有3次作业，全部是编程和计算实验
  - 编程实验与理论和算法学习同样重要
  - 非计算机专业的同学要打破对编程的高深莫测或恐惧的心理障碍
- **大作业每人独立完成!**
- 4月21日（第10周）提交大作业提案
- 6月9日（第17周）提交大作业报告，不允许晚交!
- 成绩构成：
  - 课堂表现:10分
  - 平时作业：30分
  - 大作业：60分

几点注意事项

- 课堂纪律：有问题举手；请勿交头接耳！
- 微信群使用规则：只用于与本课程有关的事情。
- **代码和作业：严禁抄袭！对抄袭行为将是零容忍！**
- **做到不抄袭，也不让别人抄袭！**
- 平时作业和大作业要求用LaTex或Word书写，不接受手写拍照
- 平时作业晚交惩罚规则：
  - 晚交1天成绩等级降低一级

共同应对挑战及基本要求

- 本课程的挑战！
  - 选课同学的基础差异大，年级不同、但考核要求一样
  - 新的深度网络模型日新月异
  - 助教人数少
- 有力条件：各类丰富的学习资料和网上课程
- 需要掌握的
  - 基本概念
  - 基础理论
  - 基本算法
  - 典型应用

Chat-GPT

DeepSeek

Chat-GPT是什么?

- OpenAI开发的聊天机器人
- GPT-3的一个改进版
- 一种大模型，参数规模1750亿
- 核心技术和算法：
  - 自监督学习
  - 预训练
  - Generative Pre-trained Transformer
  - 人类反馈强化学习（RLHF）

Chat-GPT对社会的影响?

- AI工具已经可以辅助人类进行创造性工作，AI什么时候会从创作者的辅助工具发展为具有独立创作力的智能体？
- Sam Altman （Open AI CEO)：作为创作辅助工具，AI既有用也很受欢迎，但目前来看，AI在大部分的创造性任务上的能力都有待提高，未来很长一段时间内都不能代替人类创作者。可能到100年之后，AI才可以独立完成创造性工作。
- 十年前，大部分人都认为AI取代人类工作的次序是：蓝领工作（卡车司机等）→低技能的白领工作→高技能的白领工作（程序员等），最后才会（也许永远不会）取代创造性工作。
- 现在的事实证明，AI最有可能先取代的反而是创造性工作。这也说明，预测未来是很难的，还说明人类可能不够了解自己，不清楚什么类型的技能最难、最需要调动大脑，或者错误估计了控制身体的难度。

DeepSeek 简介

- DeepSeek是幻方量化旗下的一家大模型企业。幻方量化是中国知名的私募巨头。DeepSeek成立于2023年7月份，致力于探索人工智能本质。他们发布了多个开源大语言模型，包括DeepSeek LLM、DeepSeek Coder等多个模型，在多项评测中都有非常好的表现。
- 2024年12月，DeepSeekAI开源DeepSeek V3模型，因为其良好的性能、巨大的创新和友好的开源协议引起了国内外广泛的关注。特别是其架构的创新，用较低的成本训练出媲美全球顶尖模型的效果进而引起了大家的关注。
- 2025年1月20日，DeepSeekAI开源了DeepSeek R1推理大模型，其性能接近OpenAI的o1模型，且完全开源，再次引起了全球的关注。DeepSeek-R1发布后，其AI助手迅速成为苹果iPhone应用商店中下载量最高的免费应用。

AlphaGo掀起了新一轮AI浪潮！

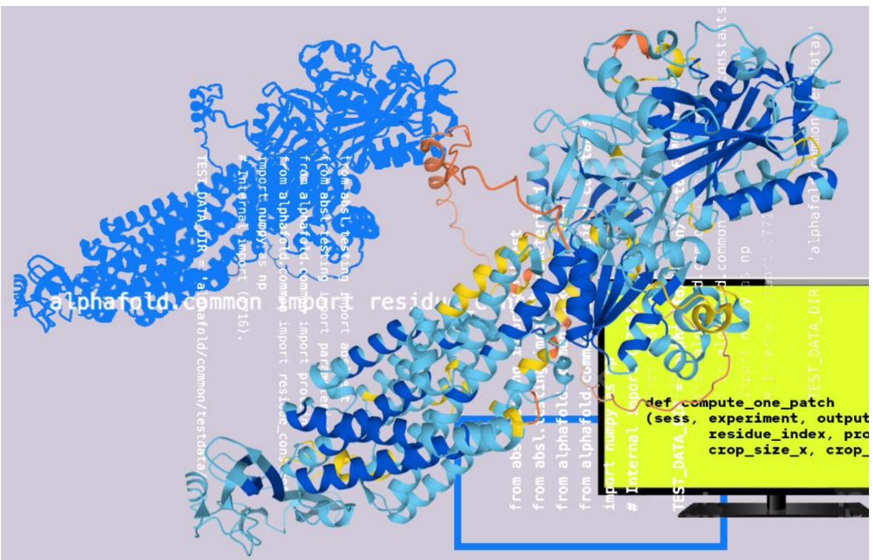
- 2016年1月，Google在Nature上发文，表示他们的AlphaGo系统在正式比赛中打败了欧洲围棋冠军。
- 2016年3月，AlphaGo成功挑战韩国围棋九段李世石，比分为4:1
- 2017年10月19日，在《自然》上发表的一篇研究论文中，Deepmind报告新版程序AlphaGo Zero：从空白状态学起，在无任何人类输入的条件下，它能够迅速自学围棋，并以100:0的战绩击败“前辈”。

《麻省理工科技评论》2021年“全球十大突破性技术”

GPT-3, or the third generation Generative Pre-trained Transformer

《麻省理工科技评论》2022年“全球十大突破性技术”

年度突破：AI预测蛋白折叠

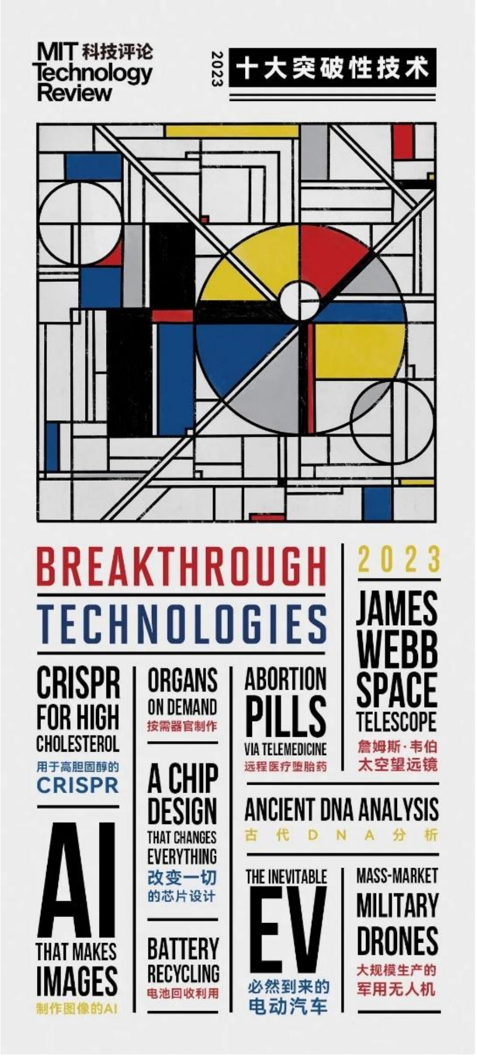


AI预测蛋白折叠

- 人体内几乎所有的生化进程都离不开蛋白质的参与。这种生物大分子由一长条氨基酸链折叠形成复杂的三维结构，如果能了解它们的性质，就可能理解它们的功能，甚至为开发药物铺平道路。
- 多年来，科学家们就试图使用计算工具，预测蛋白质的结构。然而这些工作的准确度，却难以和人工获得的结构所匹敌。
- 这正是人工智能取得突破的地方。通过深度学习的方法，这套系统能对蛋白结构进行更精准的预测，这也是电脑首次产生接近人类实验质量的蛋白结构数据。后者准确度更高，但也更耗时。
- 这些工作所能带来的真正影响，可能还需要数年时间才能得到彻底彰显。但它的潜在变革潜力，已是有目共睹。

AI for Science

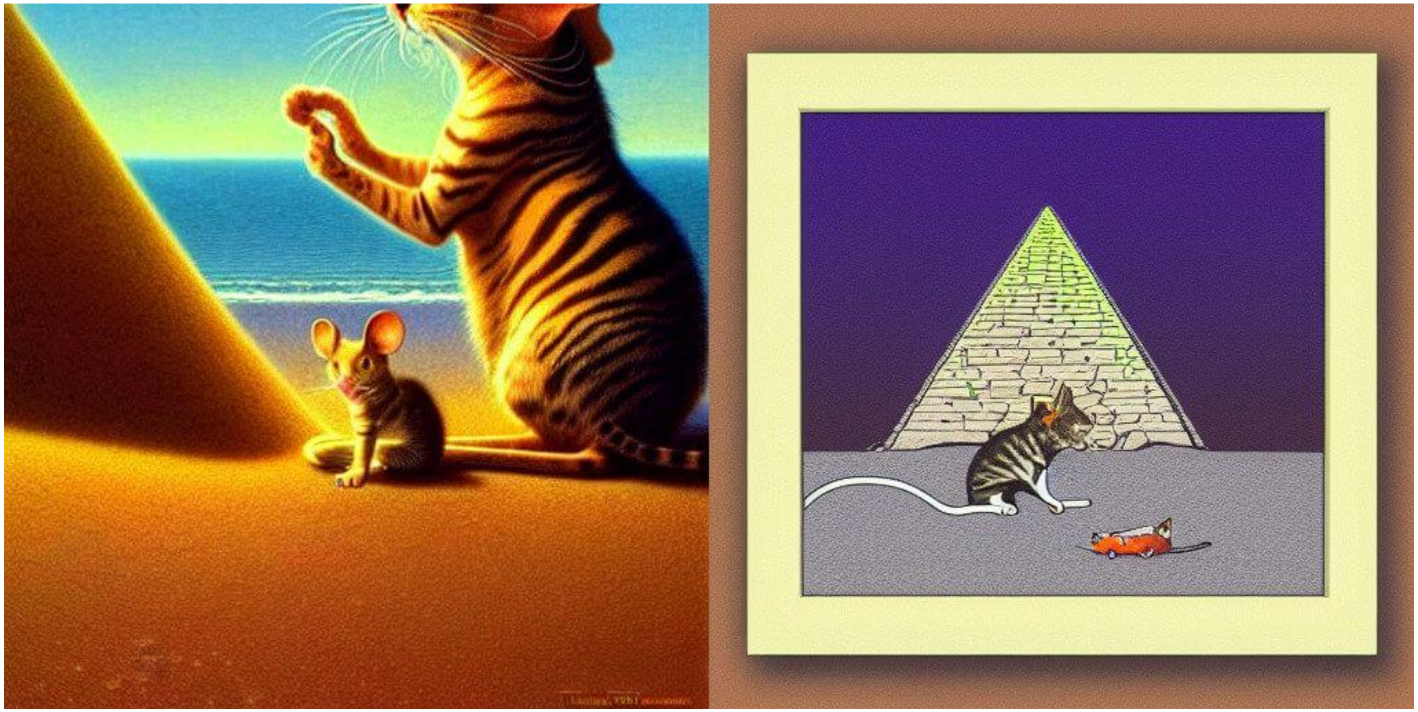
《麻省理工科技评论》2023年“全球十大突破性技术”



AI that makes images

- 对于相依靠简单的短语就能生成惊人图像的人工智能模型，正在演变为强大的创意和商业工具。
- OpenAI 在 2021 发布其文本到图像模型 DALL-E 时，开启了一个奇怪又奇妙的混搭世界。你只需输入一段简单描述，几乎任何内容都可以，程序就会在几秒内生成一张你想要的图片。2022 年 4 月发布的 DALL-E 2 可以生成更高质量的图片。谷歌还推出了自己的图像制作 AI，名为 Imagen。
- 最大的游戏改变者是稳定扩散（Stable Diffusion），这是一个开源的文本到图像模型，由英国初创公司 Stability AI 免费发布。稳定扩散不仅可以产生一些迄今为止最令人惊叹的图像，而且它被设计为可以在一台（性能尚可的）家用计算机上运行。

AI that makes images



Cat and Mouse in front of Pyramids (DALL E 2 vs Stable Diffusion)

- DALL-E 2 is the second generation of the text-to-image generative models by OpenAI
- Stable Diffusion is a machine learning-based Text-to-Image model capable of generating graphics based on text developed by Stability AI

https://nimblebox.ai/blog/stable-diffusion-ai

视频生成模型Sora

Prompt: Beautiful, snowy Tokyo city is bustling. The camera moves through the bustling city street, following several people enjoying the beautiful snowy weather and shopping at nearby stalls. Gorgeous sakura petals are flying through the wind along with snowflakes.

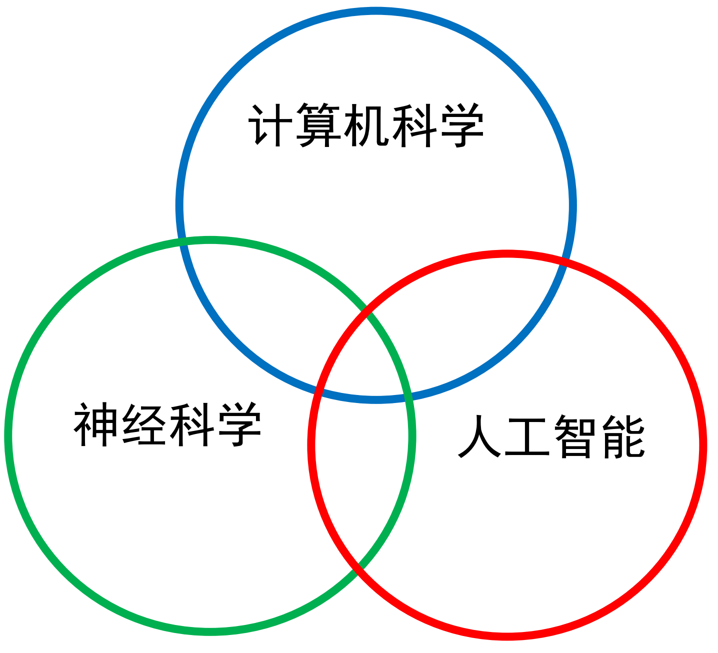
视频生成模型Sora

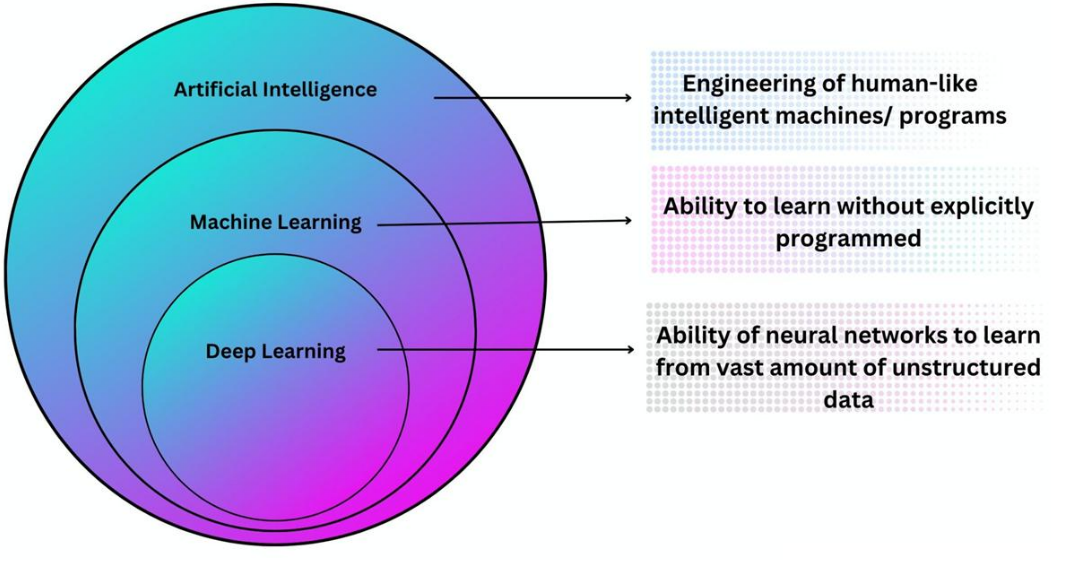
Prompt: Animated scene features a close-up of a short fluffy monster kneeling beside a melting red candle. The art style is 3D and realistic, with a focus on lighting and texture. The mood of the painting is one of wonder and curiosity, as the monster gazes at the flame with wide eyes and open mouth. Its pose and expression convey a sense of innocence and playfulness, as if it is exploring the world around it for the first time. The use of warm colors and dramatic lighting further enhances the cozy atmosphere of the image.

视频生成模型Sora

Prompt: A flock of paper airplanes flutters through a dense jungle, weaving around trees as if they were migrating birds.

本课程内容与AI的关系





6 steps to be an AI expert (in 2022)

1. Linear algebra — **MIT 18.06** - Prof. Gilbert Strang
2. Probability — **MIT 6.012** - Prof. John Tsitsiklis
3. Python — **Any** programming course, with lots of practices
4. Machine Learning — **Stanford/Coursea** - Andrew Ng
5. Deep learning for Computer Vision — **Stanford CS231n** – Prof. Fei-fei Li
6. Deep learning for Natural Language Processing

6 steps to be an AI expert (in 2022)

1 step to be an AI expert (in 2023)

Large Language Models

?? (in 2025) ??

课程的主要内容

1. 导论，感知机，感知机算法、最小均方误差算法
2. 多层感知机，BP算法
3. 性能指标，支持向量机，机器学习平台

经典模型和算法

4. 卷积神经网络
5. 自编码器，深度信念网络，
6. 多模态深度学习
7. 生成式对抗网络
8. 深度迁移学习
9. LSTM，图神经网络
10. Transformer，…
11. 自监督学习

深度模型和算法

神经网络经典模型、深度学习、大模型、…

通用人工智能

大模型：Chat-GPT

（1700亿个参数）

深度模型

经典模型

（三个参数）

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

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

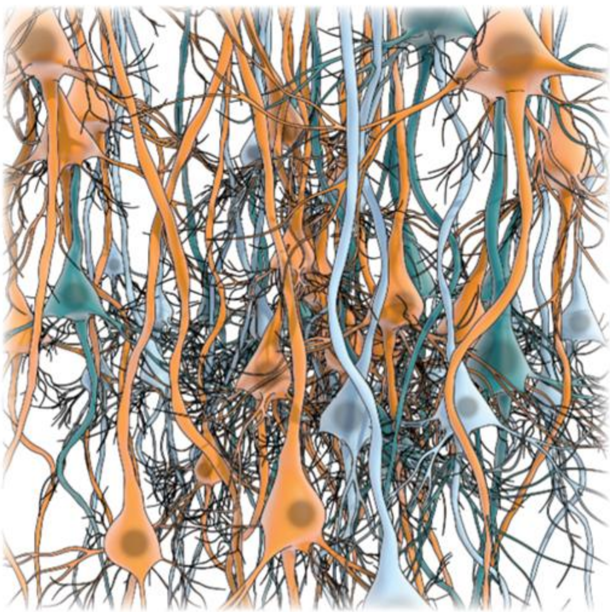
- “除人脑外，没有任何一个自然或者人工系统能够具有对新环境与新挑战的自适应能力、新信息与新技能的自动获取能力、在复杂环境下进行有效决策并稳定工作直至几十年的能力。没有任何系统能够在多处损伤的情况下保持像人脑一样好的鲁棒性，在处理复杂任务的同时，没有任何系统能媲美人脑的低功耗性”

  ——HBP建议书

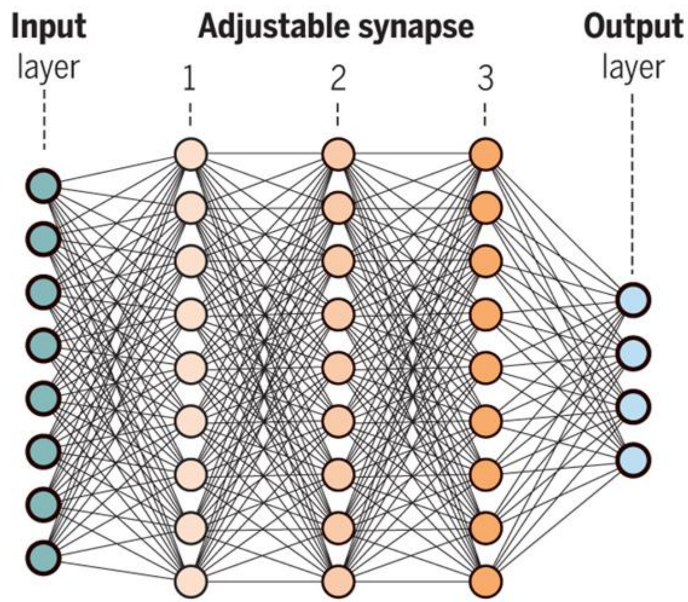
Using neuroscience to develop artificial intelligence

