

# Machine Learning and Medical Engineering Applications

## 机器学习与医学工程应用

Lecture 1 - Introduction to the course

**Quanying Liu (刘泉影)**

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# Machine Learning & NeuroEngineering (ML&NE) in 2020

- 1 - Introduction to NeuroScience
- 2 - Introduction to ML
- 3 - Random Walk Model
- 4 - Basic Parameter Estimation 1
- 5 - Basic Parameter Estimation 2
- 6 - Probability Overview
- 7 - Combining Data
- 8 - Bayesian Parameter Estimation
- 9 - MCMC
- 10 - Gibbs Sampling & JAGS
- 11 - Hierarchical Modeling
- 12 - Model Comparison
- 13 - Bayesian Model Comparison
- 14 - A brief introduction to GAN
- 15 - Gradient Descent & Error BackPropagation
- 16 - CNN & Tips to train DNNs
- 17 - Tips to train DNNs
- 18 - unsupervised learning (PCA)
- 19 - unsupervised learning (Deep Auto-encoder)
- 20 - RNN

Computational modelling

Neuroengineering techniques are integrated into the models.

Deep learning

# Machine Learning & NeuroEngineering (ML&NE) in 2021

- █ 1 - Introduction to Neuroscience
- █ 2 - Introduction to machine learning
- █ 3 - Random Walk Model
- █ 4 - Basic Parameter Estimation 1
- █ 5 - Basic Parameter Estimation 2
- █ 6 - EEG signal process & Probability Overview
- █ 7 - Brain computer interface
- █ 8 - Combining data
- █ 9 - Bayesian Parameter Estimation
- █ 10 - MCMC
- █ 11 - Gibbs Sampling & JAGS
- █ 12 - Recap (model, MLE, MAP)
- █ 13 - Python tutorial & Sampling technique Recap
- █ 14 - Hierarchical Models
- █ 15 - GD & BP & CNN
- █ 16 - CNN hands-on
- █ 17 - Visual System & CNN
- █ 18 - More about CNN
- █ 19 - Summary and Recap

Computational modelling

Add specific lectures for  
Neuroengineering techniques.

Deep learning

# Machine Learning & Medical Engineering Applications in 2022/2023

-  Lecture 1 - introduction.pdf
-  Lecture 2 - linear regression.pdf
-  Lecture 3 - python tutorial.pdf
-  Lecture 4 - Frequentist vs Bayesian.pdf
-  Lecture 5 - Ridge regression.pdf
-  Lecture 6 - Logistic Regression.pdf
-  Lecture 7 - SVM.pdf
-  Lecture 8 - SVM with soft margin.pdf
-  Lecture 9 - SVM kernel method.pdf
-  Lecture 10 - PCA.pdf
-  Lecture 11 - PCA and SVD.pdf
-  Lecture 12 - LDA.pdf
-  Lecture 14 - clustering.pdf
-  Lecture 15 - Neural Network 1.pdf
-  Lecture 16 - Neural Network 2.pdf

This course focuses on machine learning.

Neural engineering is another course.

# Goals of ML&NE

- Learn the neural basis of brain intelligence (*how brain generates intelligence*)
  - visual system
  - auditory system
  - motor system
  - decision making
  - ...
- Learn basic algorithms for artificial intelligence (*how machine generates intelligence*)
  - CNN
  - RNN
  - GAN
  - ...
- Do a course project (to bridge BI and AI)
  - propose a project to solve a scientific/technical question
  - use some AI methods on your data
  - make a course presentation
  - **Poster Day** (present your posters in front of the 工学院南楼5楼)

# Goals of ML&MEA

- Totally orientated to machine learning methods ([Basic ML theory and models](#))
  - Linear regression
  - Logistic regression
  - Support vector machine (SVM)
  - Clustering
  - Dimensionality reduction
  - Fully-connected Neural Network
  - [Convolutional neural network \(CNN\)](#)
- Programming, Implementation and Applications ([Apply ML to medical engineering](#))
  - Python programming
  - Model Implementation
  - Medical applications
- Homeworks and Exams
  - Homeworks (including theory and coding)
  - A final exam

# Logistics

- **Class hours:**
  - Tuesday, **10:20-12:10** (each week, 一教406)
  - Thursday, **19:00-20:50** (odd weeks, 一教406)
- **Lecturer:** Quanying Liu (刘泉影)
  - My Office hours: **Tuesday, 13:00-14:00**, Engineering building South (工学院南楼) 535
  - Lunch hours: Please send an **email** to make an appointment for **having lunch together**.
- **Textbook**
  - Pattern Recognition and Machine Learning, by Christopher M. Bishop
- **Reading materials (for extra learning)**
  - Machine Learning: A Probabilistic Perspective, by Kevin P. Murphy

NCC lab  
微信公众号



# Logistics



神经计算与控制实验室  
Neural Computing & Control Lab

- **TAs:**

- Junjie Yu (余俊杰)
- Menglong Zhang (张梦龙)

工学院南楼541



余俊杰

张梦龙

- **Prerequisites**

- Basic linear algebra
- Basic probability

- **Scoring:**

30% Quiz at the class

Please attend the class!

