

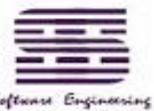
人工智能AI

主讲：余艳玮, ywyu@ustc.edu.cn

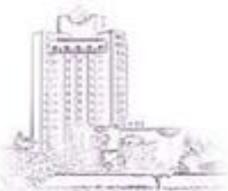
助教：赵振刚, gavin@ustc.edu.cn



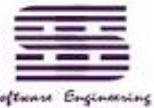
2019/9/10



关于课程教学与考核

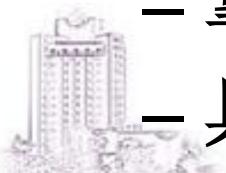


2019/9/11



为什么要开这门课？

- 课程定位（从教师的角度）
 - 培养实际解决问题能力的学生
 - 厚基础：基础知识
 - 重实践：应用驱动，鼓励学生参加**AI**竞赛
 - 宽视野：深度学习部分采用论文带读方式
- 预期的课程收获（从学生的角度）
 - 熟悉**AI**项目开发的通用流程
 - 掌握**AI**项目开发的基本技能
 - 具备开展**AI**算法基础研究的基本能力



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纵横贯通的课程架构

机器学习项目的通用工作流程

多个范例驱动

- 1 定义问题
- 2 获取数据
- 3 研究数据
- 4 准备数据
- 5 研究模型
- 6 微调模型
- 7 展示解决方案
- 8 启动、监视、维护系统

机器学习 -> 深度学习
Scikit-Learn keras

机器学习项目的通用工作流程

- 1 定义问题:** 软件架构设计、确定评价指标
- 2 获取数据:** 自动化方式
- 3 研究数据:** 可视化方式，相关性研究等
- 4 准备数据:** 数据清理、特征选择及处理
- 5 研究模型:** 确定评估方法、列出可能的模型并训练，选择最有希望的3~5个模型
- 6 微调模型:** 寻找最佳超参数，模型融合，评估泛化性能
- 7 展示解决方案:** 将工作进行文档化总结展示
- 8 启动、监视、维护系统:** 投入使用

纵横贯通的课程架构

机器学习项目的通用工作流程

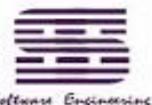
多个范例驱动

- 1 定义问题
- 2 获取数据
- 3 研究数据
- 4 准备数据
- 5 研究模型
- 6 微调模型
- 7 展示解决方案
- 8 启动、监视、维护系统

- ◆ 从机器学习到深度学习：
 - 回归问题，分类问题
 - CNN、RNN、GAN
 - 迁移学习
- ◆ 如何训练模型？（“三步曲”）
- ◆ 如何选择最佳超参数？
- ◆ 如何评估和提升模型泛化性能
- ◆ 欠拟合？过拟合？
 - 怎么判断？怎么解决

机器学习 -> 深度学习

Scikit-Learn keras



课程提纲

- 第一章 绪论（6学时）
- 第二章 端到端的机器学习项目（3学时）
- 第三章 回归（6学时）
- 第四章 分类（3学时）
- 第五章 集成学习（3学时）
- 第六章 神经网络入门（6学时）
- 第七章 神经网络用于计算机视觉（9学时）
- 第八章 神经网络用于文本和序列（6学时）
- 第九章 生成式深度学习（3学时）
- 第十章 深度学习回顾及展望（3学时）

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课程要求

- 编程：
 - **Python**语言
 - 科学基础库：如**Numpy, SciPy, Pandas, Matplotlib**
 - **Scikit-Learn**库：
 - 为机器学习模型和数据处理提供了统一的**API**接口
 - **Keras**库：模型级(**model-level**)
 - 后端引擎： **Tensorflow / Theano/ CNTK.....**
 - 可以认为是深度学习界的**Scikit-Learn**
 - **Tensorflow 2.0**中纳入了**Keras**，即**Tf.keras**
 - 推荐使用**Jupyter**笔记本来运行教材中代码

Installation

功能强大，支持涂鸦

Dependencies

scikit-learn requires:

- Python (>= 3.5)
- NumPy (>= 1.11.0)
- SciPy (>= 0.17.0)
- joblib (>= 0.11)

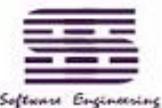
Scikit-Learn库建立在Python科学栈的核心模块（如 Numpy, SciPy, Pandas, Matplotlib）之上

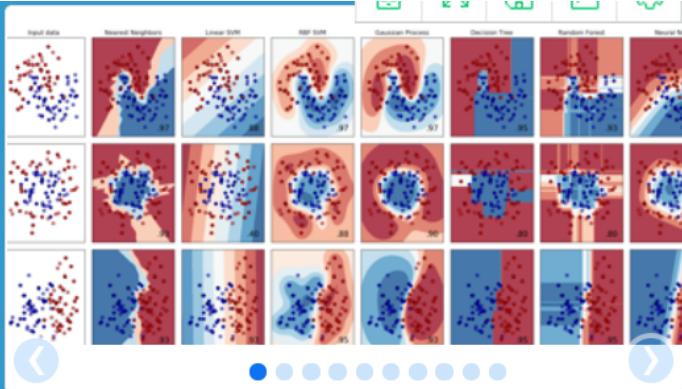
Scikit-learn 0.20 was the last version to support Python 2.7 and Python 3.4. scikit-learn 0.21 and later require Python 3.5 or newer.