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

Outline of Lecture 1

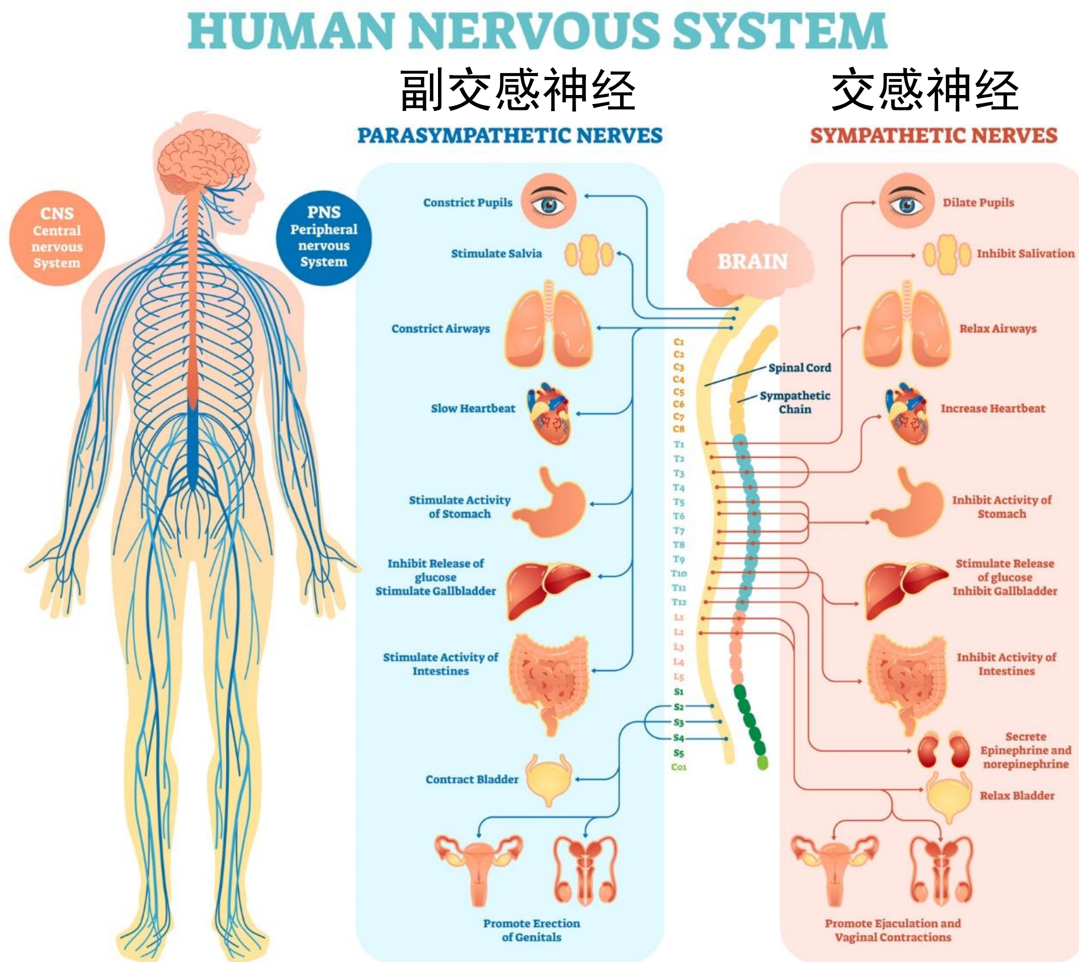
- Introduction to brain
- What is a neural network ?
- Simple neuron model
- Neural network history
- Network architectures
- Learning paradigms
- Learning tasks
- Recommended textbooks
- Neural network journals and conference

A Very Short Introduction to Brain

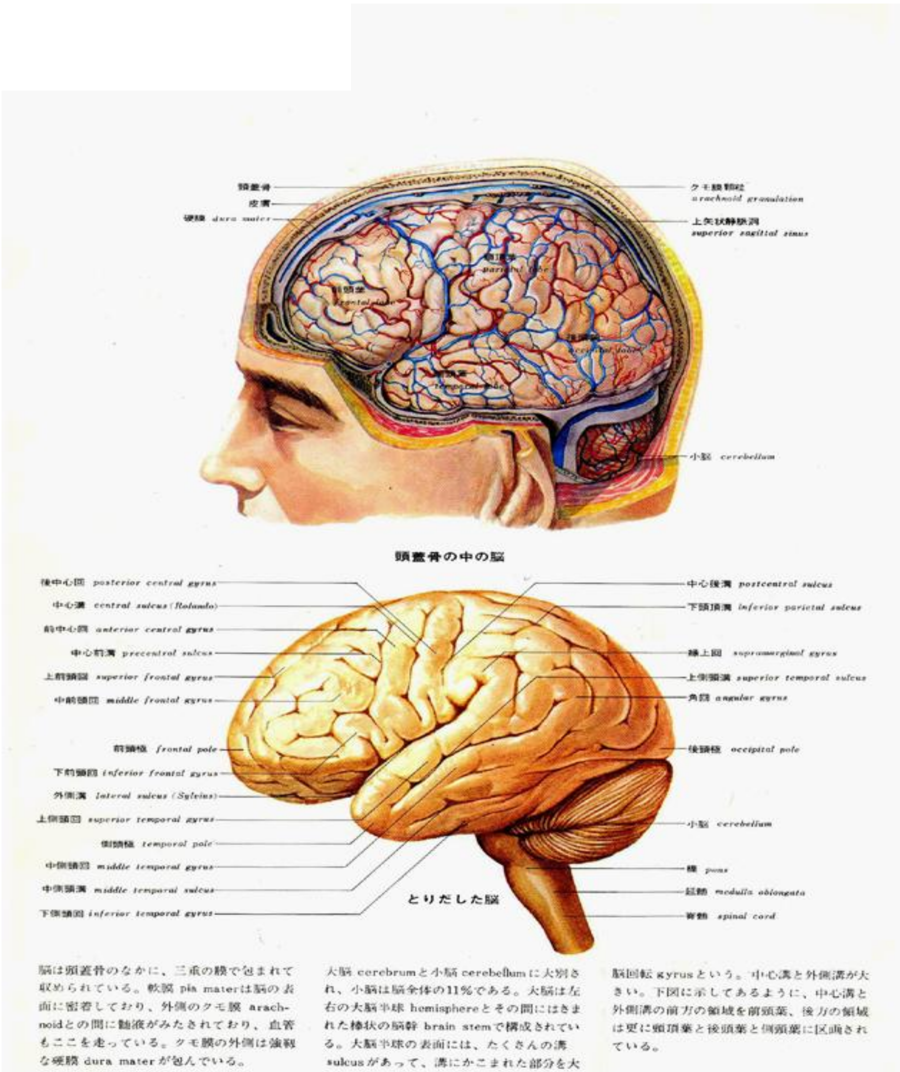
Human Nervous System

中枢神经系统

外周神经系统

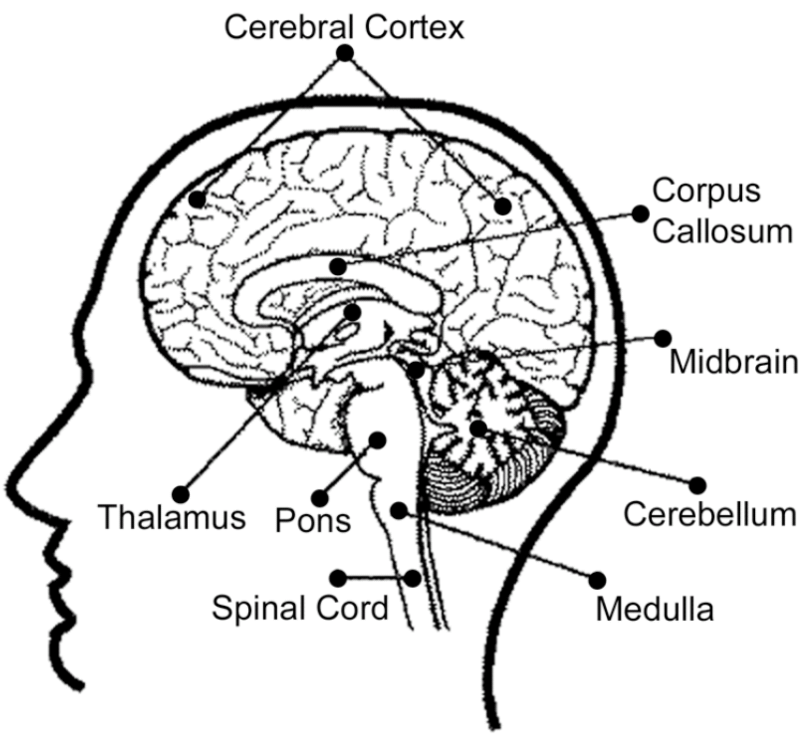


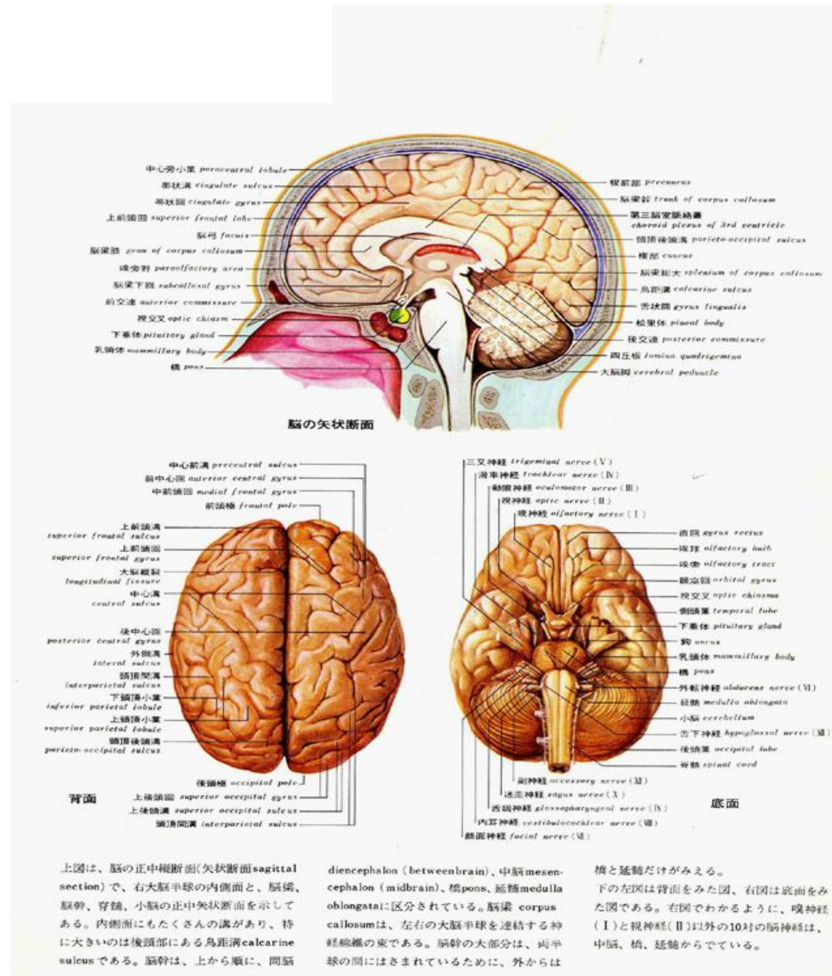
The Human Brain



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

Parts of the Human Brain



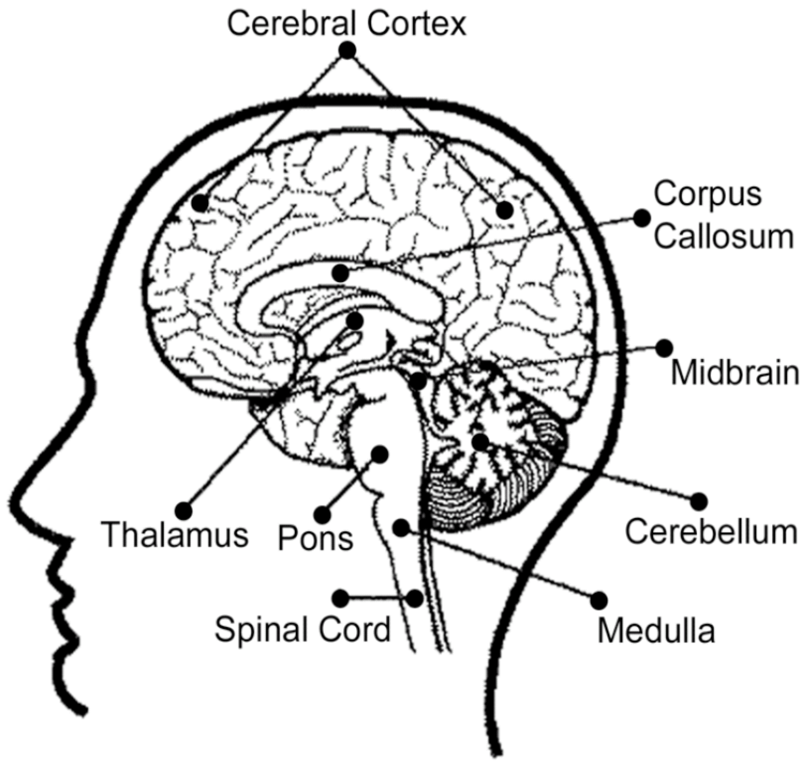


Cerebral Cortex 大脑皮层

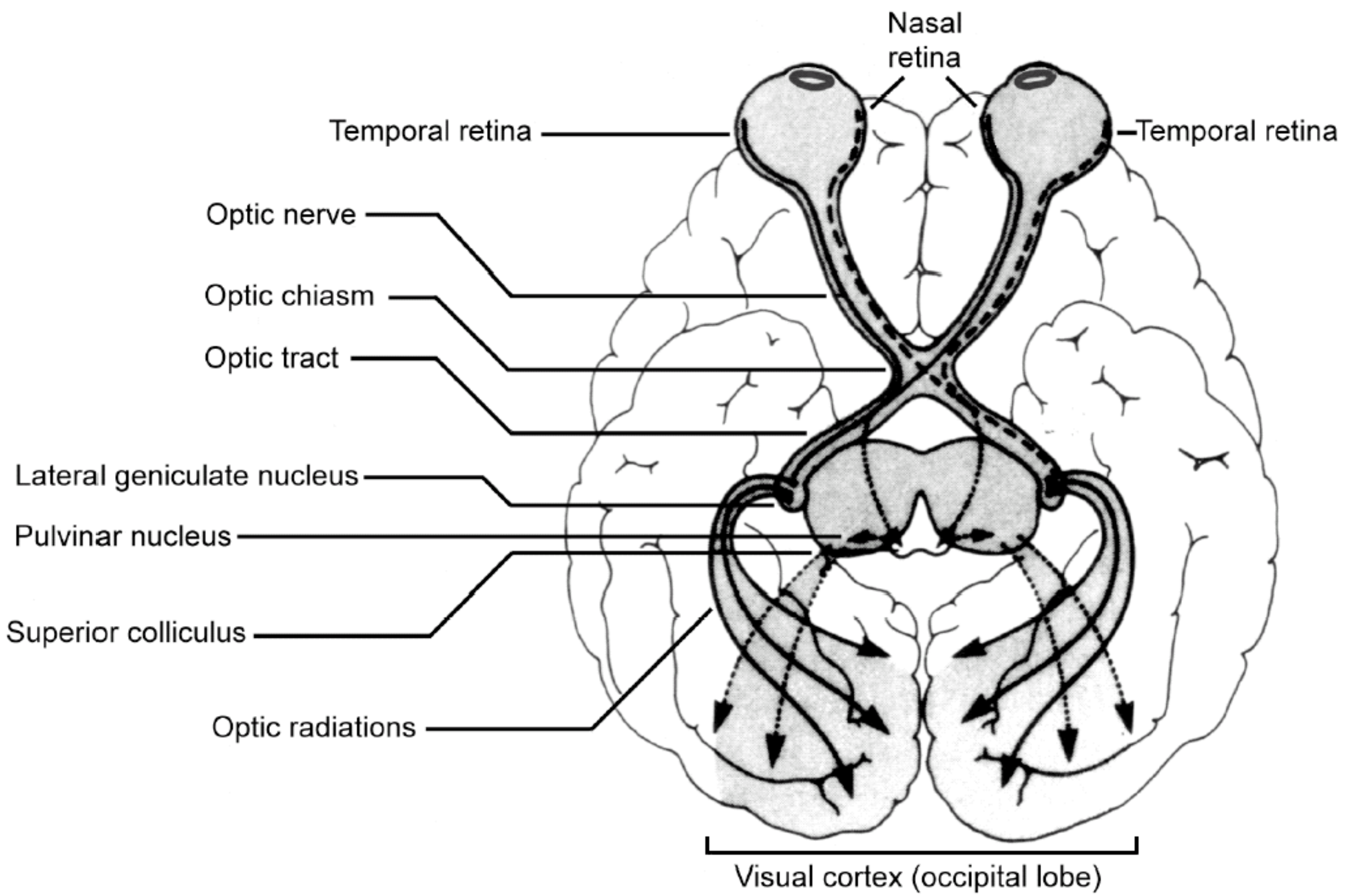
- “Cortex” from the Latin for “bark” (of a tree)
- The cortex is a sheet of tissue that makes up the outer layer of the brain (2 to 6mm)
- The right and left sides of the cerebral cortex are connected by a thick band of nerve fibers
- FUNCTIONS: Thought, voluntary movement, language, reasoning, perception

Cerebellum 小脑

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

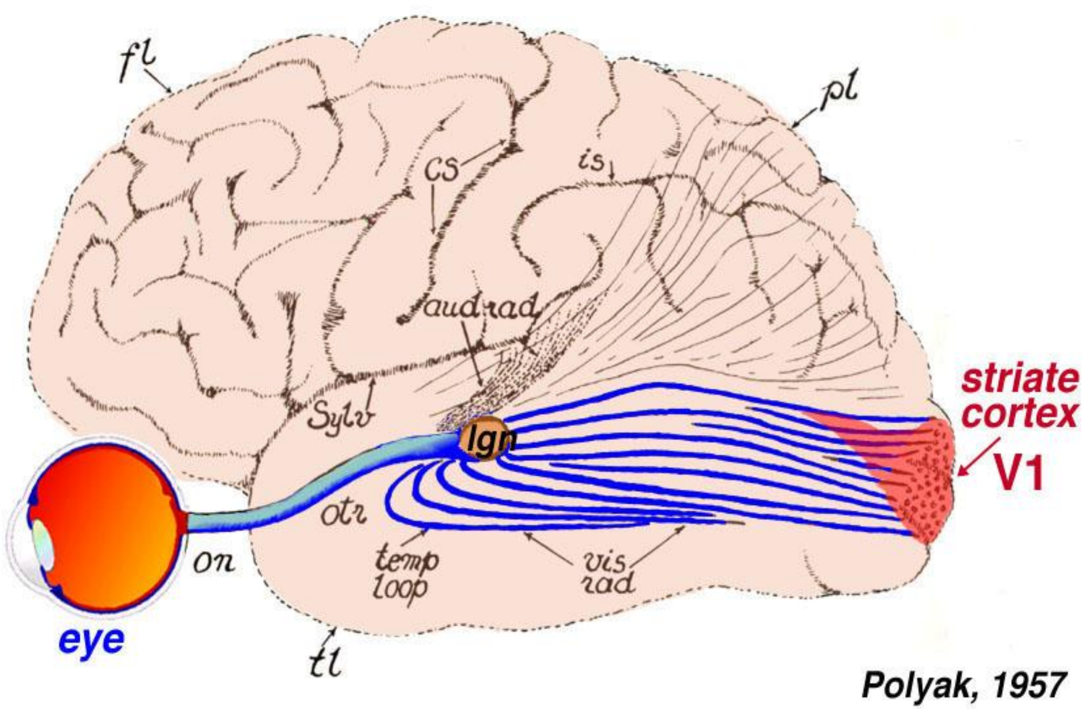


Visual Cortex



Visual Cortex （视觉皮层）

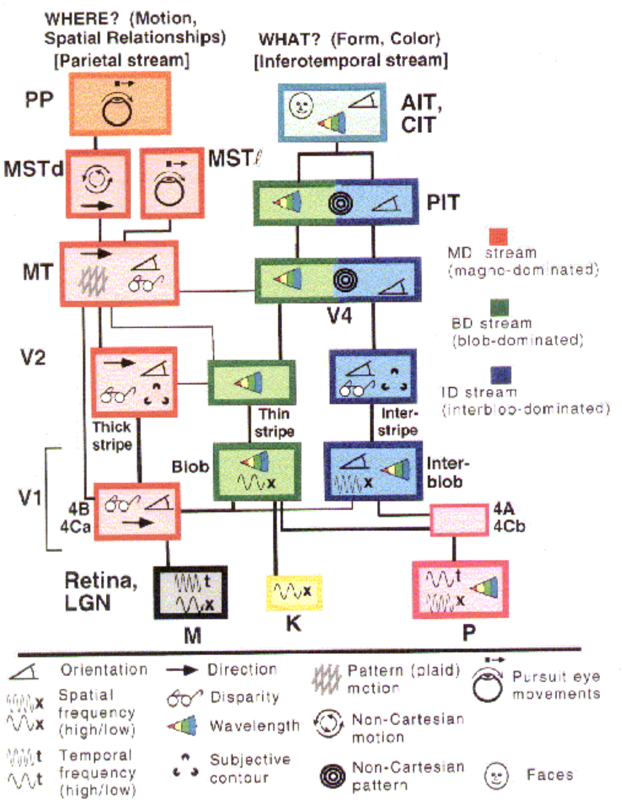
- 至少有70～80%以上的外界信息是由视觉系统接受、处理和感知的；
- 人类大脑皮层约一半的区域参与视觉信息的分析。