40% Homework sets

A homework set includes two parts (theory and coding)

30% Final Exam

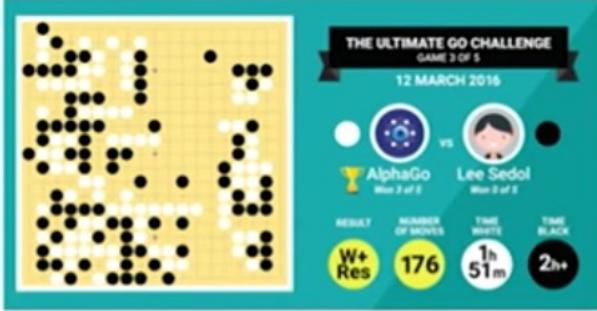
Not hard



# Q1

Why are you interested in machine  
learning?

# Machine learning is everywhere.



AlphaGo



da Vinci Surgical System



Autonomous Vehicles

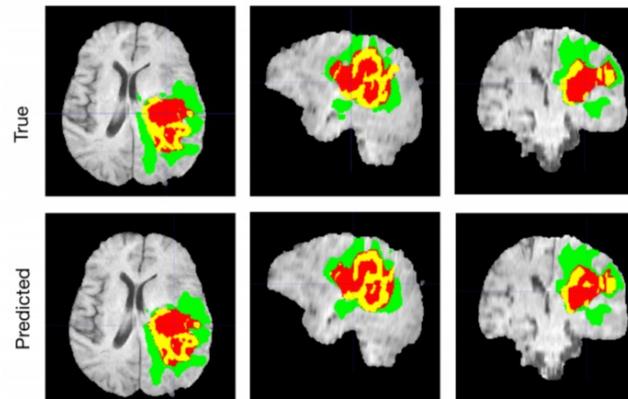


Image processing

ChatGPT 3.5 ▾

You

How to design a syllabus for an undergraduate-level course in machine learning

ChatGPT

Designing a syllabus for an undergraduate-level course in machine learning requires careful consideration of foundational concepts, practical applications, and hands-on experience. Here's a suggested outline:

## Course Title: Introduction to Machine Learning

### Course Description:

This course provides an introduction to the fundamental concepts, algorithms, and applications of machine learning. Topics include supervised learning, unsupervised learning, reinforcement learning, and neural networks. Emphasis is placed on understanding the theoretical foundations as well as practical implementation through programming assignments.

### Prerequisites:

- Basic knowledge of linear algebra
- Basic understanding of probability and statistics
- Proficiency in at least one programming language (preferably Python)

### Learning Objectives:

- Understand the core concepts and algorithms in machine learning.
- Implement machine learning algorithms from scratch.
- Apply machine learning techniques to real-world datasets.
- Evaluate and interpret machine learning models.

ChatGPT

# Large models: a way towards AGI



ChatGPT

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### Learning Objectives:

- Understand the core concepts and algorithms in machine learning.
- Implement machine learning algorithms from scratch.
- Apply machine learning techniques to real-world datasets.
- Evaluate and interpret machine learning models.

### Topics Covered:

#### 1. Introduction to Machine Learning

- Definition and scope of machine learning
- Types of machine learning: supervised, unsupervised, reinforcement learning
- Applications of machine learning

#### 2. Foundations of Machine Learning

- Linear algebra review: vectors, matrices, operations
- Probability and statistics for machine learning
- Data preprocessing and feature engineering

#### 3. Supervised Learning

- Linear regression
- Logistic regression
- Decision trees and ensemble methods (Random Forests, Gradient Boosting)

#### 4. Unsupervised Learning

- K-means clustering
- Hierarchical clustering
- Principal Component Analysis (PCA)

#### 5. Neural Networks and Deep Learning

- Introduction to artificial neural networks
- Feedforward neural networks
- Convolutional Neural Networks (CNNs)
- Recurrent Neural Networks (RNNs)
- Introduction to TensorFlow or PyTorch

# Large models: a way towards AGI

## 6. Evaluation and Model Selection

- Cross-validation
- Performance metrics (accuracy, precision, recall, F1 score)
- Bias-variance tradeoff

## 7. Advanced Topics in Machine Learning

- Support Vector Machines (SVM)
- Dimensionality reduction techniques (t-SNE, UMAP)
- Reinforcement Learning basics

### Instructional Methods:

- Lectures: Presenting theoretical concepts and algorithms
- Coding Assignments: Implementing algorithms in Python, using libraries like NumPy, Pandas, and scikit-learn
- Case Studies: Analyzing real-world datasets and applying machine learning techniques
- Discussions: Exploring current research papers and practical applications of machine learning

### Assessment Methods:

- Coding assignments: Implementing machine learning algorithms and analyzing results
- Midterm and final exams: Testing theoretical understanding and problem-solving skills
- Project: Applying machine learning techniques to a real-world dataset and presenting findings