Scikit-learn plotting capabilities (i.e., functions start with "plot_" and classes end with "Display") require Matplotlib (>= 1.5.1). For running the examples Matplotlib >= 1.5.1 is required. A few examples require scikit-image >= 0.12.3, a few examples require pandas >= 0.18.0.



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scikit-learn

Machine Learning in Python

- Simple and efficient tools for data mining and data analysis
- Accessible to everybody, and reusable in various contexts
- Built on NumPy, SciPy, and matplotlib
- Open source, commercially usable - BSD license

Classification

Identifying to which category an object belongs to.

Applications: Spam detection, Image recognition.

Algorithms: SVM, nearest neighbors, random forest, ...

— Examples

Regression

Predicting a continuous-valued attribute associated with an object.

Applications: Drug response, Stock prices.

Algorithms: SVR, ridge regression, Lasso, ...

— Examples

Clustering

Automatic grouping of similar objects into sets.

Applications: Customer segmentation, Grouping experiment outcomes

Algorithms: k-Means, spectral clustering, mean-shift, ...

— Examples

Dimensionality reduction

Reducing the number of random variables to consider.

Applications: Visualization, Increased efficiency

Algorithms: PCA, feature selection, non-negative matrix factorization.

— Examples

Model selection

Comparing, validating and choosing parameters and models.

Goal: Improved accuracy via parameter tuning

Modules: grid search, cross validation, metrics.

— Examples

Preprocessing

Feature extraction and normalization.

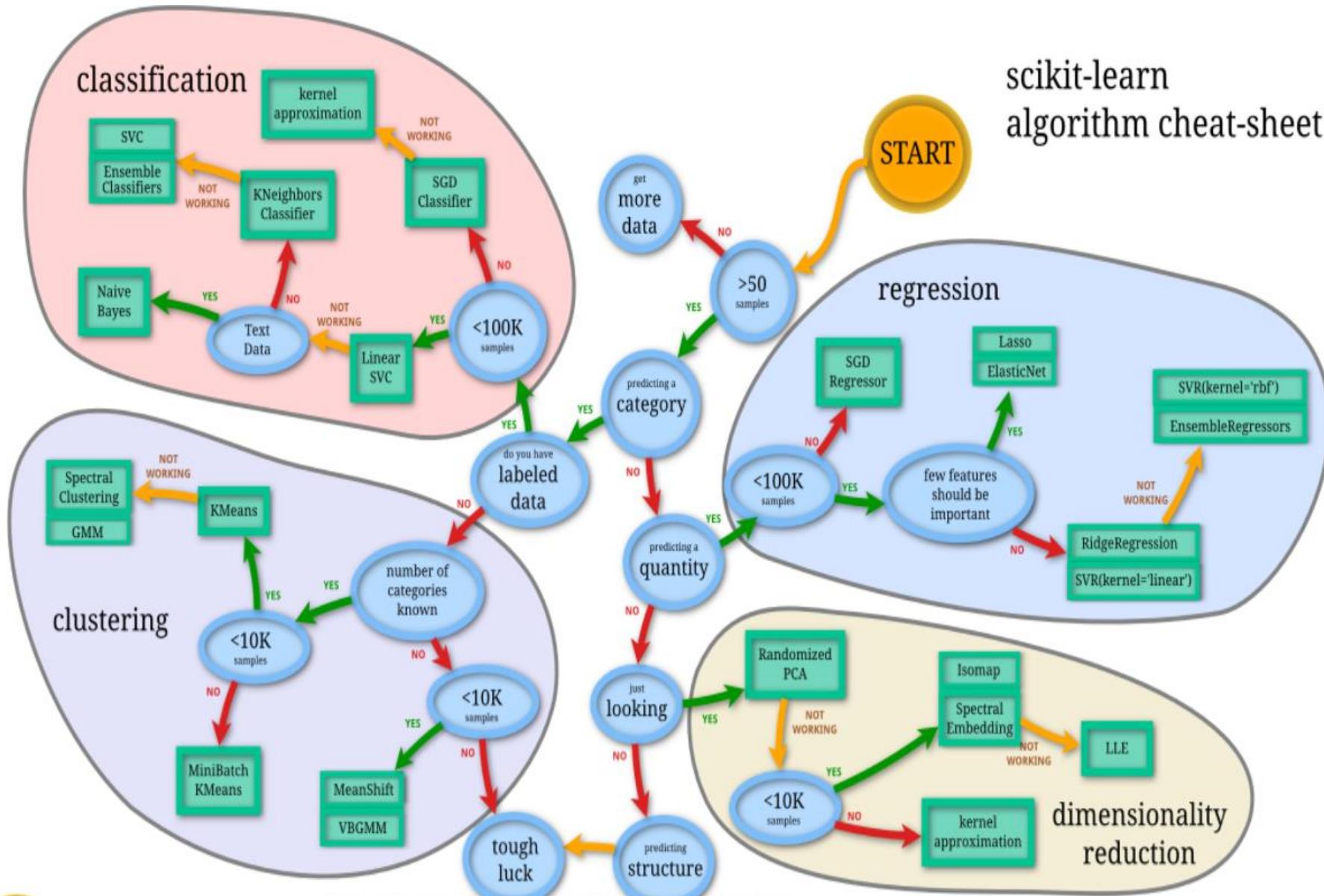
Application: Transforming input data such as text for use with machine learning algorithms.