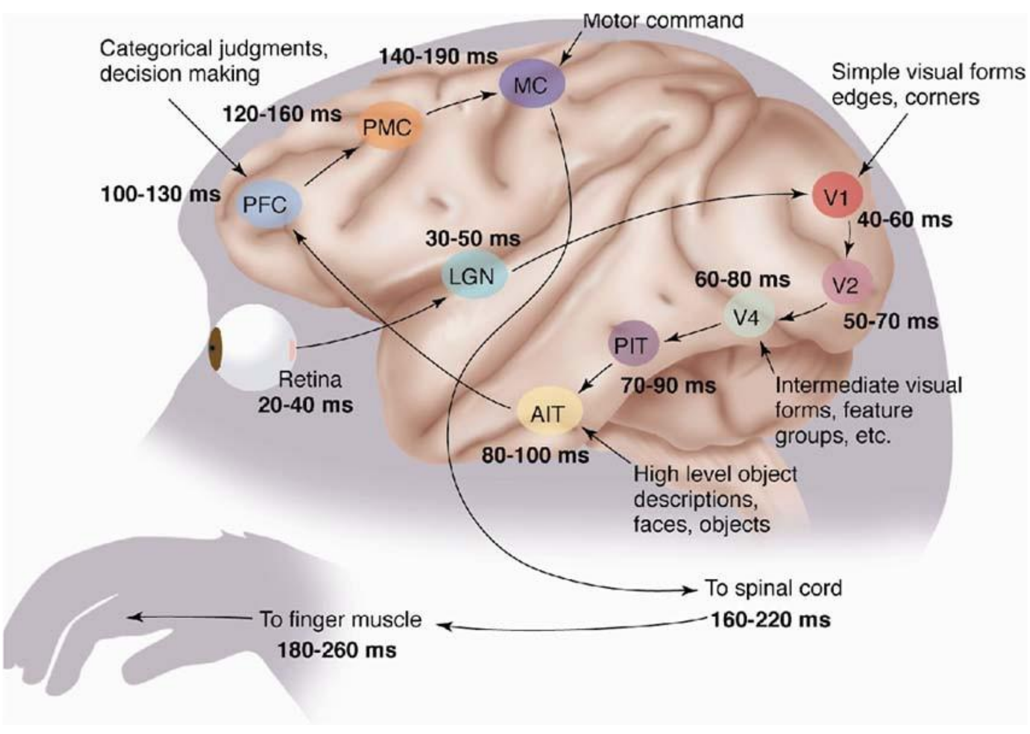


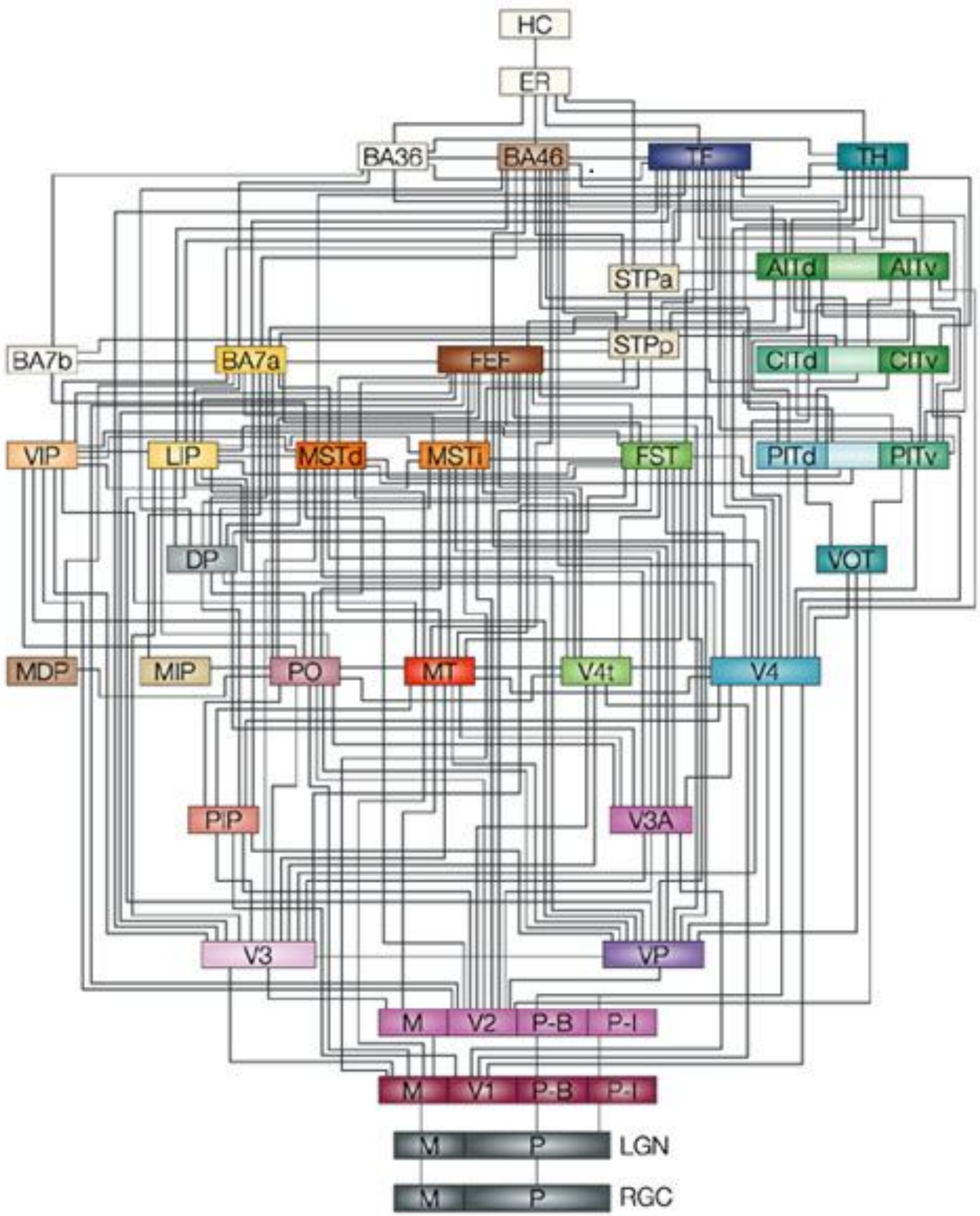
LGN:外侧膝状体核

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





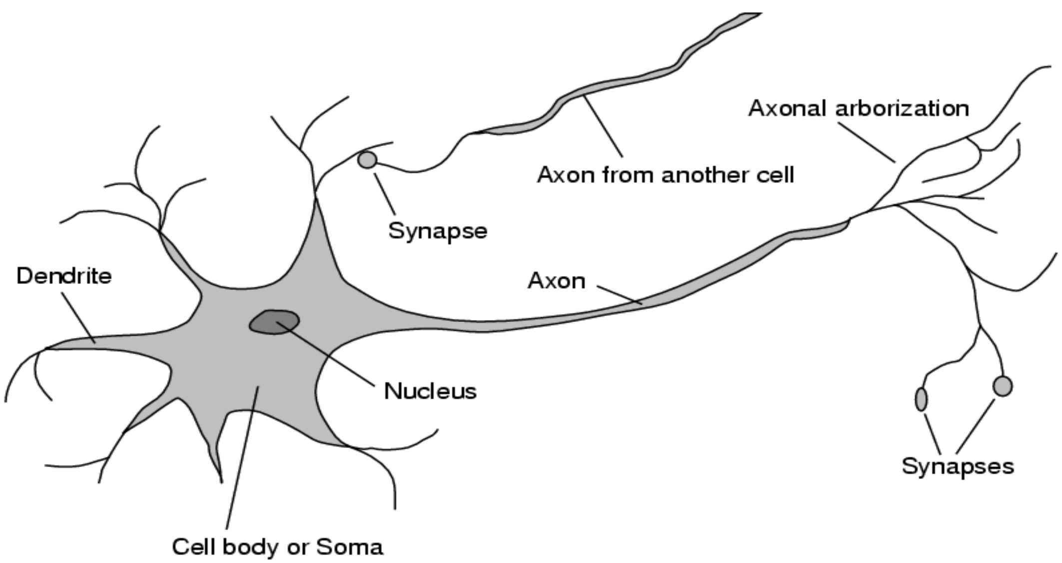


猴视觉皮层既平行又分级的30多个视觉皮层区域间连接的示意图

- 30多个视皮层区
- 10多个等级
- 305条视觉联系

What is a Neuron ?

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



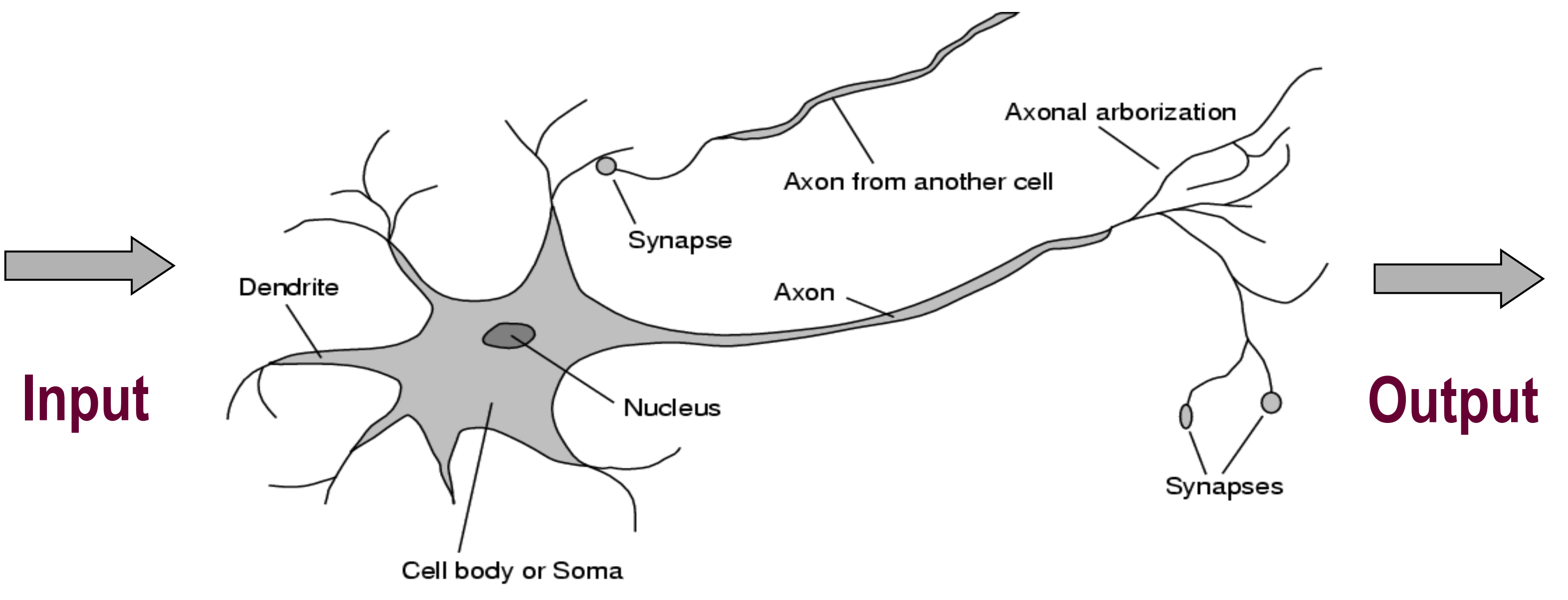
Axon : 轴突

Dendrite: 树突

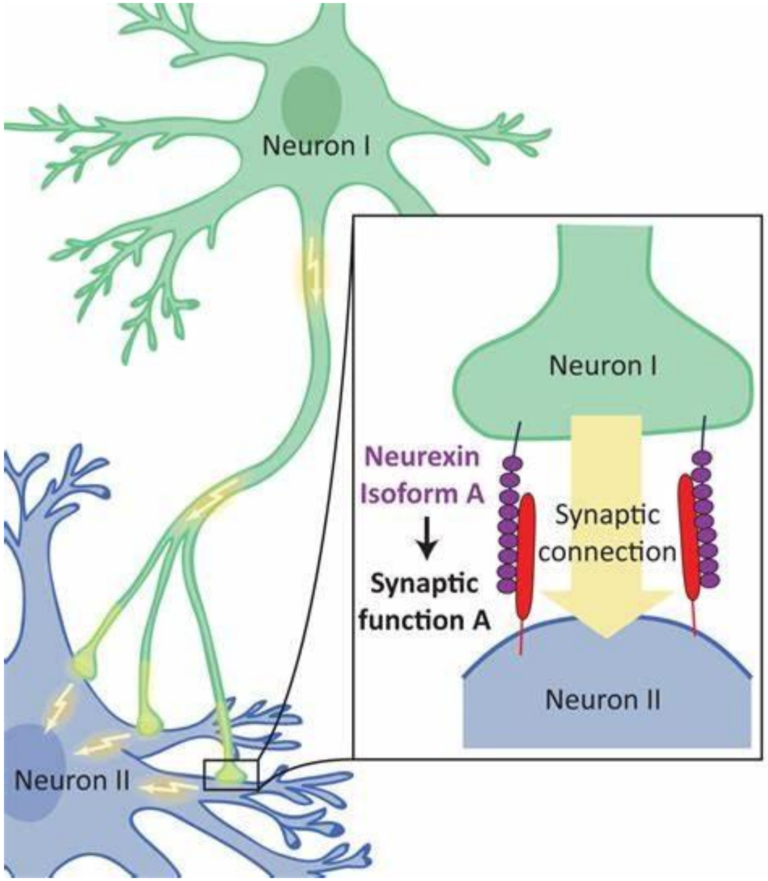
Synapse: 突触

Neurons vs. Other Cells

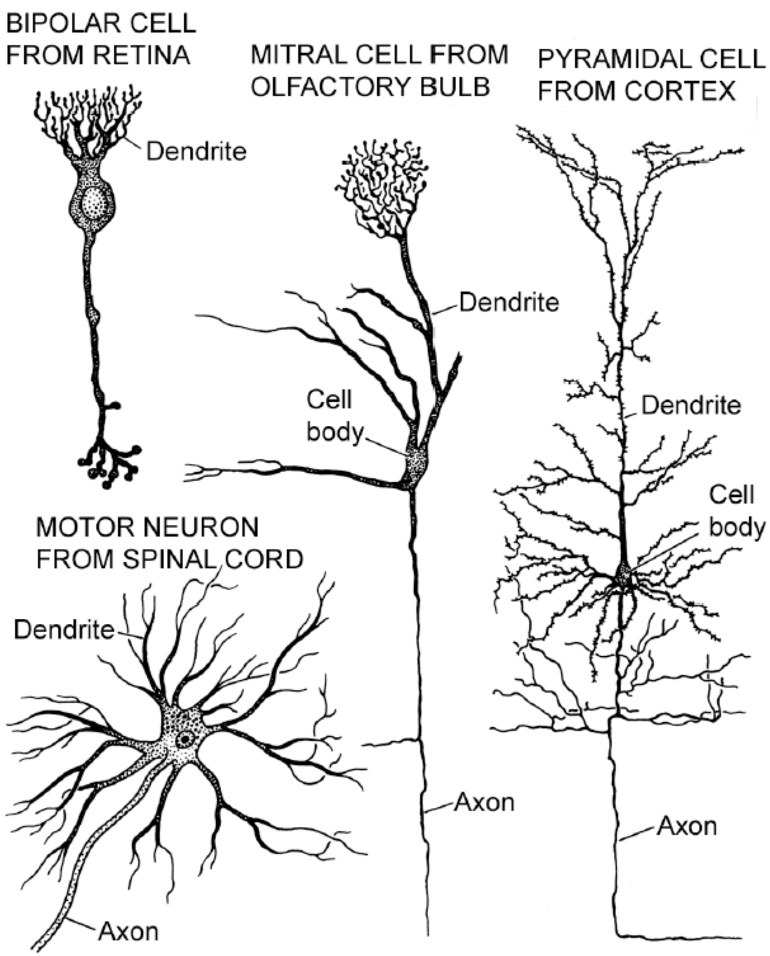
- Specialized extensions: dendrites and axons
- Neurons communicate with each other through an electrochemical process



Synaptic Connection



Different Neurons

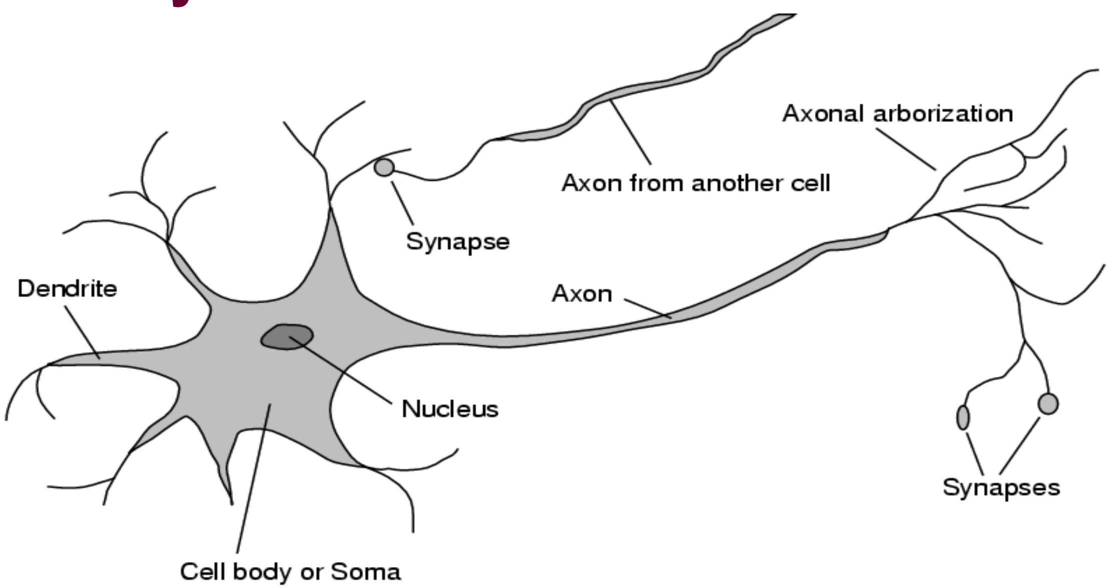


- Neurons come in many different shapes and sizes
- Some of the smallest neurons have cell bodies that are only 4 microns wide, while some of the biggest neurons have cell bodies that are 100 microns wide