### Additional Resources:

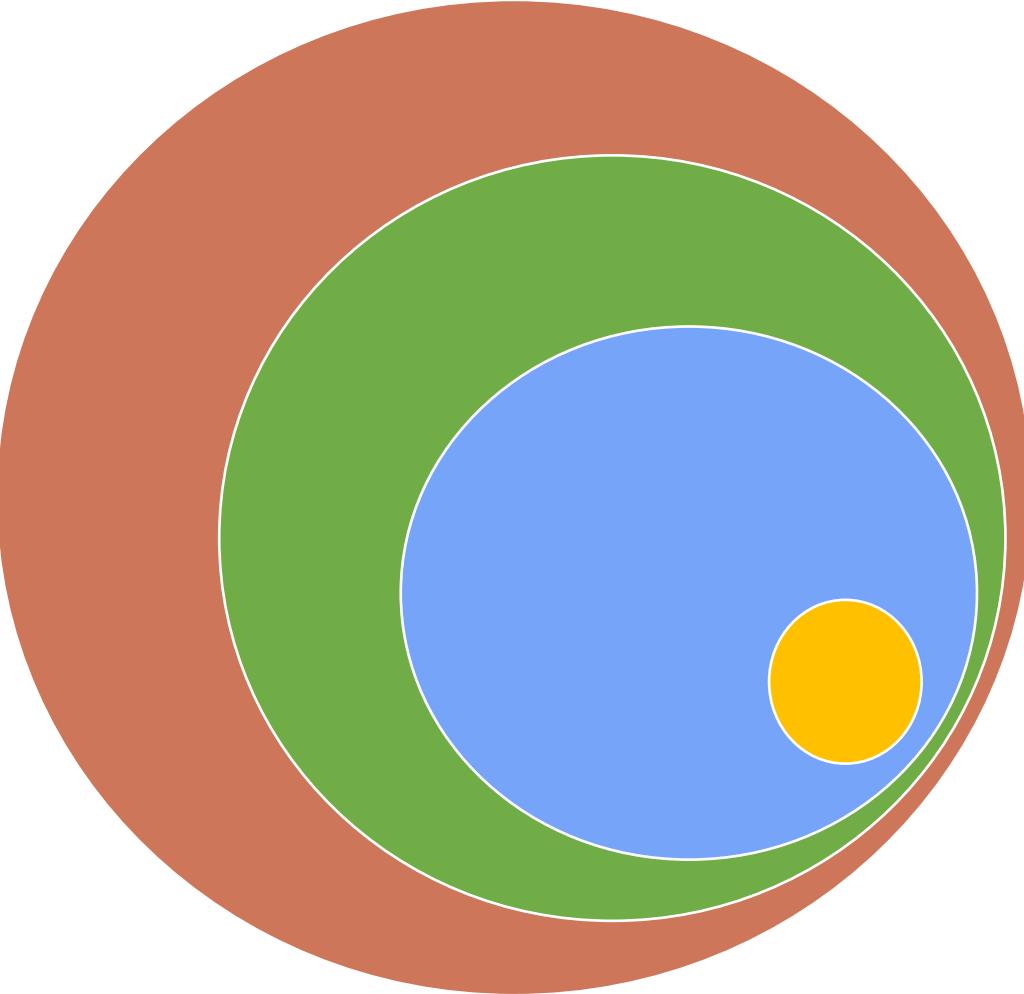
- Online tutorials (e.g., Coursera, Udacity, Kaggle)
- Research papers in machine learning journals (e.g., Journal of Machine Learning Research, NeurIPS proceedings)

### Conclusion:

This syllabus provides a comprehensive overview of machine learning concepts, algorithms, and applications suitable for undergraduate students. It combines theoretical understanding with practical implementation, enabling students to gain both conceptual knowledge and hands-on experience in the field of machine learning.

**Q2**

**What is machine learning?**



# **Artificial Intelligence**

general way for any non-human intelligence

## **Machine Learning**

methods to let machines learn by themself

## **Deep Learning**

a particular kind of machine learning using deep neural networks

## **Large language model**

a deep learning algorithm that can perform a variety of natural language processing tasks

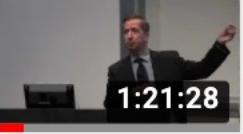
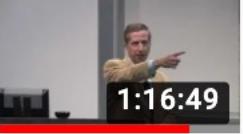
# 6 steps to be an **AI** expert

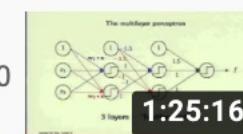
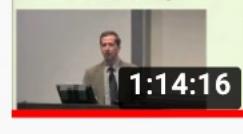
- 
- 1 Linear algebra      [MIT 18.06 - Prof. Gilbert Strang](#)
  - 2 Probability      [MIT 6.012 - Prof. John Tsitsiklis](#)
  - 3 Python      [Any programming course, with lots of practices](#)
  - 4 Machine Learning      [Stanford/Coursera - Andrew Ng](#)
  - 5 Convolutional Neural Networks for Visual Recognition  
[Stanford CS231n – Prof. Fei-fei Li](#)
  - 6 Graph models/generative models/...

# Caltech Machine Learning course

CS 156, by Prof. Yaser Abu-Mostafa

<https://www.youtube.com/watch?v=mbyG85GZ0PI&list=PLD63A284B7615313A>

▶		Lecture 01 - The Learning Problem caltech	1:21:28
2		Lecture 02 - Is Learning Feasible? caltech	1:16:49
3		Lecture 03 -The Linear Model I caltech	1:19:44
4		Lecture 04 - Error and Noise caltech	1:18:22
5		Lecture 05 - Training Versus Testing caltech	1:16:58
6		Lecture 06 - Theory of Generalization caltech	1:18:12

7		Lecture 07 - The VC Dimension caltech	1:13:31
8		Lecture 08 - Bias-Variance Tradeoff caltech	1:16:51
9		Lecture 09 - The Linear Model II caltech	1:27:14
10		Lecture 10 - Neural Networks caltech	1:25:16
11		Lecture 11 - Overfitting caltech	1:19:49
12		Lecture 12 - Regularization caltech	1:15:14
13		Lecture 13 - Validation caltech	1:26:12
14		Lecture 14 - Support Vector Machines caltech	1:14:16
15		Lecture 15 - Kernel Methods caltech	1:18:19
16		Lecture 16 - Radial Basis Functions caltech	1:22:08
17		Lecture 17 - Three Learning Principles caltech	1:16:18
18		Lecture 18 - Epilogue caltech	1:09:28