Micron=100万分之一米

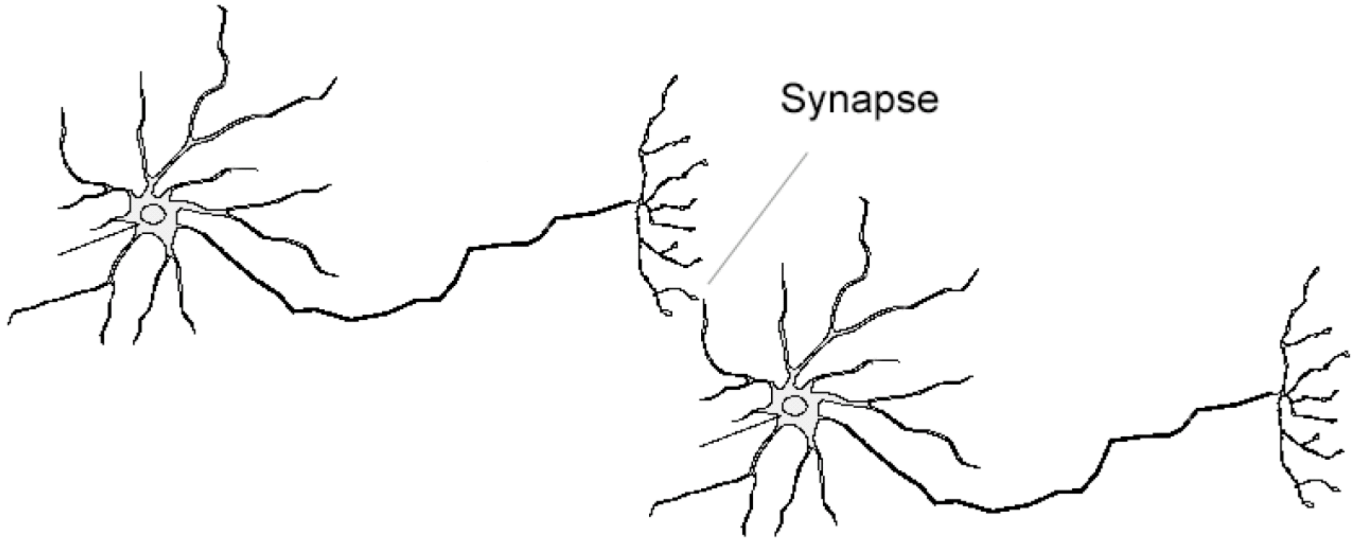
Axons and Dendrites

- 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



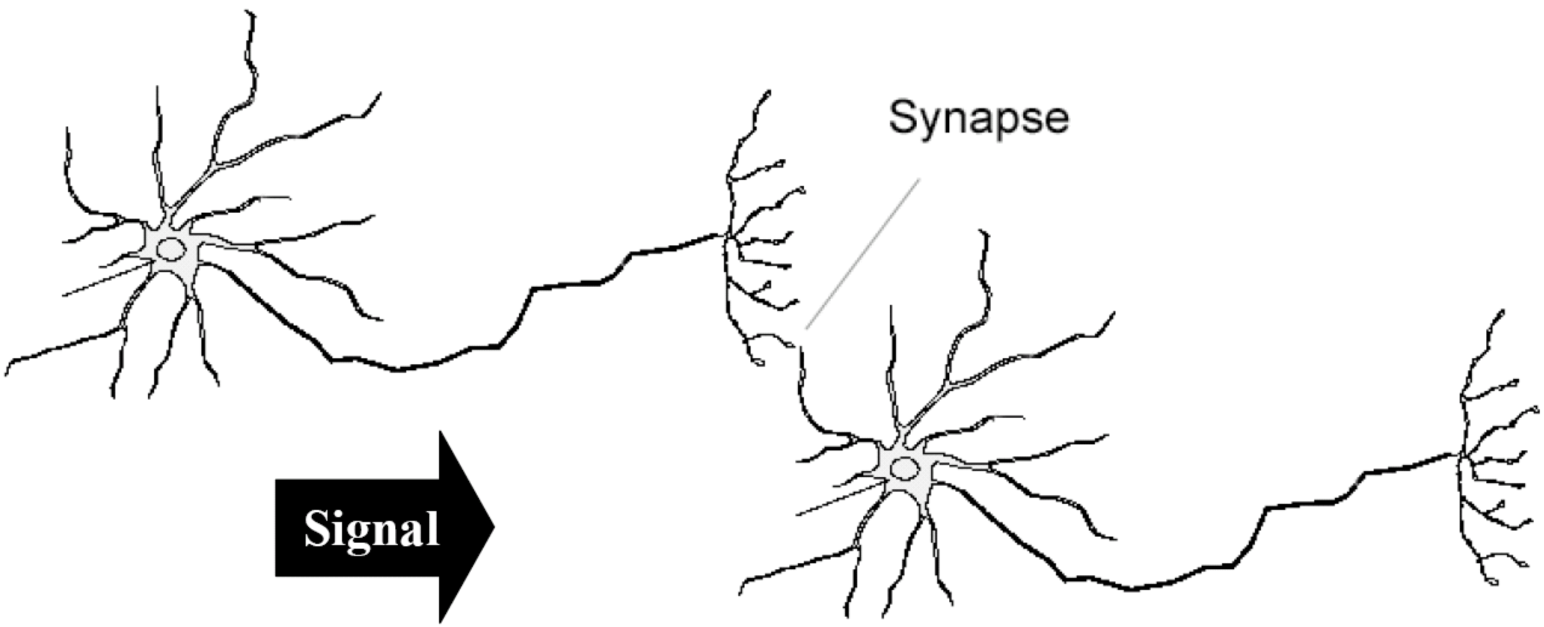
Synapses

- Neurons communicate through specialized junctions called ***synapses***

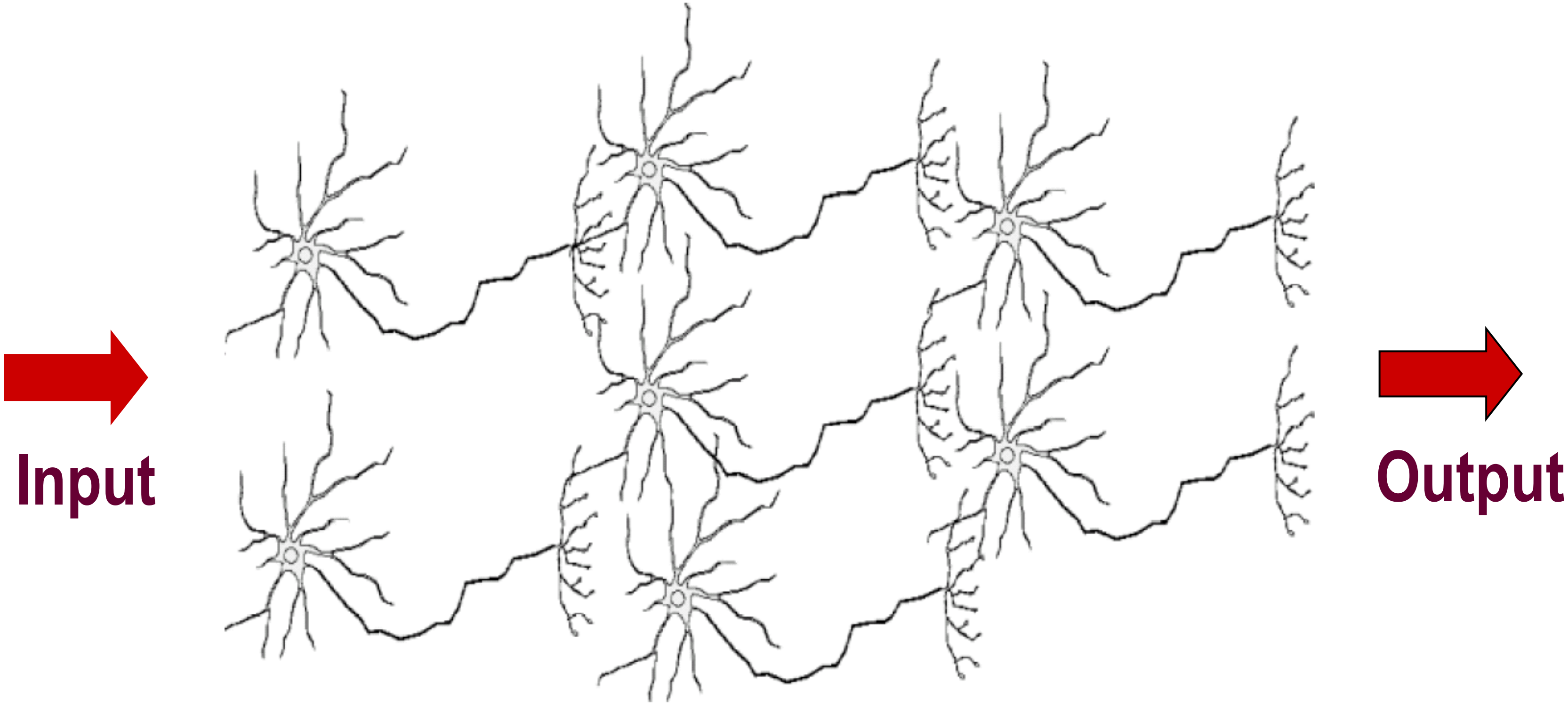


Axonal Signals

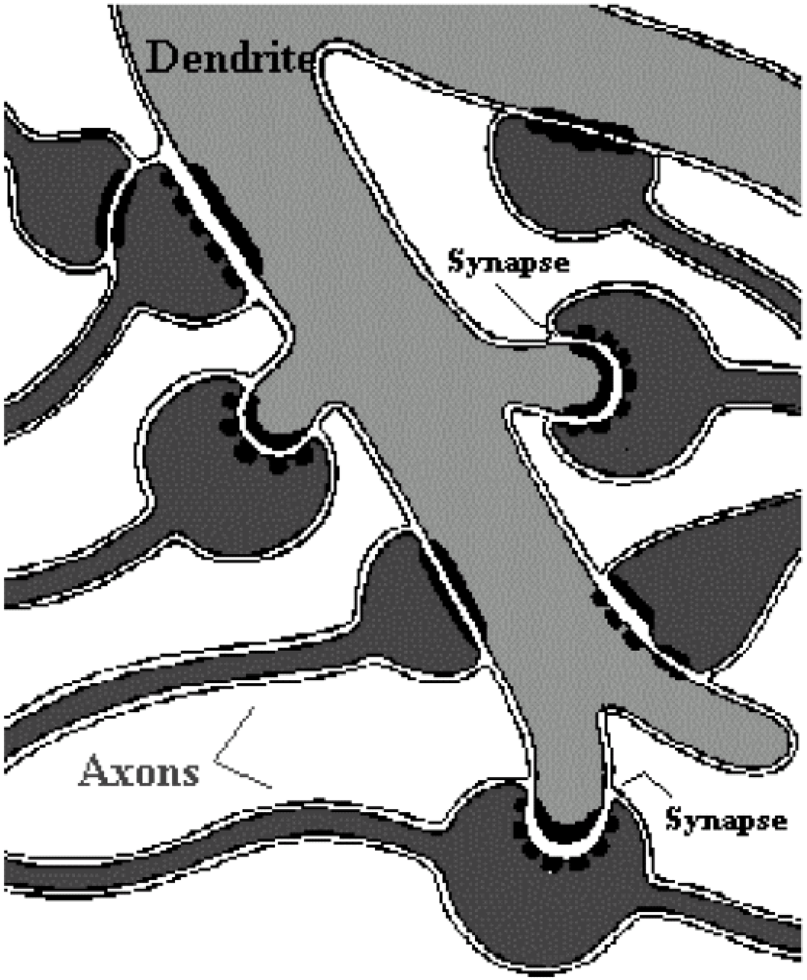
- An electrical signal
- 20 m/s to 100 m/s



A Neural Network

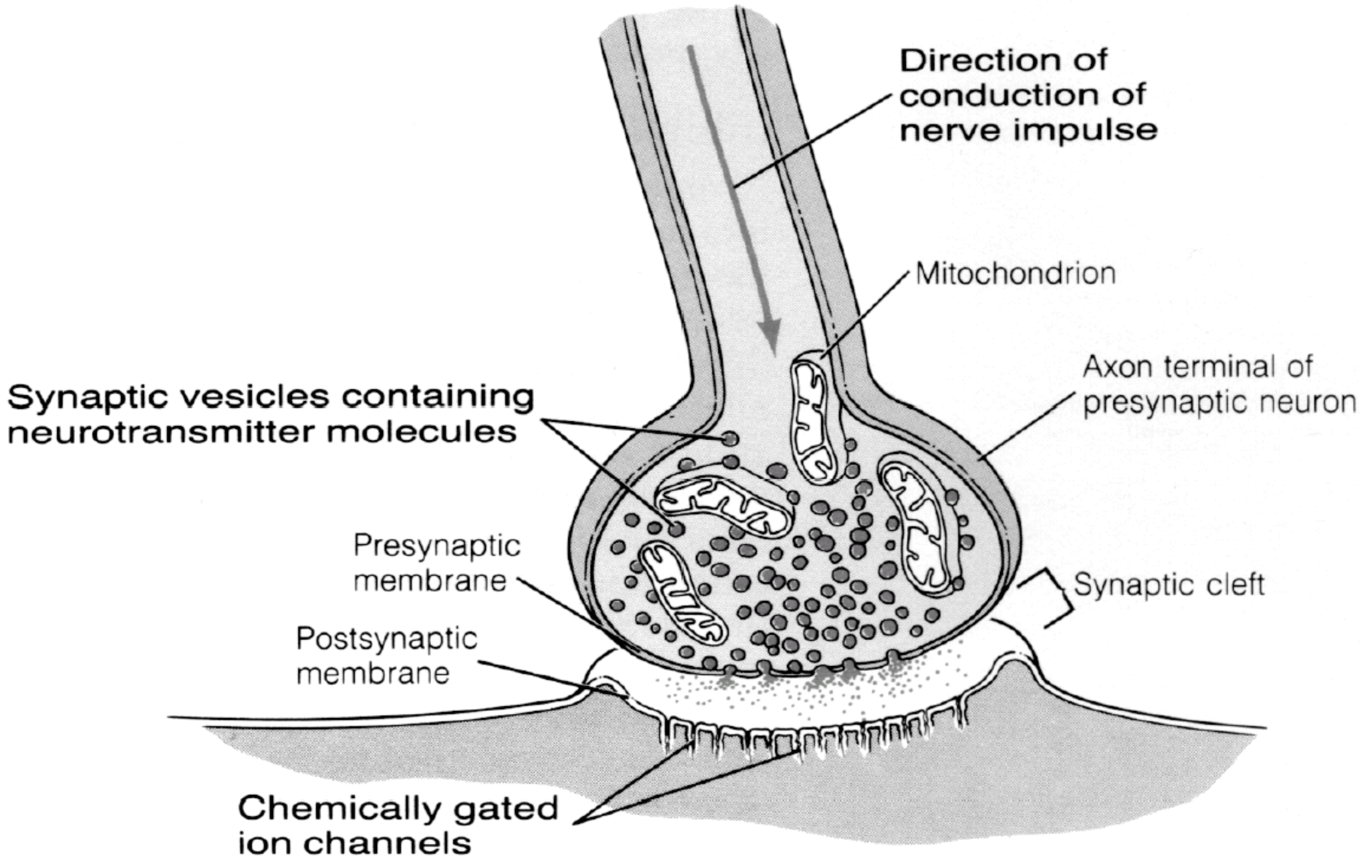


Synapses and Dendrites



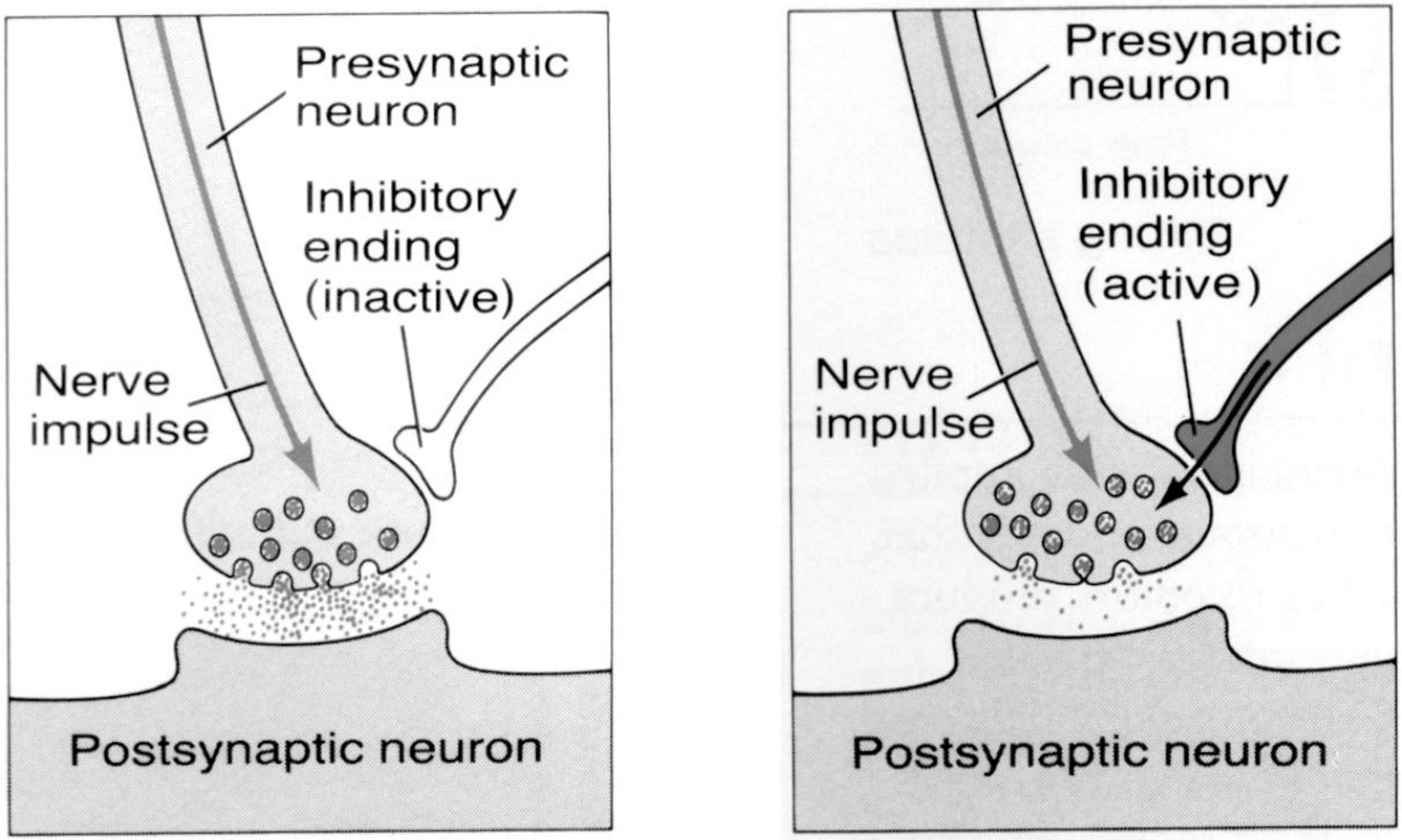
- Axon releases chemical transmitters into the synaptic cleft

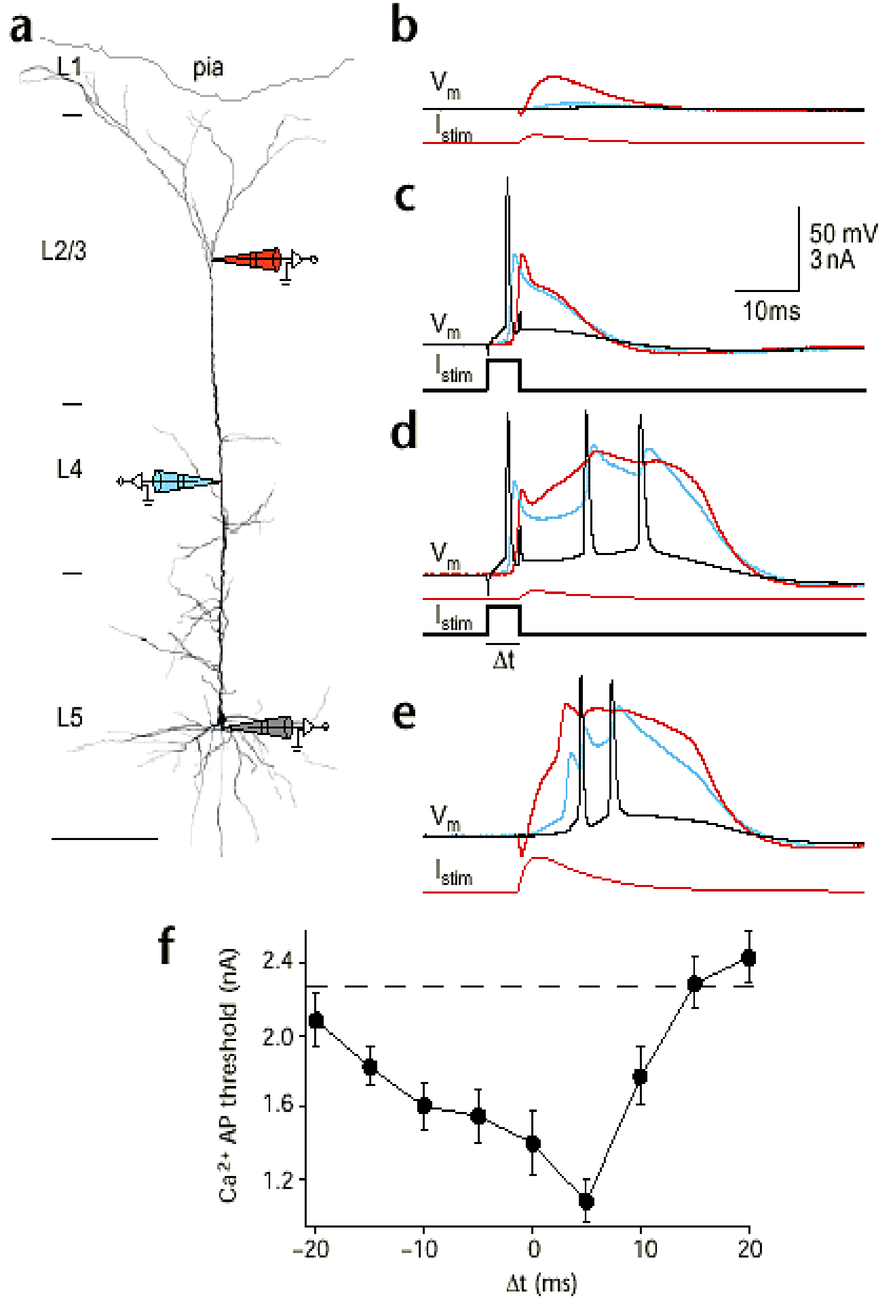
Synapse

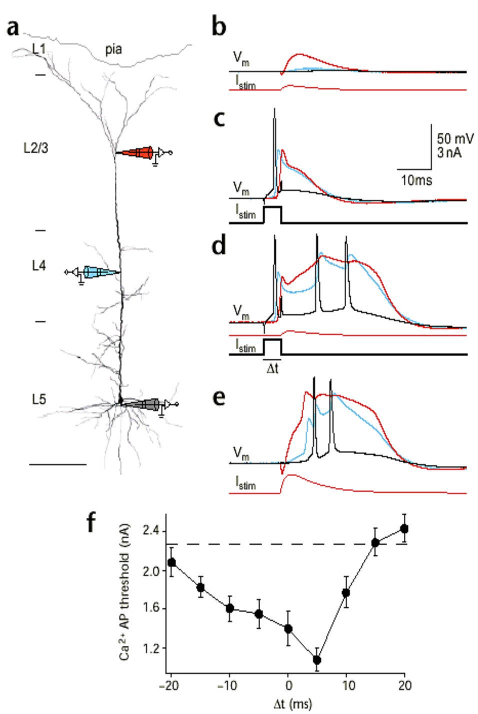


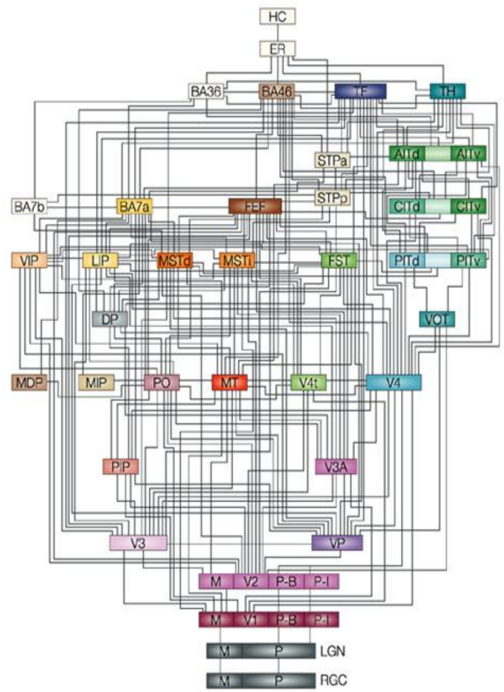
Direction of conduction of nerve impulse
Mitochondrion
Axon terminal of presynaptic neuron
Synaptic vesicles containing neurotransmitter molecules
Presynaptic membrane
Synaptic cleft
Postsynaptic membrane
Chemically gated ion channels

Inhibition


Presynaptic neuron
Inhibitory ending (inactive)
Nerve impulse
Postsynaptic neuron
Presynaptic neuron
Inhibitory ending (active)
Nerve impulse
Postsynaptic neuron

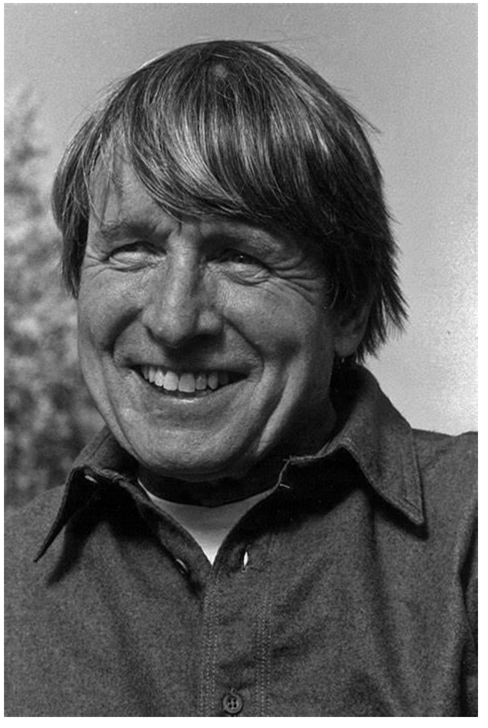

a
L1
pia
L2/3
L4
L5
b
V_m
I_{stim}
c
50 mV
3 nA
10ms
V_m
I_{stim}
d
V_m
I_{stim}
Δt
e
V_m
I_{stim}
f
Ca^{2+} AP threshold (nA)
2.4
2.0
1.6
1.2
-20
-10
0
10
20
Δt (ms)

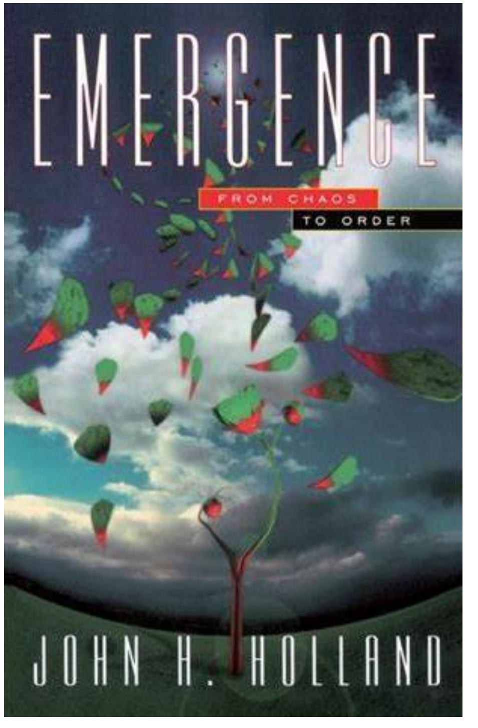




Our knowledge of organizing neurons in system level is rather poor !

John H. Holland (1998)





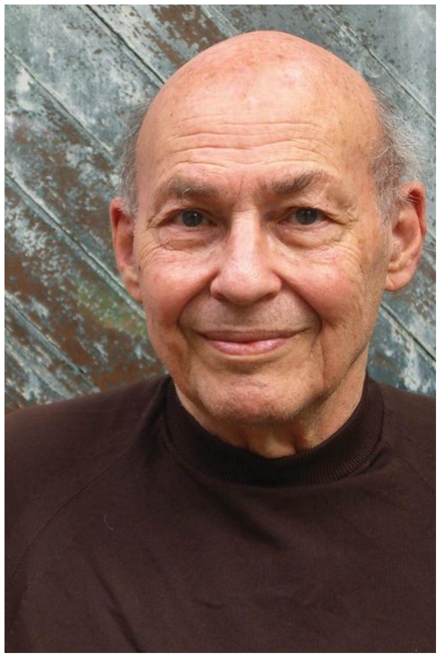
Emergence: From Chaos to Order

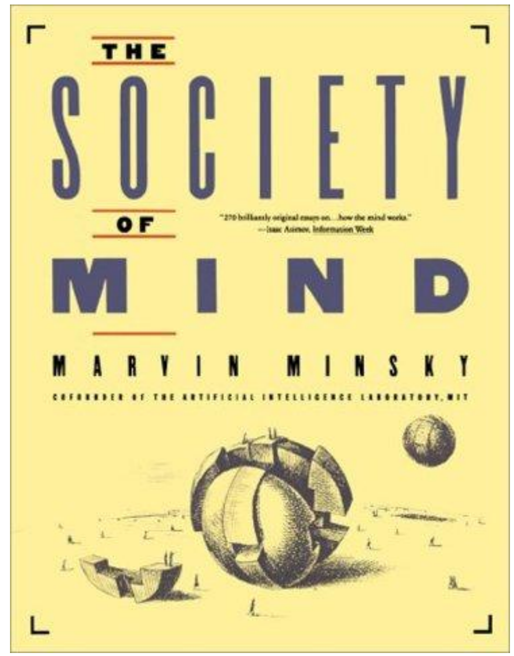
A Theory of Emergence

“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"

Comparing Brains with Digital Computers

	Computer	Human Brain
Computational units	$1\,\text{CPU},\ 10^5$ 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}

Small Biological Model

- 果蝇大规模神经连接图谱
- 果蝇全脑连接组包含127,978 个神经元和2,613,129 个连接
- 巨型强连通组件：网络中几乎所有神经元都可以通过有向路径相互连接 。
- rich-club现象: 高度连接的神经元倾向于相互连接，形成一个“富人俱乐部”。
- 三节点模体: 网络中三节点模体的分布揭示了大脑中不同类型信息处理回路的相对频率 。

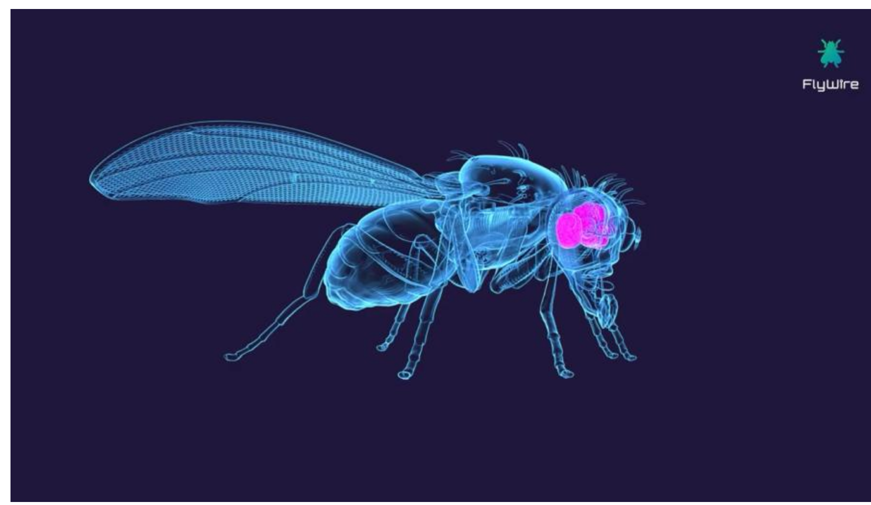
Article | Open access | Published: 02 October 2024

Network statistics of the whole-brain connectome of *Drosophila*

Albert Lin, Runzhe Yang, Sven Dorkenwald, Arie Matsliah, Amy R. Sterling, Philipp Schlegel, Szi-chieh Yu, Claire E. McKellar, Marta Costa, Katharina Eichler, Alexander Shakeel Bates, Nils Eckstein, Jan Funke, Gregory S. X. E. Jefferis & Mala Murthy

Nature **634**, 153–165 (2024) | Cite this article

20k Accesses | **2** Citations | **133** Altmetric | Metrics



Small Biological Model vs. Large Language Model

特征	果蝇生物小模型	语言大模型
网络结构	由神经元和突触组成的复杂生物网络，具有高度的复杂性和非线性。主要包括：巨型强连通组件和rich-club子网络模块。	通常基于人工设计的Transformer架构，使用自注意力机制处理长序列数据，具有高度的模块化和可扩展性。
训练方式	自然发生，通过学习和进化形成神经网络连接结构。闭环学习，目前尚不完全清楚。	使用大量的文本数据进行训练，通过反向传播算法、梯度下降算法等调整模型参数，开环学习，使其学习语言的规律和模式。
网络参数	神经元和突触的数量和连接强度，果蝇大脑包含约10万个神经元和数百万个突触。	Transformer架构中各个模块的权重和偏置，参数数量可从数千万到数千亿不等。
智能能力	体现果蝇的生物智能，例如学习、记忆、导航、决策等。研究人员通过分析果蝇模型的网络结构和神经元活动来理解果蝇的智能行为机制。	体现强大的语言理解和生成能力，例如文本摘要、机器翻译、问答、对话等。

Small Biological Model vs. Large Language Model

- 虽然果蝇模型和语言大模型都是神经网络，但它们在本质上存在很大差异。

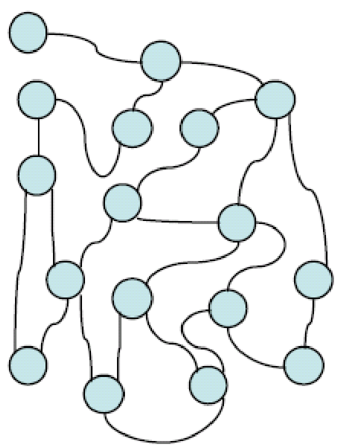
- 果蝇的网络结构异常复杂：具有巨型强连通组件，rich-club现象和三节点模体子网络，其学习和产生智能是通过闭环训练和信息传递达到的。而大模型结构相对简单， 训练通过开环BP算法完成。

- 果蝇的网络参数在10万个神经元，而大模型在数千万到数千亿不等。

- 果蝇是具有智能的，而大模型是具有知识的，大模型是否具有智能，目前还存疑。

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.)

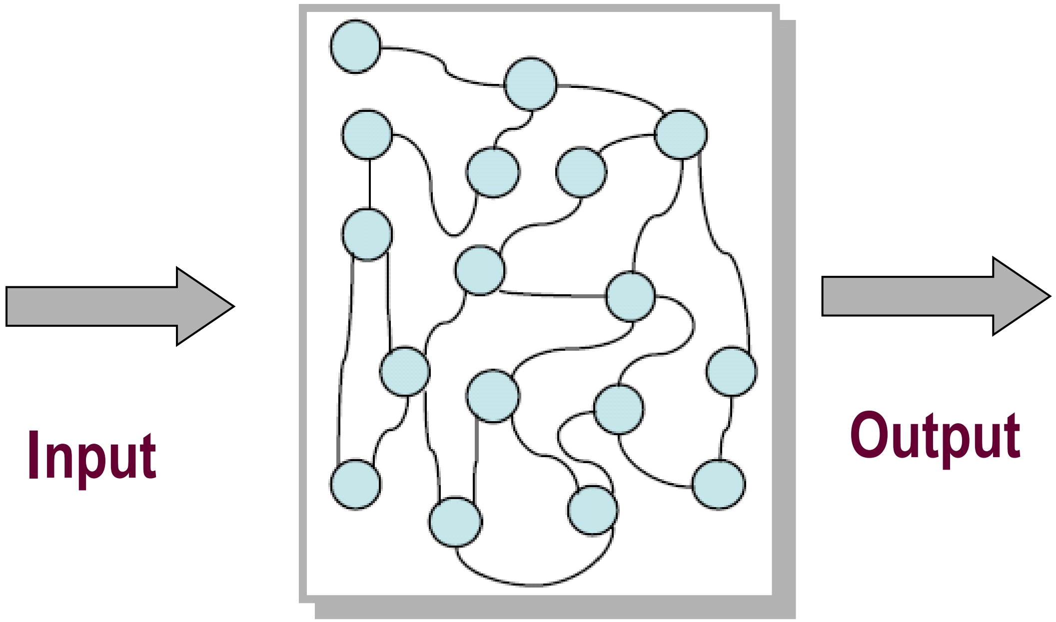
- **A NN is a massively parallel distributed processor made up of simple processing unit, which has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects:**
  - **Knowledge is acquired by the network from its environment through *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
  - CNN（卷积神经网络）
  - GAN（生成式对抗网络）
  - LSTM（长短期记忆网络）

- 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

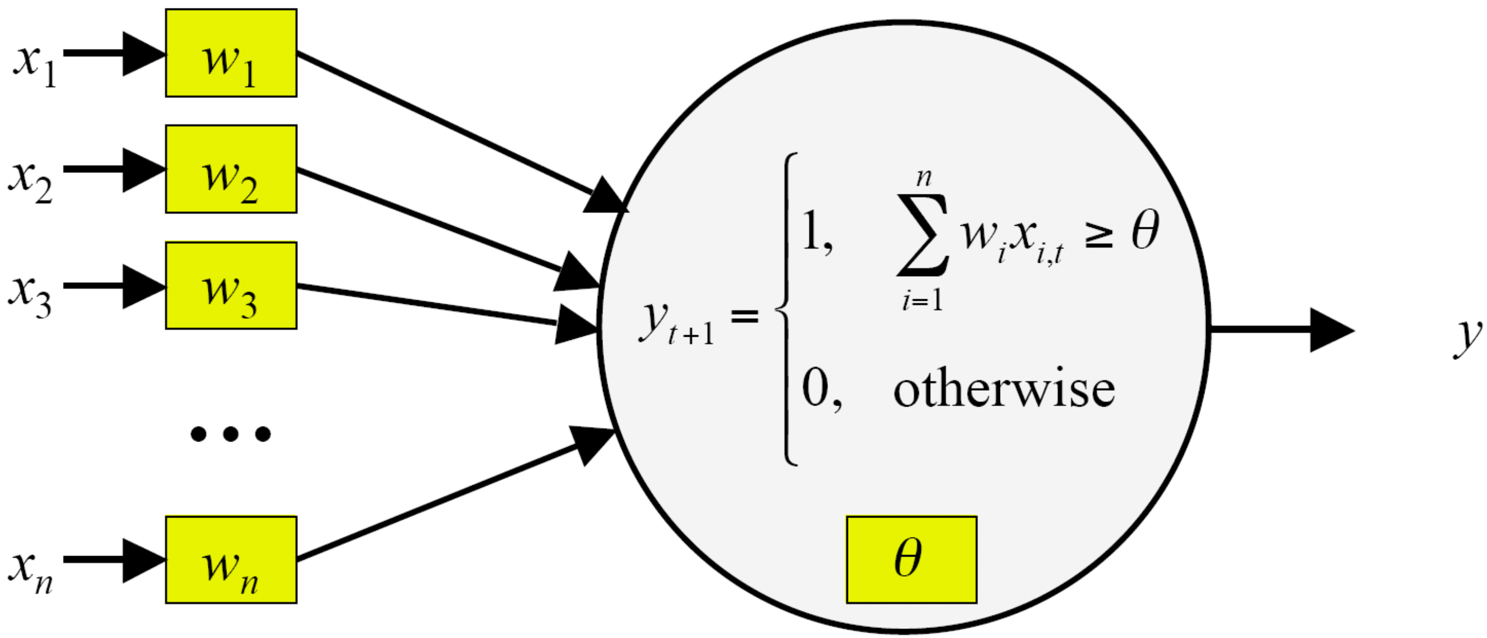


Neural Network History

- 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

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

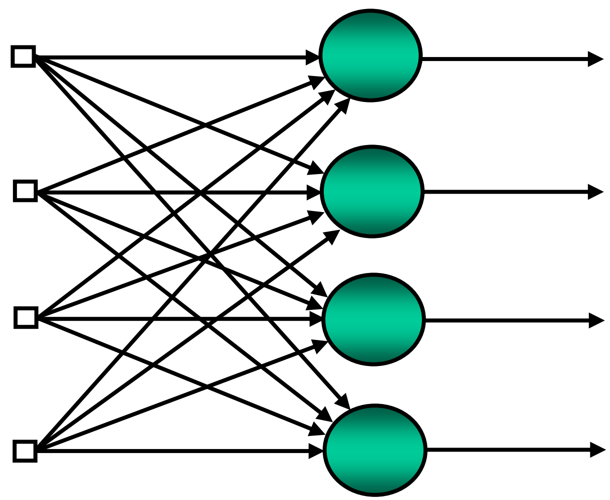
Developed deep learning algorithms and successfully applied to unsupervised feature learner.