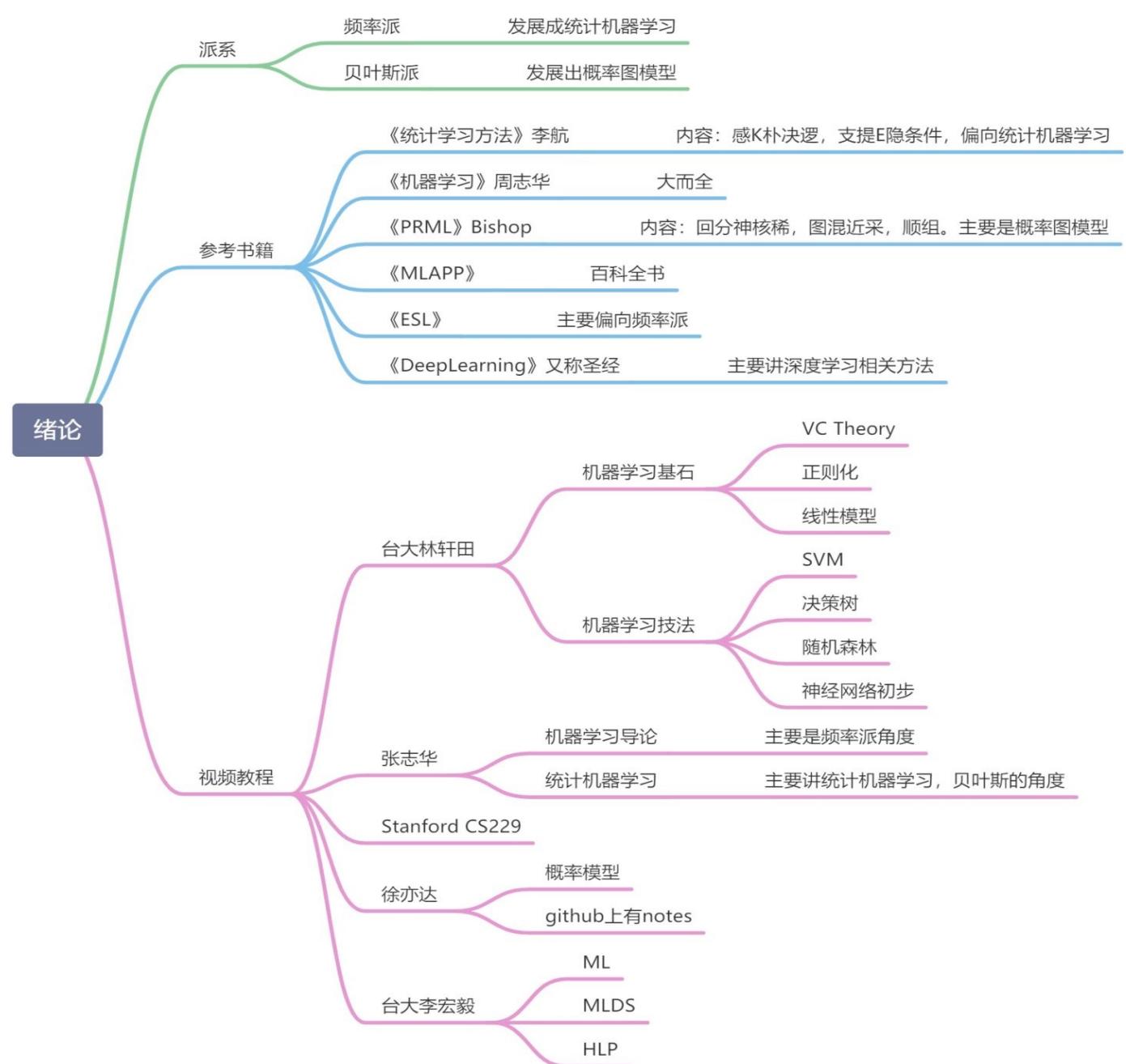
B站大学

【机器学习】白板推导  
系列, by shuhai008

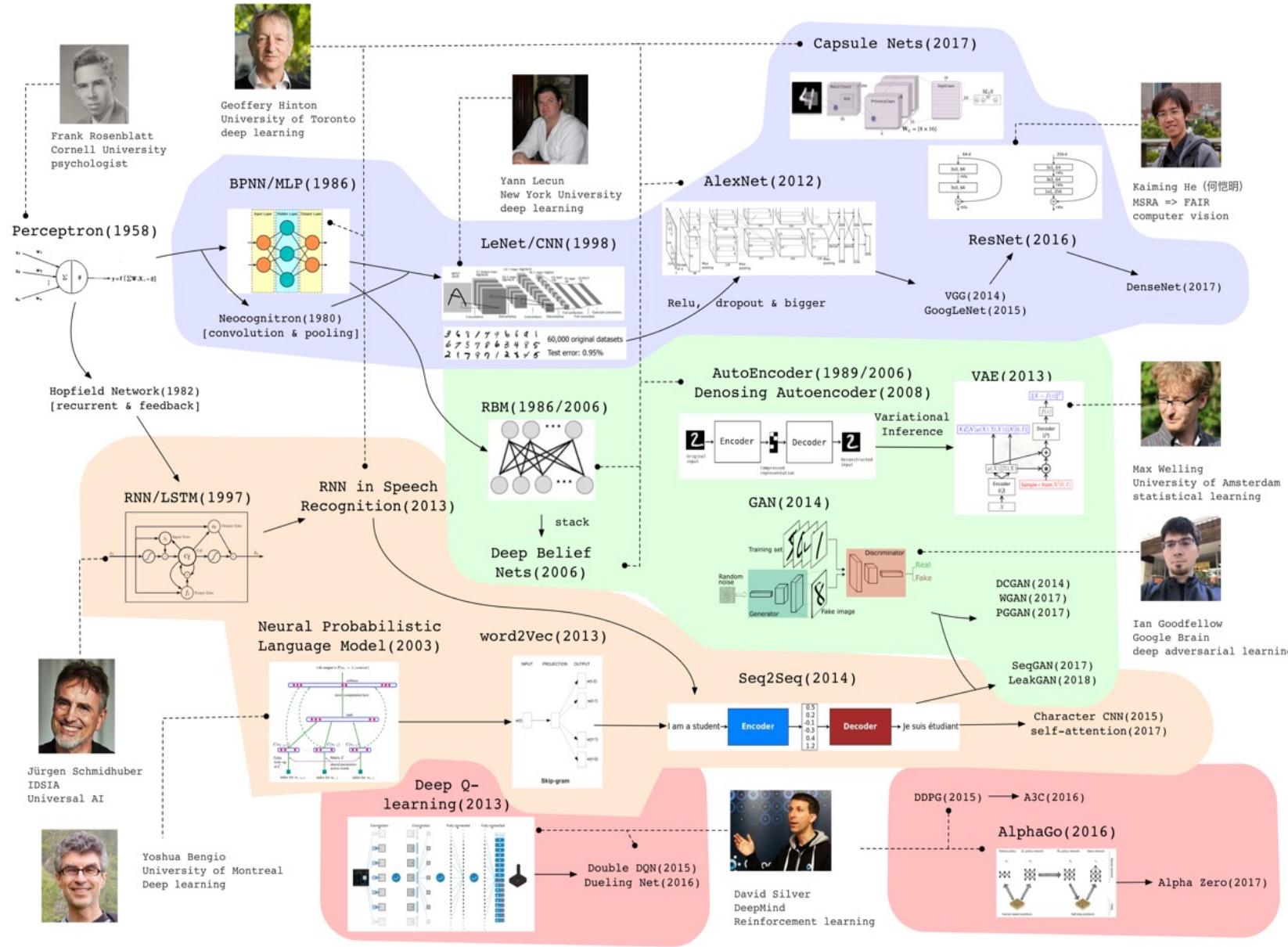
<https://www.bilibili.com/video/BV1aE411o7qd>

包罗万象，因有尽有  
纯理论推导

# 机器学习白板推导



# 《2020 中国人工智能白皮书》



## Computer Vision and CNN

- 1979, *Neocognitron* by Fukushima
- 1986, *Backpropogation MLP* by Hinton
- 1998, *LeNet-5* by LeCun
- 2012, *AlexNet* by Hinton
- 2016, *ResNet* by 何恺明
- 2020, *ViT* by google

## Generative Models

- 1986-2006, *RBM* by Hinton
- 1989/2006, *AutoEncoder* by Hinton
- 2014, *GAN* by Goodfellow
- 2014, *DCGAN* by Goodfellow
- 2017, *WGAN* by Goodfellow
- 2017, *PGGAN* by Goodfellow
- 2017, *SeqGAN* by Ian Goodfellow
- 2018, *LeakyGAN* by Ian Goodfellow
- 2015, *Character CNN* by Max Welling
- 2017, *self-attention* by Max Welling

## Sequence Models

- 1982, *Hopfield Network* by Hopfield
- 1997, *LSTM* by Schmidhuber
- 2013, *RNN* by Hinton
- 2017, *transformer* by Google
- 2022, *chatGPT* by openAI

## Reinforcement Learning

- 2013, *Deep Q-learning* by Silver
- 2016, *AlphaGo* by DeepMind
- 2020, *AlphaFold* by DeepMind

# Data Generation: Stable Diffusion for image generation

<https://stablediffusionweb.com/#demo>

black and white illustration of bloodborne, close-up street view of a Victorian town at night, horrible, moon rising, super detailed, minimalist composition

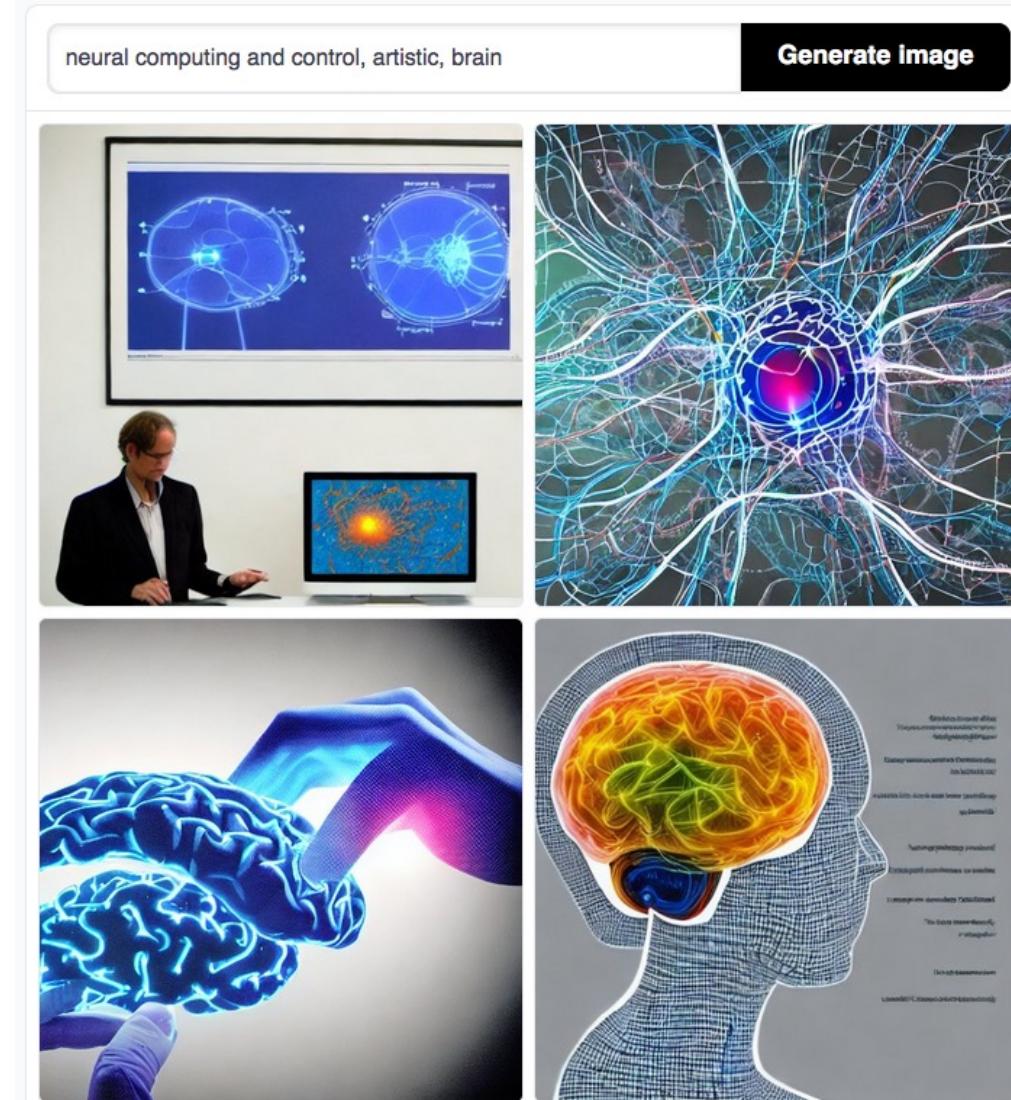
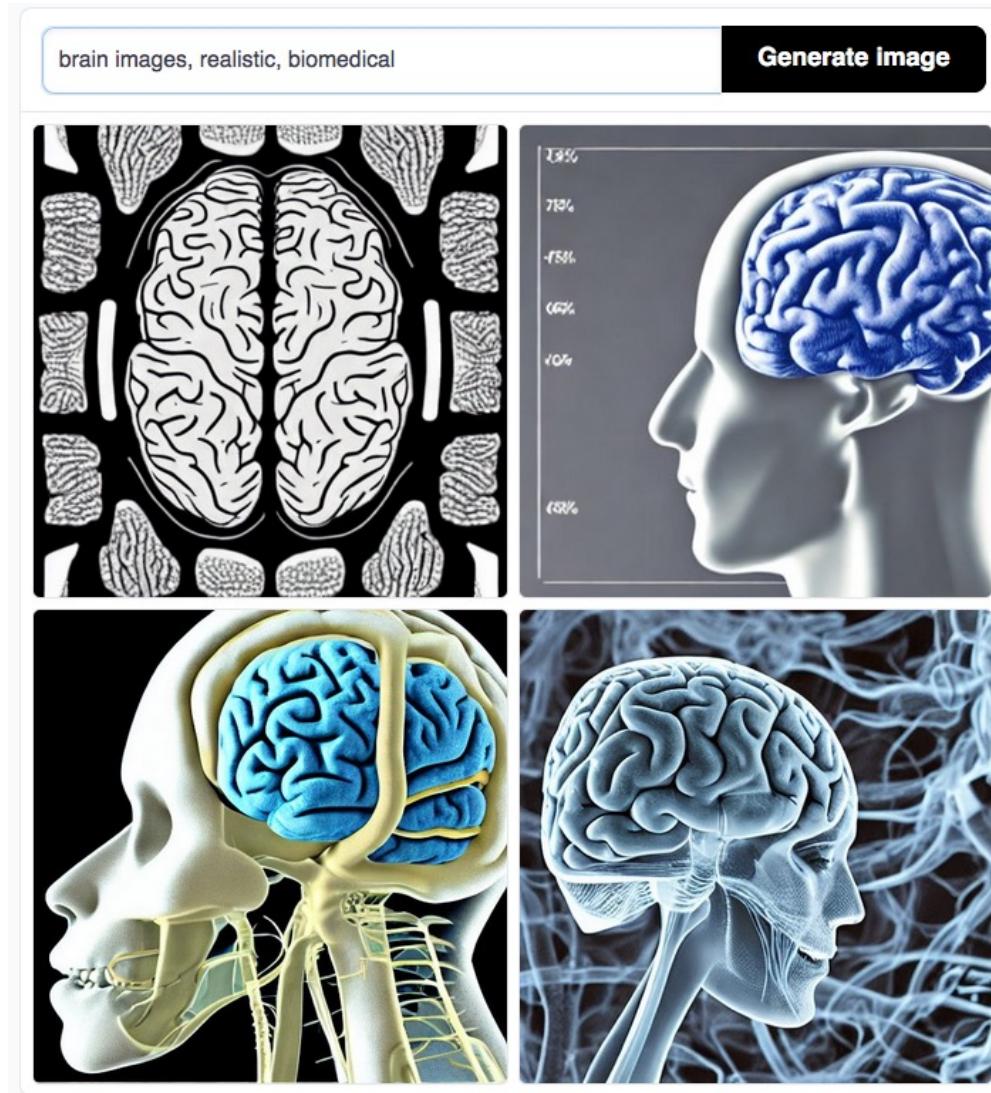


fine watercolor painting portrait of a girl holding a lazy cat, neat, elegant



# Data Generation: Stable Diffusion for image generation

<https://stablediffusionweb.com/#demo>



# 6 steps to be a **medical AI expert**

- 
- 1 Be an AI expert
  - 2 Understand data: bioelectrical signals, biomedical images
  - 3 Understand diseases
  - 4 Know how to talk with medical doctors
  - 5 Know how to talk with engineers
  - 6 Define THE problem and solve it with AI