This Lesson: Part 3

- Network architectures
- Learning paradigms
- Learning tasks

Network Architectures

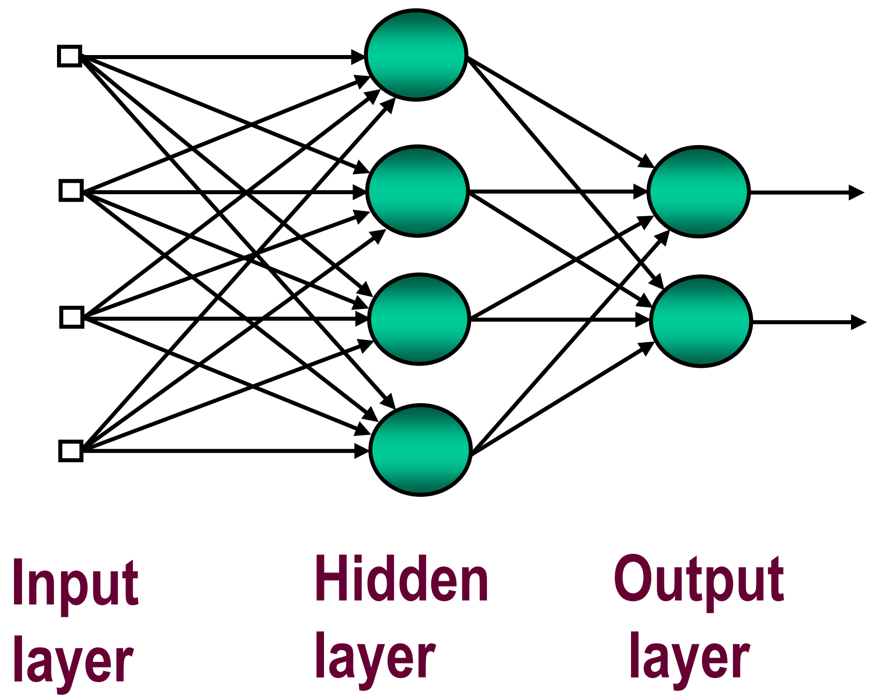
- Single-Layer Feedforward Networks
- Multilayer Feedforward Networks
- Recurrent Networks



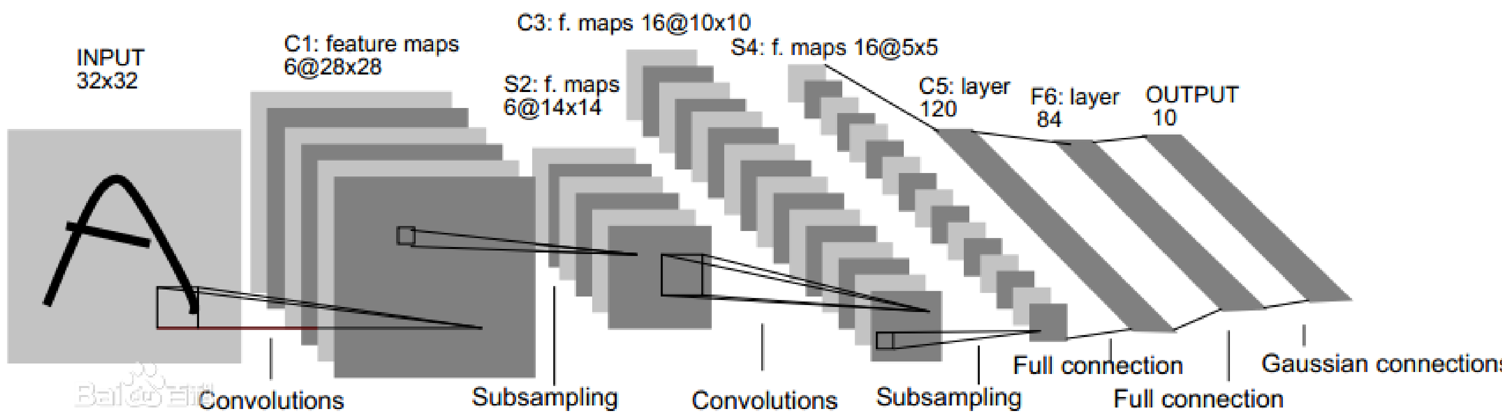
Input layer

Output layer

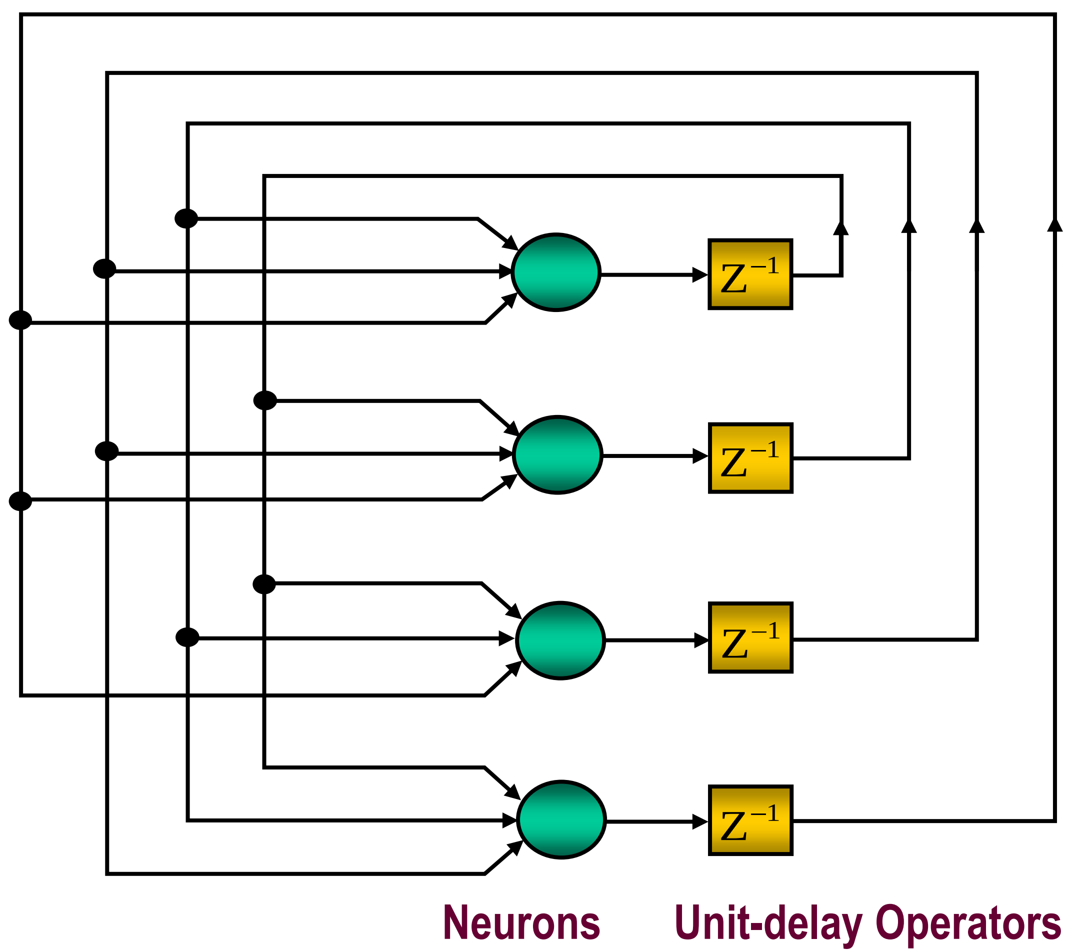
Multilayer Feedforward Networks



Deep Learning Structure



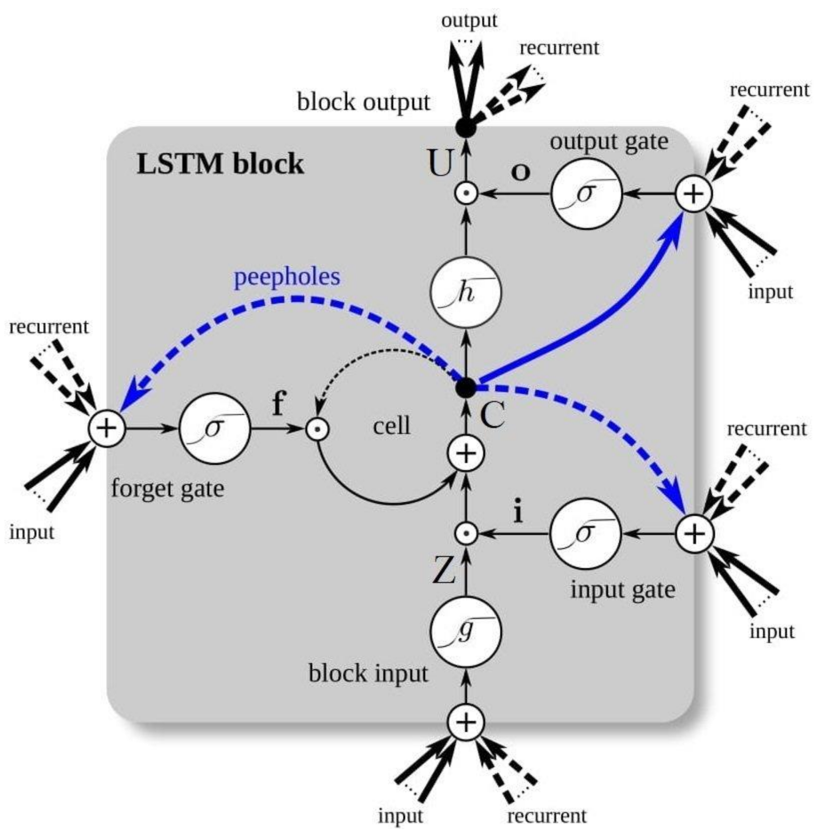
Recurrent Networks



Hopfield Neural Network

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.



Static and Dynamic Systems

- **Static system**

  A system is called static if output of system is dependent on present value of input.

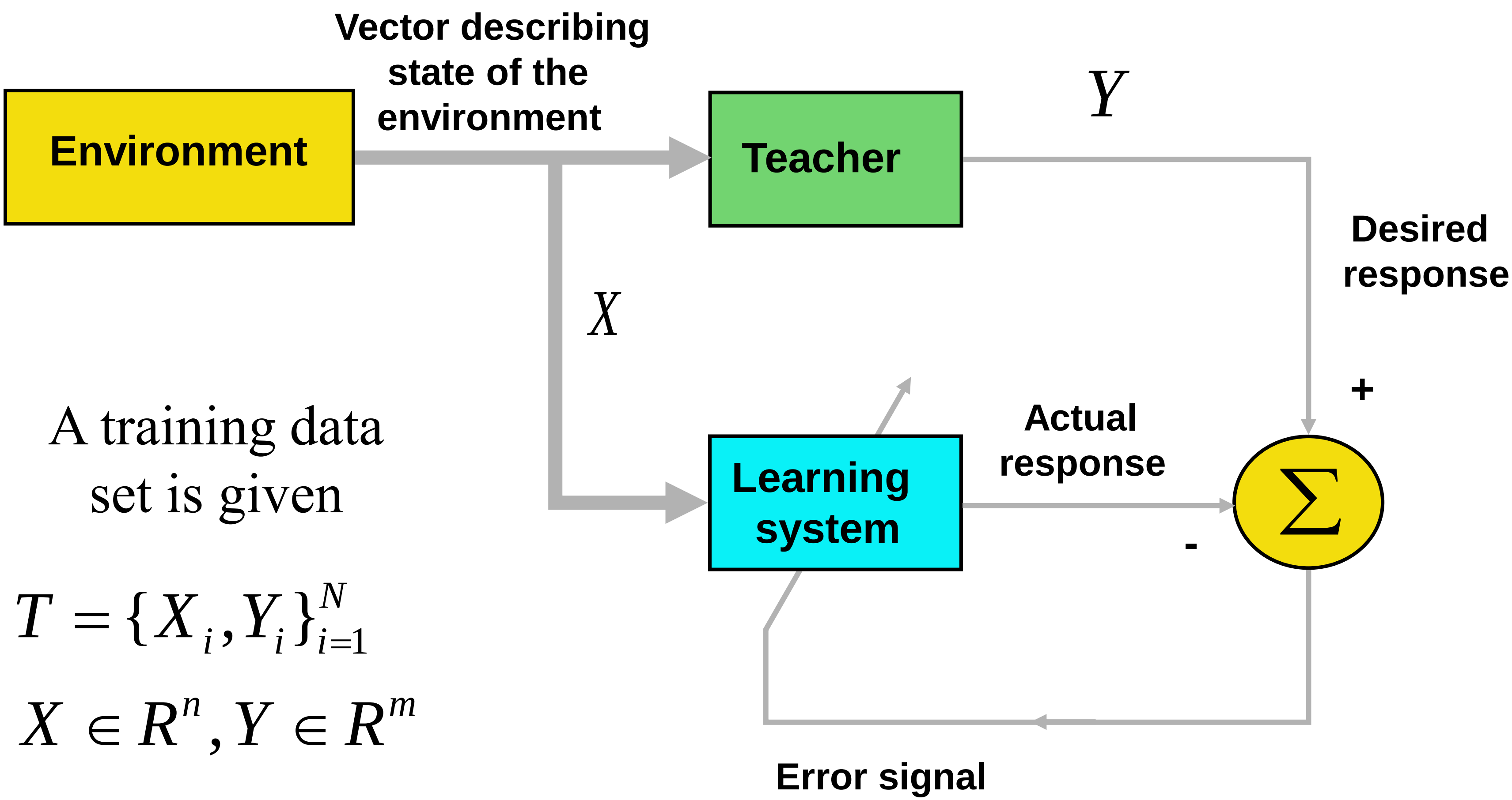
- **Dynamic system**

  A system is called dynamic if output of system dependents on past or future values of input at any instant of time

Learning Paradigms

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

Supervised Learning



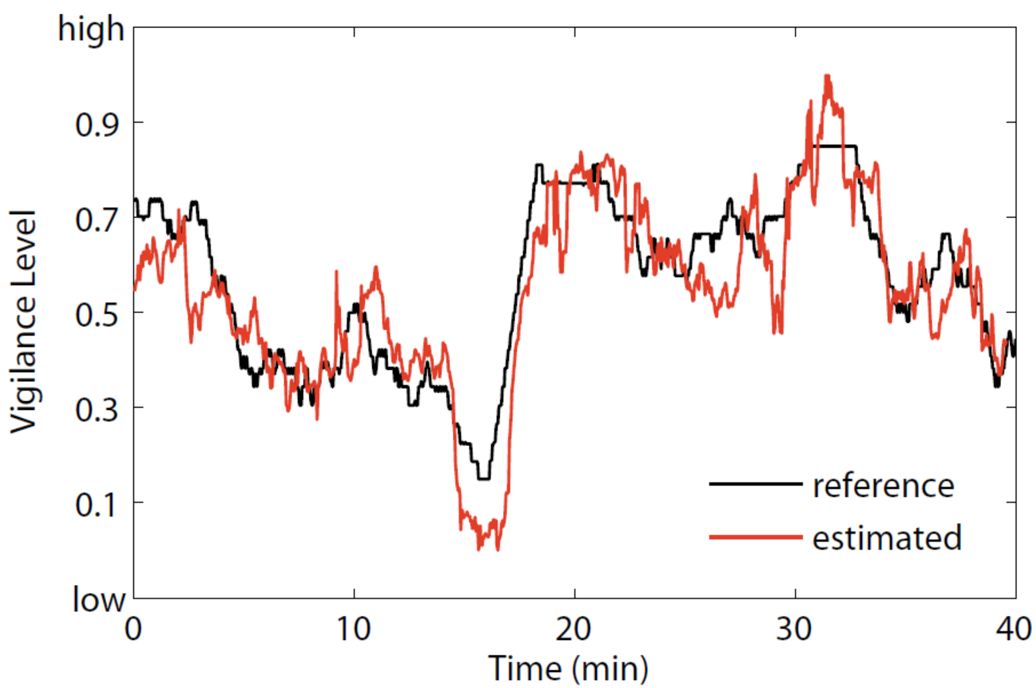
A training data set is given

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

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

监督学习的两类学习任务

- 分类(Classification): 教师信号是离散值
- 预测 (Prediction): 教师信号是连续值
  也叫回归 (Regression)，或
  函数逼近 (Function Approximation)



A training data set is given

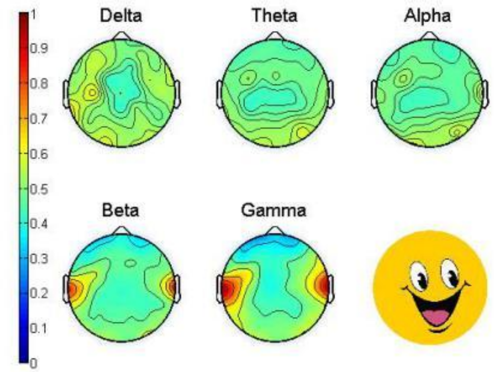
$$T = \{X_i, Y_i\}_{i=1}^{N}$$

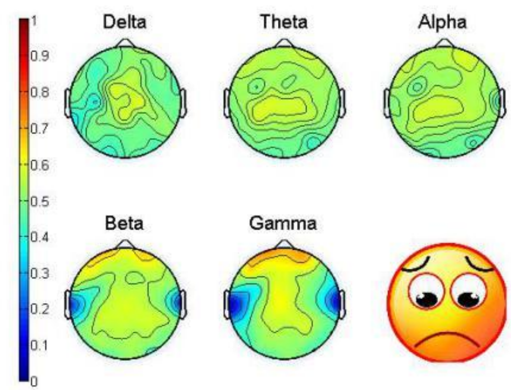
$$X \in R^n, Y \in R^m$$

实际的分类问题：基于脑电的情绪识别

Positive movies

Negative movies

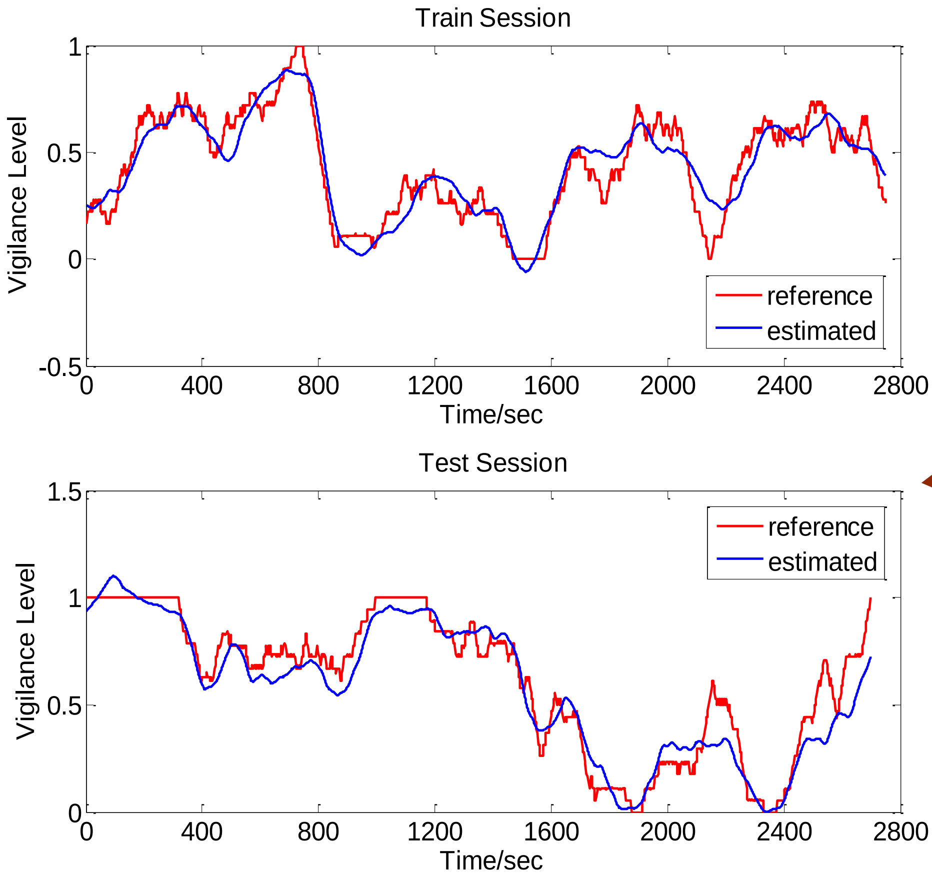




实际的预测问题：司机疲劳检测

实际的预测问题：司机疲劳检测

- Kernel-based supervised regression method



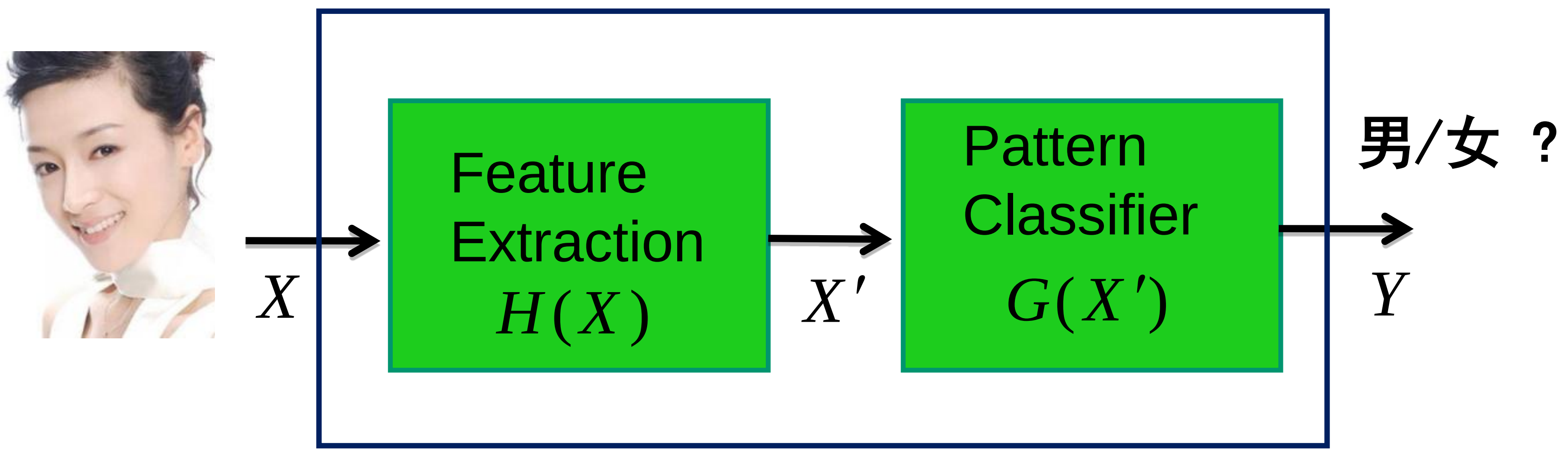
Data Set	Training	Test
1	0.8538	0.7773
2	0.9207	0.8213
3	0.9357	0.8973
4	0.9306	0.8945
5	0.9464	0.9560
6	0.9376	0.9227
7	0.9414	0.8569
8	0.8245	0.8282
9	0.8451	0.8021
Mean	0.9040	0.8618

Training session and test session are two different sessions

实际的分类问题：性别识别与年龄估计

基于机器学习的性别识别系统

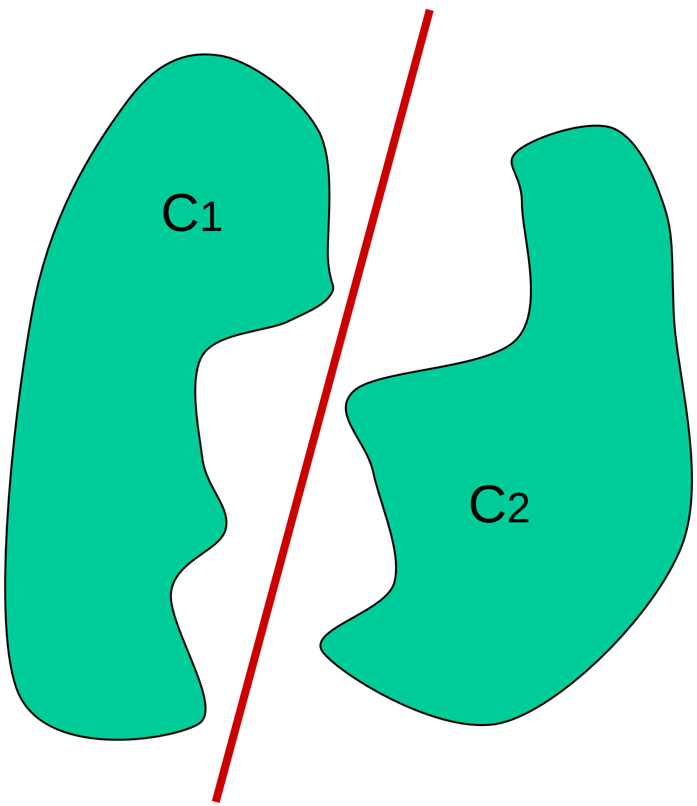
- 系统 输入：人脸图像（X）
- 系统输出：男/女(Z)
- 问题：如何用机器学习方法构造系统？

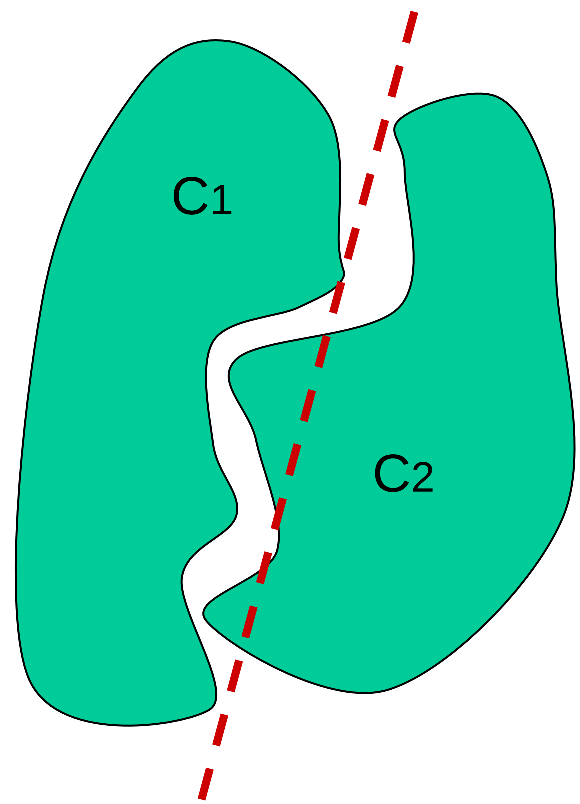


性别识别系统

模式分类任务：线性可分与非线性可分

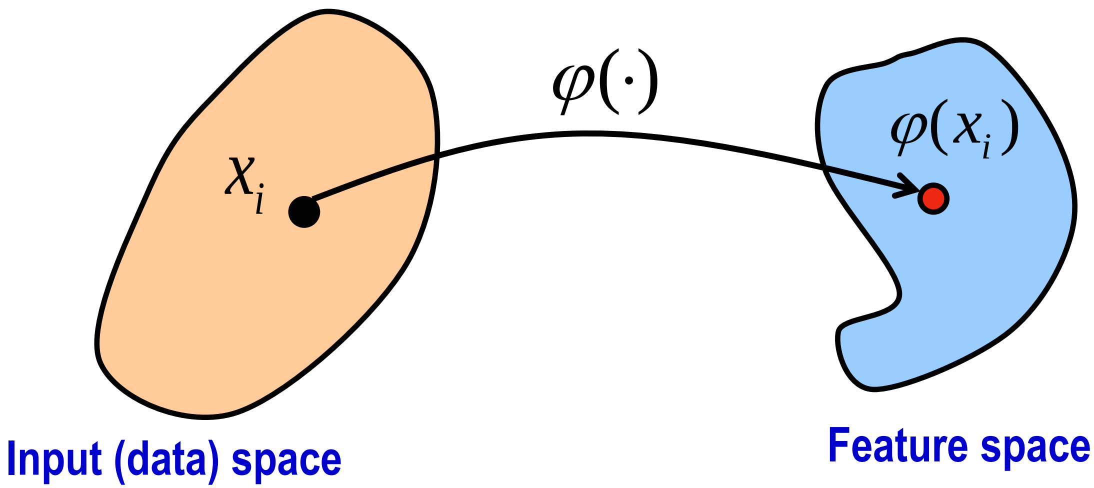
- 线性可分(Linear Separable)
- 线性不可分（Linear Non-separable）





特征提取与特征选择

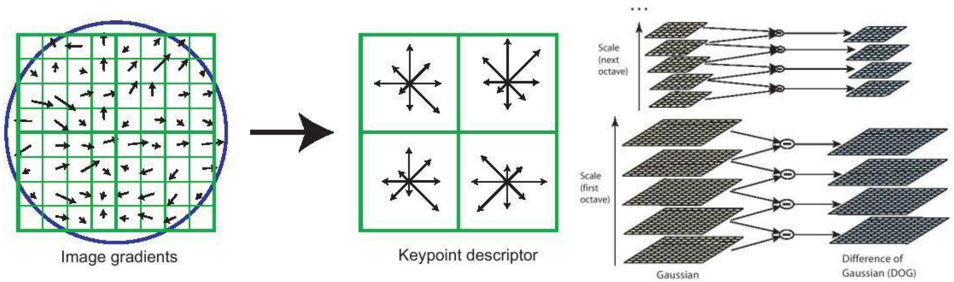
- 特征提取或抽取（Feature Extraction）
  - 对某一模式的一组测量值进行变换或映射以突出该模式具有代表性特征的方法
- 特征选择（Feature Selection）



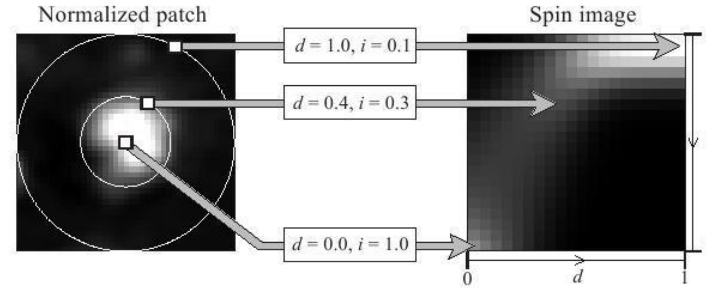
特征工程

Feature Engineering

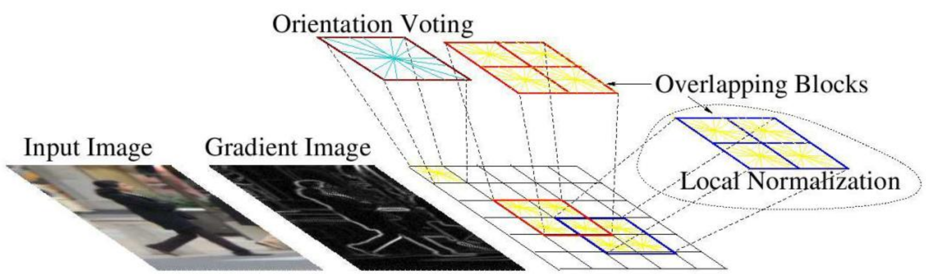
Computer vision features



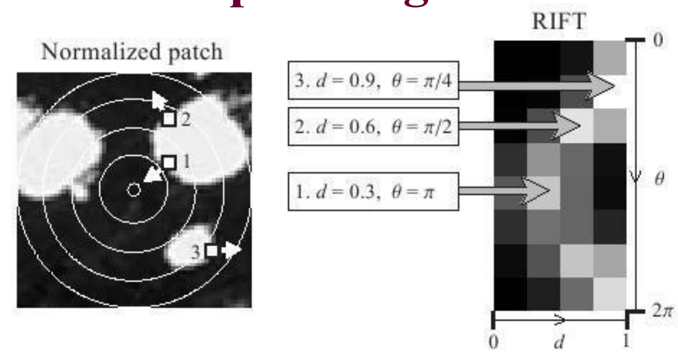
SIFT



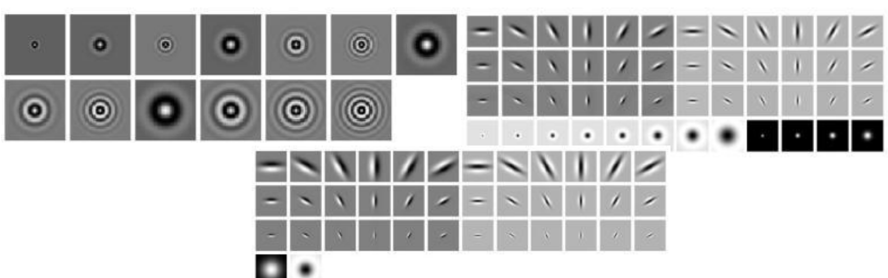
Spin image



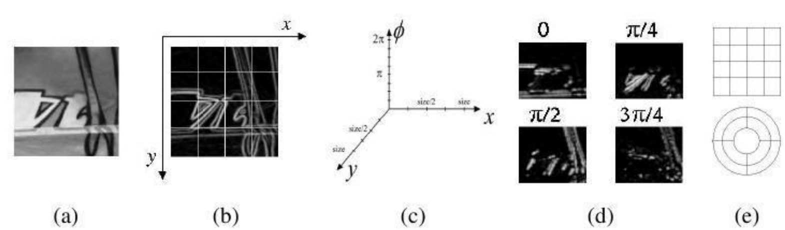
HoG



RIFT



Textons

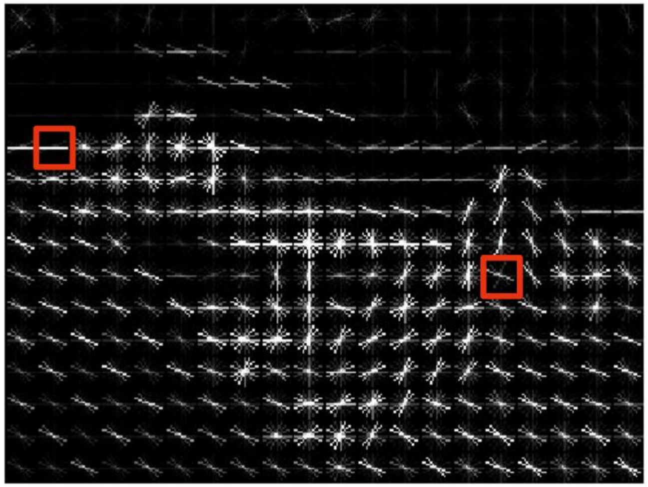


GLOH

Computer vision features

Example: Histogram of Oriented Gradients (HoG)

Divide image into 8x8 pixel regions
Within each region quantize edge direction into 9 bins

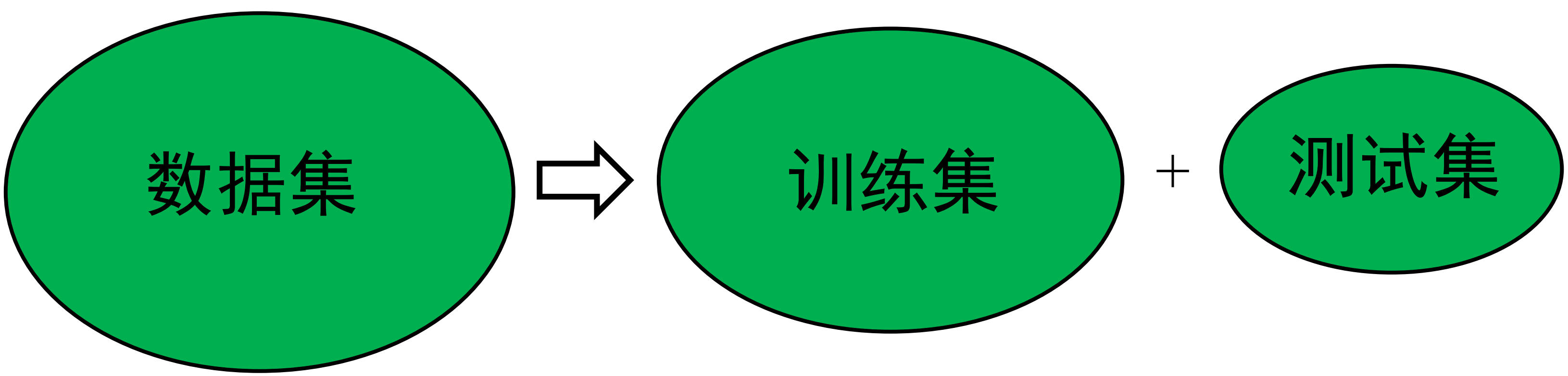


Example: 320x240 image gets divided into 40x30 bins; in each bin there are 9 numbers so feature vector has 30*40*9 = 10,800 numbers

Lowe, "Object recognition from local scale-invariant features", ICCV 1999
Dalal and Triggs, "Histograms of oriented gradients for human detection," CVPR 2005

监督学习的两个不同阶段

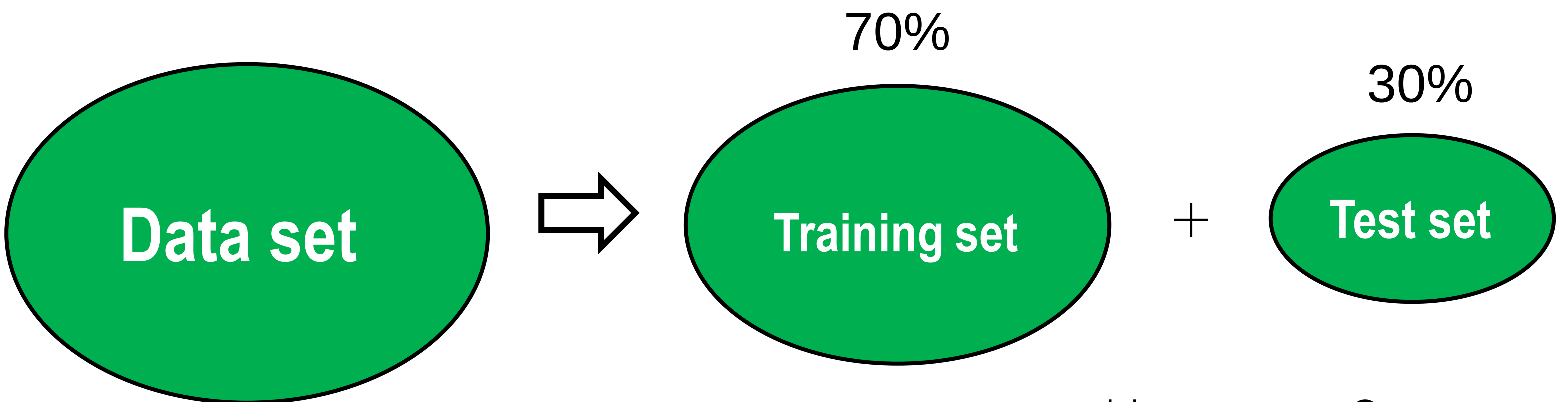
- 学习阶段或称训练阶段
  - 训练数据集
- 预测阶段或称识别阶段
  - 测试数据集
- 学习系统的一般化能力或泛化能力



$$T_{All} = T_{Train} \bigcup T_{Test}\text{；}\quad T_{Train} \bigcap T_{Test} = \Phi$$

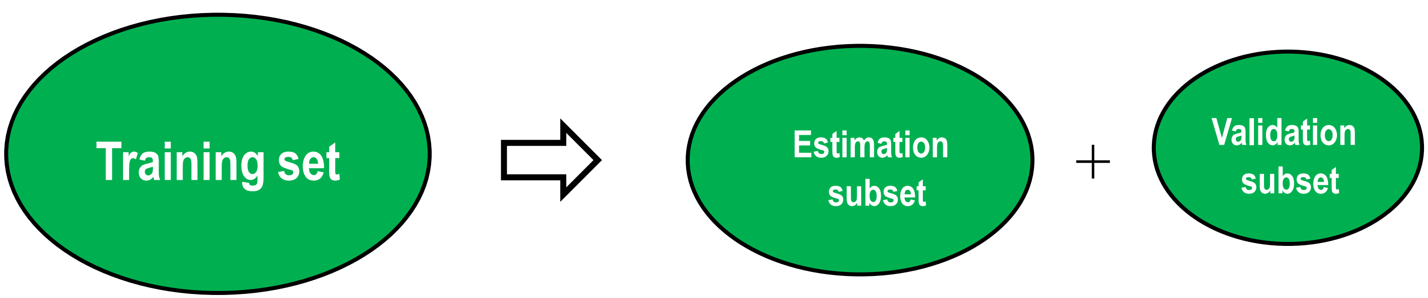
Cross-Validation（交叉验证）

- **Partition of data set：**



$$T_{All} = T_{Train} \cup T_{Test}\ ;\quad T_{Train} \cap T_{Test} = \Phi$$

- **The training set is further partitioned into two disjoint subsets:**
  - **Estimation subset, used to train the model**
  - **Validation subset, used to test or validate the model**



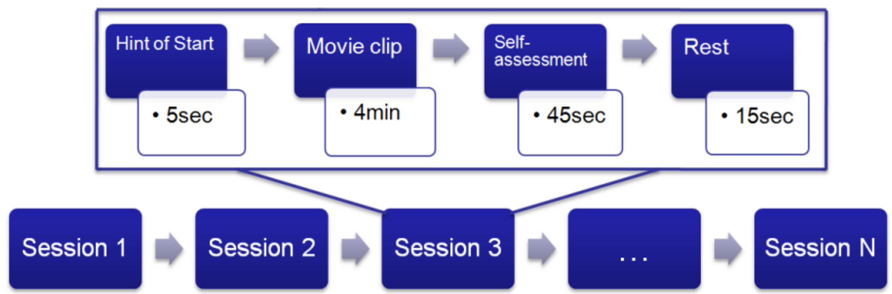
$$T_{Tran} = T_{Esti} \cup T_{Vali}\ ;\quad T_{Esti} \cap T_{Vali} = \Phi$$

Multifold Cross-Validation（多重交叉验证）

- Divide data set of *N* examples into K subsets, 1<*K*<=*N*
- The model is trained on all the subsets except for one
- The validation error is measured by testing it on the subset left out
- This procedure is repeated for a total of *K* trials, each time using a different subset for validation
- The performance of the model is assessed by averaging the squared error under validation over all the trials of the experiment
- Leave-one-out method（留一方法）: *K*=*N*；每次*N-1*个样本用来训练模型，余下的一个样本用于测试，实验重复*N*次

数据集划分的几个原则

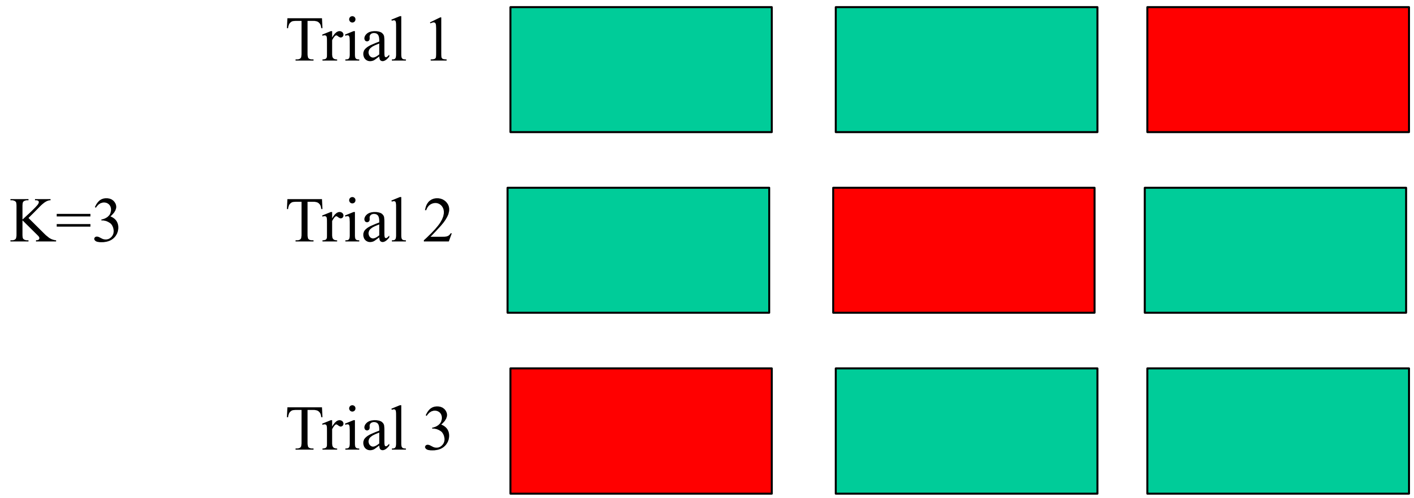
- 没有一个理论的比列或最佳比例，但通常训练集的数据要多于测试集
- 对于一个新的数据集，如何划分需要根据问题的特点合理地划分
- 如果与已有的算法比较，必须严格遵照已有论文的划分比列



Fifteen video clips are totally used for each experiment. There are a 5s hint for starting, a 45s self-assessment and a 15s rest in each session. For evaluation, we use the data from the **first nine** sessions as training data and the data from **remaining six** sessions as testing data in the whole experiment.