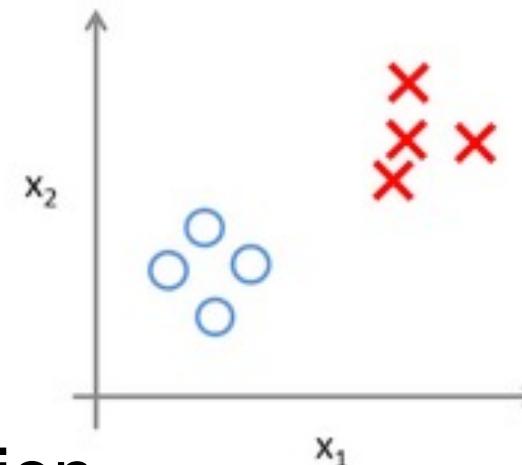
# Categories of Machine Learning

## Supervised Learning

Given labels

e.g. classification, regression

Supervised Learning

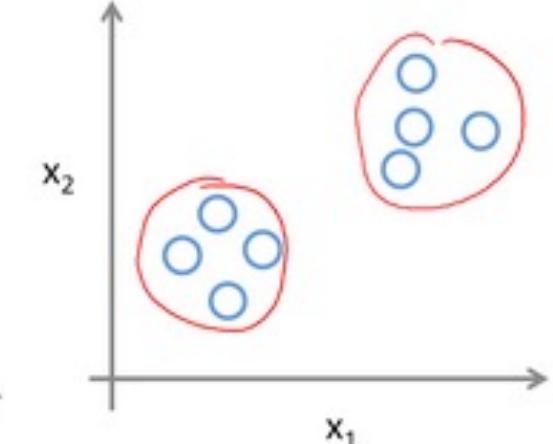


## Unsupervised Learning

No labels

e.g. clustering, data reconstruction

Unsupervised Learning



## Semi-supervised Learning

Some labeled data, and some unlabeled data

**Transductive learning:** unlabeled data is the testing data

**Inductive learning:** unlabeled data is not the testing data

**Reinforcement learning:** labels are the reward/punishment

# 3 Key Components of Machine Learning

## 1. Data

- Without labels: a data point ( $x$ ), a dataset ( $X$ )
- With labels: a pair of data ( $x, y$ ), a dataset ( $X, Y$ )

## 2. Model

- **Model**: the high-level concept, a function (input, output)
- **Loss function** (objective function) : the goal of machine learning
- **Parameters**: the variables to be learned/estimated

## 3. Optimization algorithm

- The algorithm to minimize the loss function (or maximize the objective function)

# **Examples (regression)**

- 1. Linear regression**
- 2. Linear regression with L1 regularization (LASSO regression)**
- 3. Linear regression with L2 regularization (ridge regression)**

# **Examples (classification)**

## **1. Logistic regression**

## **2. Logistic regression with L1 regularization**

The usefulness of L1 is that it can push feature coefficients to 0, creating a method for feature selection.

# Machine learning is everywhere.



ChatGPT 3.5 ▾



You

How to design a syllabus for an undergraduate-level course in machine learning

After the ML course, you will still do **NOT** know how to do these.

Please do not be frustrated.

You are a big step towards them.

(You just need learn more courses, and do research



Autonomous Vehicles



Image processing

- Understand the core concepts and algorithms in machine learning.
- Implement machine learning algorithms from scratch.
- Apply machine learning techniques to real-world datasets.
- Evaluate and interpret machine learning models.

ChatGPT



业余时间，做点科普

B站账号：NCC\_lab



神经计算与控制实验室  
Neural Computing & Control Lab

本科生毕业答辩系列

技术干货

BI  
&  
AI  
课程

**Intelligent Medical Engineering 智能医学工程导论**

- Lecture 3 – Artificial General Intelligence (AGI) & cognitive function  
Quanying Liu (刘泉影)  
SUSTech, BME department  
Email: liuyq@sustech.edu.cn  
BME811201 Spring term, 2023  
01:41:45
- Intelligent Medical Engineering 智能医学工程导论**
- Lecture 2 - Convolutional Neural Networks (CNN)  
Quanying Liu (刘泉影)  
SUSTech, BME department  
Email: liuyq@sustech.edu.cn  
IEB112001 Spring term, 2023  
01:54:33
- Relationship between structure and function**
- Brain structure (T1, T2, DTI images) ↔ Brain functional dynamics (~ $10^{11}$  neurons, ~10<sup>3</sup> brain regions)
- fMRI
- 01:51:41
- Examples**
- 中文版 Google Translate chatGPT
- Training and testing TFCNN on a variety of subjects allows for a more robust model. This is also an interesting application of transfer learning. TFCNN is trained for identifying differences in brain activity, but can also be used for other applications such as predicting personality based on brain activity.
- 03:27

**合集·南方科技大学BME5012《人脑智能与机器智能》课程全集-刘泉影**

18 播放全部 更多 >

- 【BI&AI】 Lecture 1 – Introduction**  
Quanying Liu (刘泉影)  
SUSTech, BME department  
Email: liuyq@sustech.edu.cn  
BME5012, Fall term, 2022  
01:54:32
- 【BI&AI】 Lecture 2 – Visual system**  
Quanying Liu (刘泉影)  
SUSTech, BME department  
Email: liuyq@sustech.edu.cn  
BME5012, Fall term, 2022  
01:52:22
- 【BI&AI】 Lecture 3 – GD & BP & CNN & Hands-on**  
Quanying Liu (刘泉影)  
SUSTech, BME department  
Email: liuyq@sustech.edu.cn  
BME5012, Fall term, 2022  
02:00:29
- 【BI&AI】 Lecture 4 – What do neurons in AI/brain**  
Quanying Liu (刘泉影)  
SUSTech, BME department  
Email: liuyq@sustech.edu.cn  
BME5012, Fall term, 2022  
01:32:45

**基于迁移学习的大脑认知任务相似性分析**

院系: 统计与数据科学系 专业: 统计  
负责人: 高庆远 刘泉影(助理教授)

**南方科技大学-生物医学工程系-神经计算与控制实验室-2019级本科生**

10:53

559 6-3

**生物医学工程系 神经计算与控制实验室**

**基于 MRI 和 fMRI 的脑网络图论分析及其在脑疾病中的应用**

11911436 Yin Mowen  
Instructed by Prof. Quanying Liu

SUSTech 07:25

615 6-3

# One more thing...

Li

You

模型发展如此迅速，我却如此懒惰，如何是好？  
以不变应万变。

Please translate these Chinese sentences into English



ChatGPT

"The models are developing so rapidly, yet I am so lazy. What should I do? Remain unchanged to adapt to everything."

# One more thing...

The models are developing so rapidly, yet I am so lazy to learn these models. What should I do?



ChatGPT

If the models are developing rapidly, but you feel lazy to learn them, you might want to consider taking small steps to overcome your inertia. Here are a few suggestions:

1. **Set achievable goals:** Break down your learning into small, manageable tasks. Start with simpler concepts or models and gradually work your way up to more complex ones.
2. **Create a study schedule:** Allocate specific times in your day or week dedicated to learning. Consistency is key, even if it's just dedicating 20-30 minutes a day.
3. **Find motivation:** Understand why learning these models is important to you. Whether it's for personal growth, career advancement, or a specific project, having a clear motivation can help you stay focused.
4. **Use interactive resources:** Explore interactive tutorials, online courses, or workshops where you can engage with the material in a more dynamic way. This can make learning more enjoyable and less intimidating.
5. **Join a study group:** Connect with peers who are also learning about the same models. Sharing experiences, discussing challenges, and collaborating on projects can provide accountability and support.
6. **Reward yourself:** Set up rewards for reaching milestones in your learning journey. Treat yourself to something you enjoy after completing a challenging concept or finishing a project.
7. **Start with practical applications:** Instead of diving straight into theory, begin with practical applications of the models. Implement them in projects or real-world scenarios to see their impact firsthand, which can make learning more engaging.

Remember, progress is more important than perfection. Even small steps forward can lead to significant growth over time.

AI models are developing so fast that it is basically impossible to learn all models. what should I do?

Given the rapid development of AI models, it's indeed impractical to learn every single model thoroughly. Here's what you can do to navigate this situation:

1. **Focus on fundamentals:** Rather than trying to learn every model, focus on understanding the fundamental concepts and principles that underpin various AI techniques. This includes topics like linear algebra, calculus, probability, and statistics, as well as core concepts in machine learning and deep learning.
2. **Identify key areas of interest:** Explore different areas within AI and identify those that align with your interests, career goals, or specific applications you're interested in. This could be computer vision, natural language processing, reinforcement learning, etc.
3. **Stay updated selectively:** Keep yourself informed about the latest developments in AI, but be selective about the models and techniques you choose to delve deeper into. Prioritize those that are most relevant to your interests and goals.
4. **Emphasize learning frameworks and tools:** Instead of focusing solely on individual models, invest time in learning popular AI frameworks and tools like TensorFlow, PyTorch, scikit-learn, etc. These skills will allow you to adapt to new models and technologies more easily as they emerge.
5. **Hands-on practice:** Engage in practical projects and hands-on exercises to apply your knowledge and gain experience working with different AI models. This will help reinforce your understanding and develop problem-solving skills.
6. **Collaborate and network:** Collaborate with peers, join AI communities, and participate in online forums or meetups where you can exchange ideas, learn from others, and stay updated on the latest trends and developments in AI.
7. **Continual learning:** Understand that learning in the field of AI is a lifelong process. Stay curious, keep exploring new ideas, and be open to continuously updating your skills and knowledge as the field evolves.

By focusing on fundamentals, identifying key areas of interest, and staying updated selectively, you can navigate the rapid pace of AI model development while still building a strong foundation and staying relevant in the field.

## 《庄子·内篇·养生主第三》

吾生也有涯，而知也无涯。

以有涯随无涯，殆已！已而为知者，殆而已矣！

为善无近名，为恶无近刑，缘督以为经，可以保身，  
可以全生，可以养亲，可以尽年。

# 大脑智能与人工智能的融合

<https://www.bilibili.com/video/BV1qL4y1s7V7>