Illustration of the hold-out method

三折交叉验证：



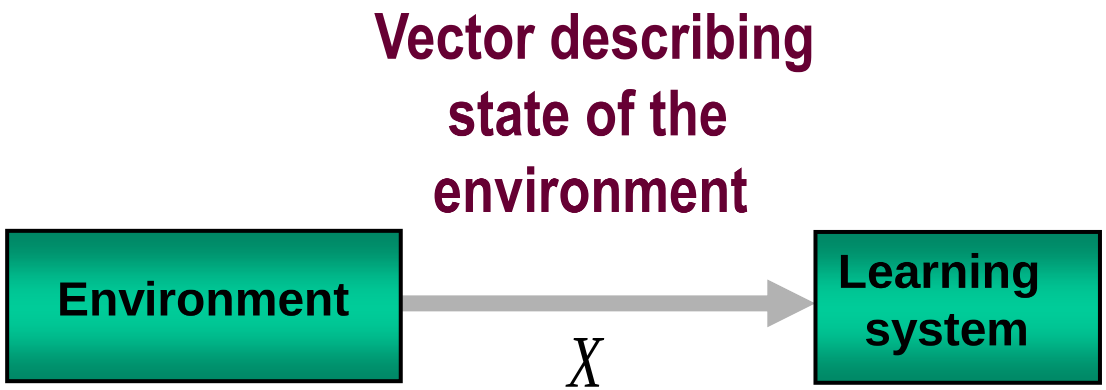
10折交叉验证(10-fold cross validation)：将数据集分成十份，轮流将其中9份做训练1份做测试，10次的结果的均值作为对算法精度的估计。

训练集和测试集的独立同分布假设

- 传统机器学习理论基于训练数据集与测试数据集具有独立分布的假设
- 上述假设过于理想，在解决实际问题时，通常难以成立。例如，脑电信号存在严重的个体差异或场景差异问题。
- 迁移学习方法可以克服上述问题

Unsupervised Learning

Unsupervised Learning:
No labeled training examples are now available

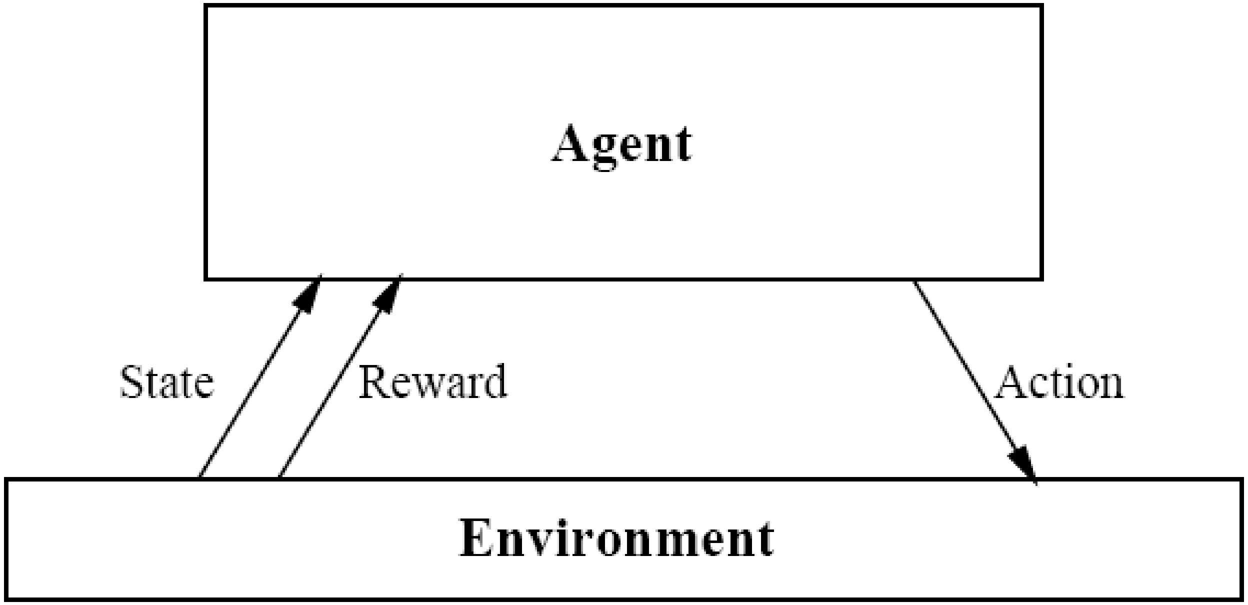


A training set without label is given

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

$$X \in R^n$$

Reinforcement Learning

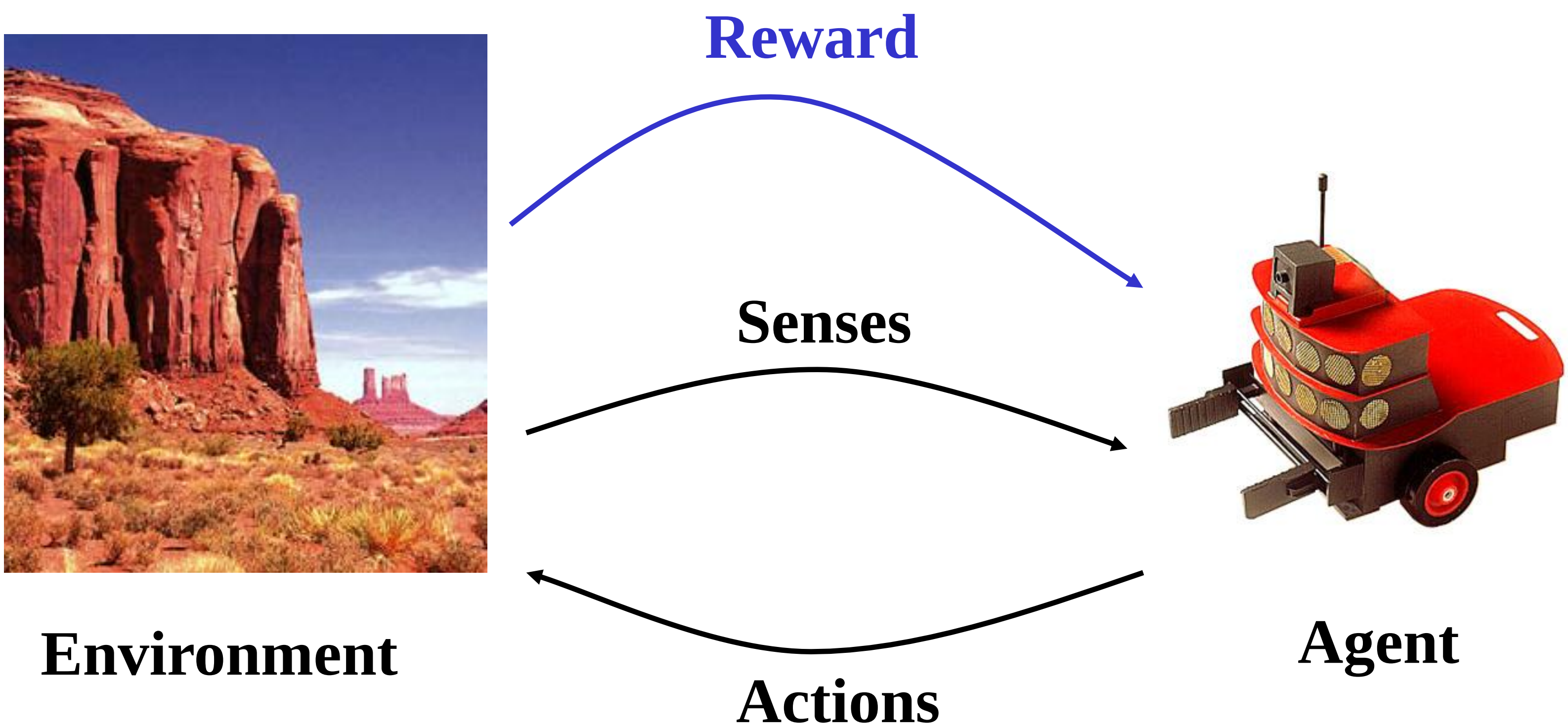


$$s_0 \xrightarrow[r_0]{a_0} s_1 \xrightarrow[r_1]{a_1} s_2 \xrightarrow[r_2]{a_2} \ldots$$

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

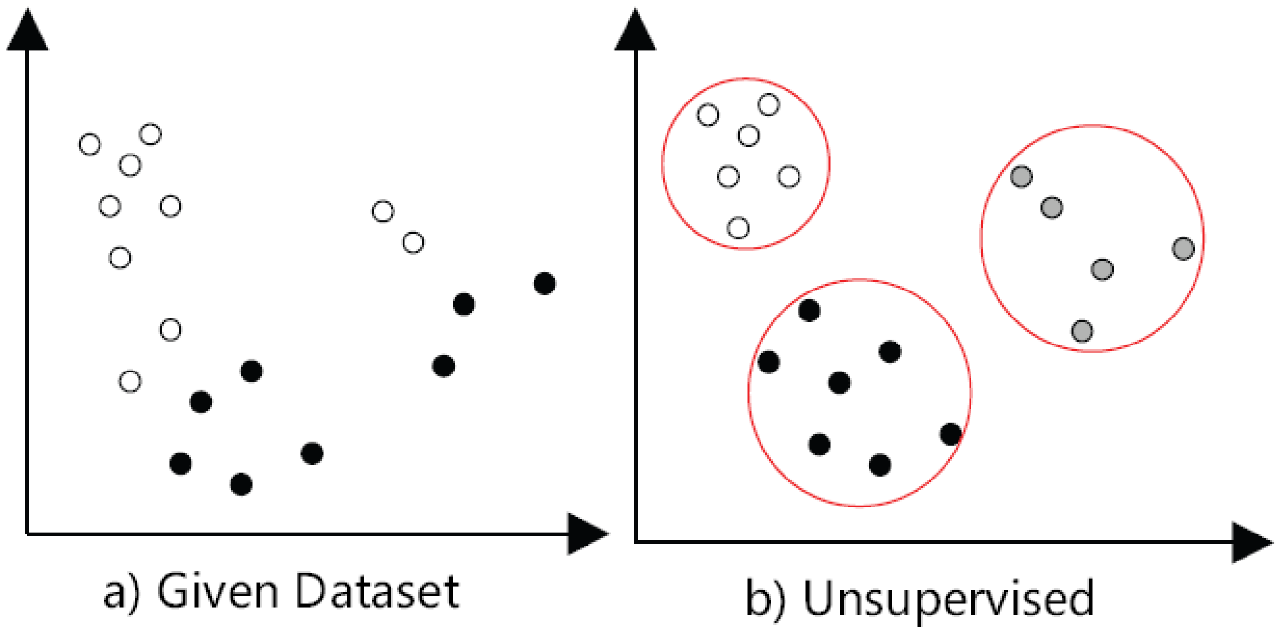


Learning Paradigms

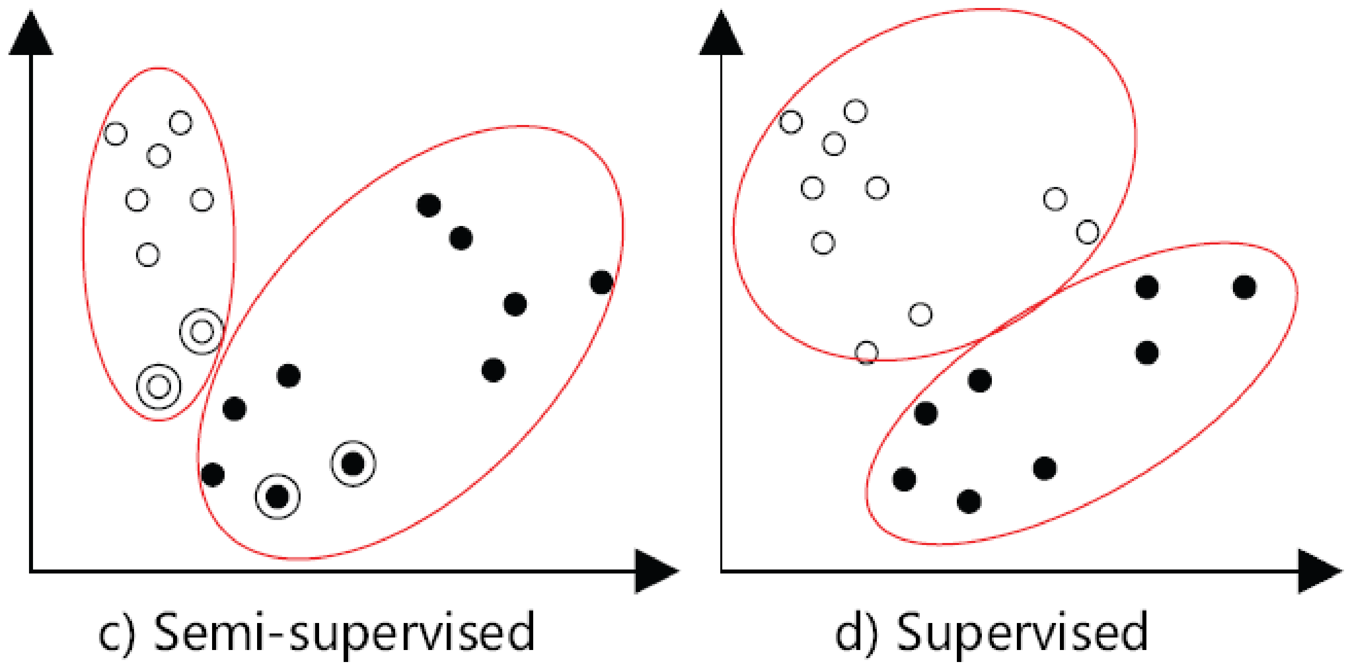
- Semi-supervised Learning
- Semi-supervised clustering
- Supervised clustering
- Transfer learning 迁移学习
- Multi-task learning
- Self-supervised learning 自监督学习
- Federated Learning
- Lifelong learning

……

Unsupervised Clustering



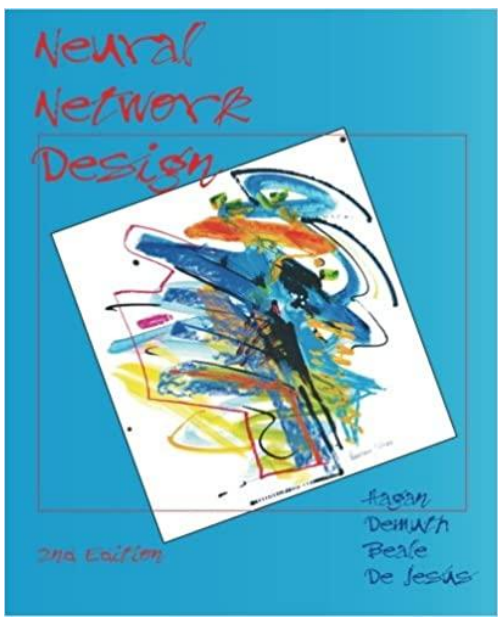
Semi-supervised vs Supervised



Recommended Textbooks 1

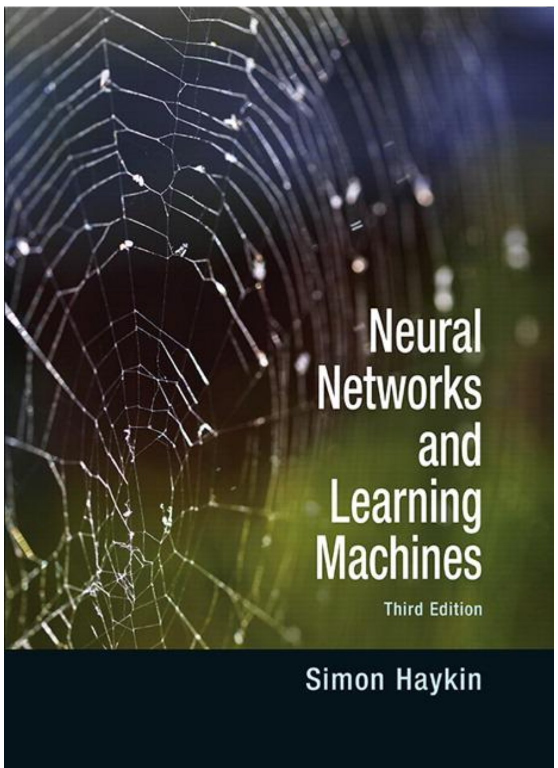
- ***Neural Network Design***, 2nd ed. Martin T. Hagan, Howard. B. Demuth, and Mark H. Beale, PWS Publ. Company, 2014

  (神经网路设计,机械工业出版社,2002) （入门的优秀教材）



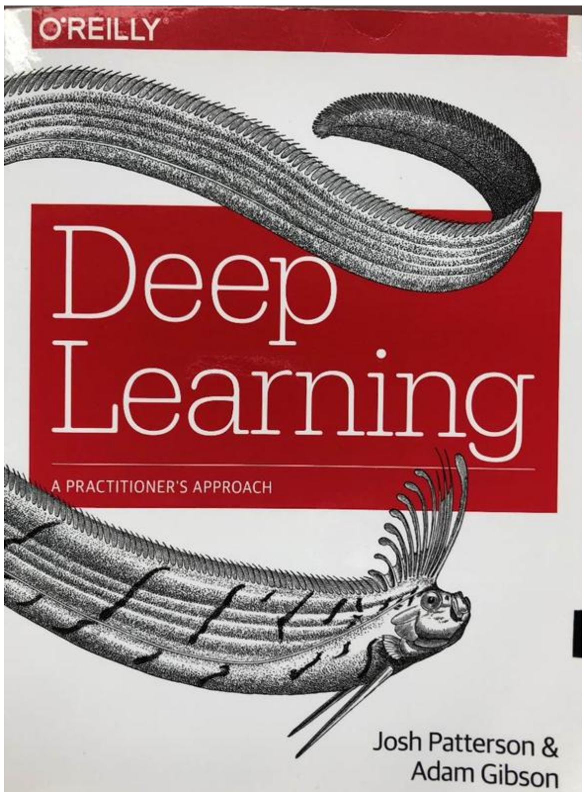
Recommended Textbooks 2

- *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)



Recommended Textbooks 3

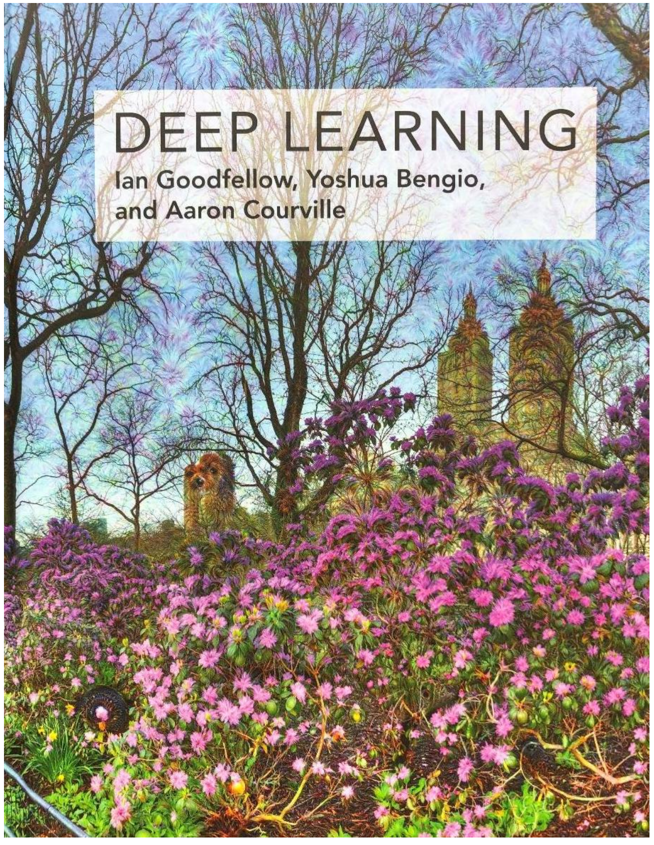
- *Deep Learning, A Practitioner's Approach*, Josh Patterson & Adam Gibson, OREILLY, 2017



Recommended Textbooks 4

- ***Deep Learning,***

  Ian Goodfellow, Yoshua Bengio, Aaron Courville, 2016, MIT Press



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

- International Conference on Machine Learning (ICML)
- International Conference on Learning Representations (ICLR)
- Neural Information Processing Systems (NeurIPS)
- Computer Vision and Pattern Recognition Conference (CVPR)
- International Joint Conference on Artificial Intelligence (IJCAI)
- AAAI Conference on Artificial Intelligence

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.

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

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- 量子位（微信号：QbitAI）
- 神经现实（微信号：neureality）
- 机器之心 （微信号：almosthuman2014）
- AI科技评论 （aitechtalk）

Stanford Machine Learning course

CS 229, by Andrew Ng

https://www.bilibili.com/video/BV19e411W7ga/

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