Modules: preprocessing, feature extraction.

— Examples



scikit-learn
algorithm cheat-sheet



Back

scikit
learn

[https://scikit-learn.org/stable/tutorial/machine learning map/index.html](https://scikit-learn.org/stable/tutorial/machine_learning_map/index.html)

Tensorflow2.0—架构

TRAINING

Read & Process Data

Tf.data, feature columns

TensorFlow
Hub

Premade
Estimator

Tf.keras

Distribution Strategy

CPU

GPU

TPU

DEPLOYMENT

Tensorflow Serving

Cloud, on-prem

Tensorflow Lite

Android, iOS, Raspberry Pi

Tensorflow.js

Browser and Node Server

Other Language Bindings

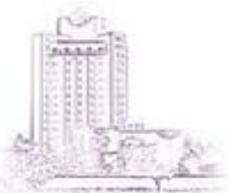
C, Java, Go, C#, Rust, R, ...

Saved Model

考核方式

- 最终成绩由以下组成：（**末尾淘汰8%**）
 - 作业： **10%**
 - 晚1天交，成绩9折；晚3天交，成绩8折；超过3天，不接受。
 - **4次实验： 20% （Python, Tensorflow, Keras）**
 - **Project（组队）： 20%**
 - 3人一组
 - 期中考试： 调研报告， **10%**
 - 期末考试： 半开卷， **40%**
 - **加分：**
 - 小助教： 实验课上帮助学生完成编程， 额外奖励**+1分/次**
 - 优秀实验/作业的分享（**2分**）
 - **扣分：** 随机抽查考勤， 缺勤一次扣一分。

第一章 绪论



2019/9/10



1 人工智能

2 机器学习

3 深度学习



2019/9/10

1 人工智能

1.1 无处不在的AI

1.2 什么是AI?

1.3 三次AI热潮

1.4 三类AI从业者

1.5 AI关键技术及发展趋势

1.6 AI相关的争议性话题

1.7 跟上AI领域的最新进展



人工智能标准化白皮书
(2018 版)

指导单位：国家标准化管理委员会工业二部

编写单位：中国电子技术标准化研究院
二零一八年一月

1.1 无处不在的AI





微软小冰为代表的智能助理类应用



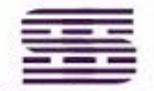
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用谷歌照片检索出所有海鸥照片和视频



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Prisma在一只猫的照片基础上完成特定风格的画作



美图秀秀的手绘自拍功能，秒变小鲜肉

新一代搜索引擎

Google

who killed dumbledore

ALL NEWS VIDEOS IMAGES MAPS

en.wikipedia.org

Snape

“Dumbledore, already aware that **Voldemort** had set **Draco** the task of killing Dumbledore, and now aware that the curse had given him at most another year of life, then arranged with **Snape** that **Snape** was to kill Dumbledore when the time came, presumably when **Draco Malfoy** failed.”

Muggles' Guide to Harry Potter/Major Events/Dumbledore's Death - ...
Wikibooks › wiki › Dumbledore's_Death

2019/9/10

向Google提问并直接得到答案

机器翻译

••••• 中国移动 上午10:15 77%

中文



英语

🔊 中文



记得微软小冰吗？手机上最喜闻乐见的人工智
能助理之一。与其他人工智能助理应用相比，
小冰的语音识别能力，语音合成技术，基于大
语料库的自然语言对话引擎，都有着非常独
到，可圈可点的地方。

Jídé wēiruǎn xiǎo bīng ma? Shǒujī shàng zuì xǐwé...



🔊 英语



Remember Microsoft's Little Ice? One of the
most loved AI assistants on the phone.
Compared with other artificial intelligence
assistant applications, Xiaobing's speech
recognition ability, speech synthesis
technology and large-scale corpus-based
natural language dialogue engine all have a
very unique and remarkable place.

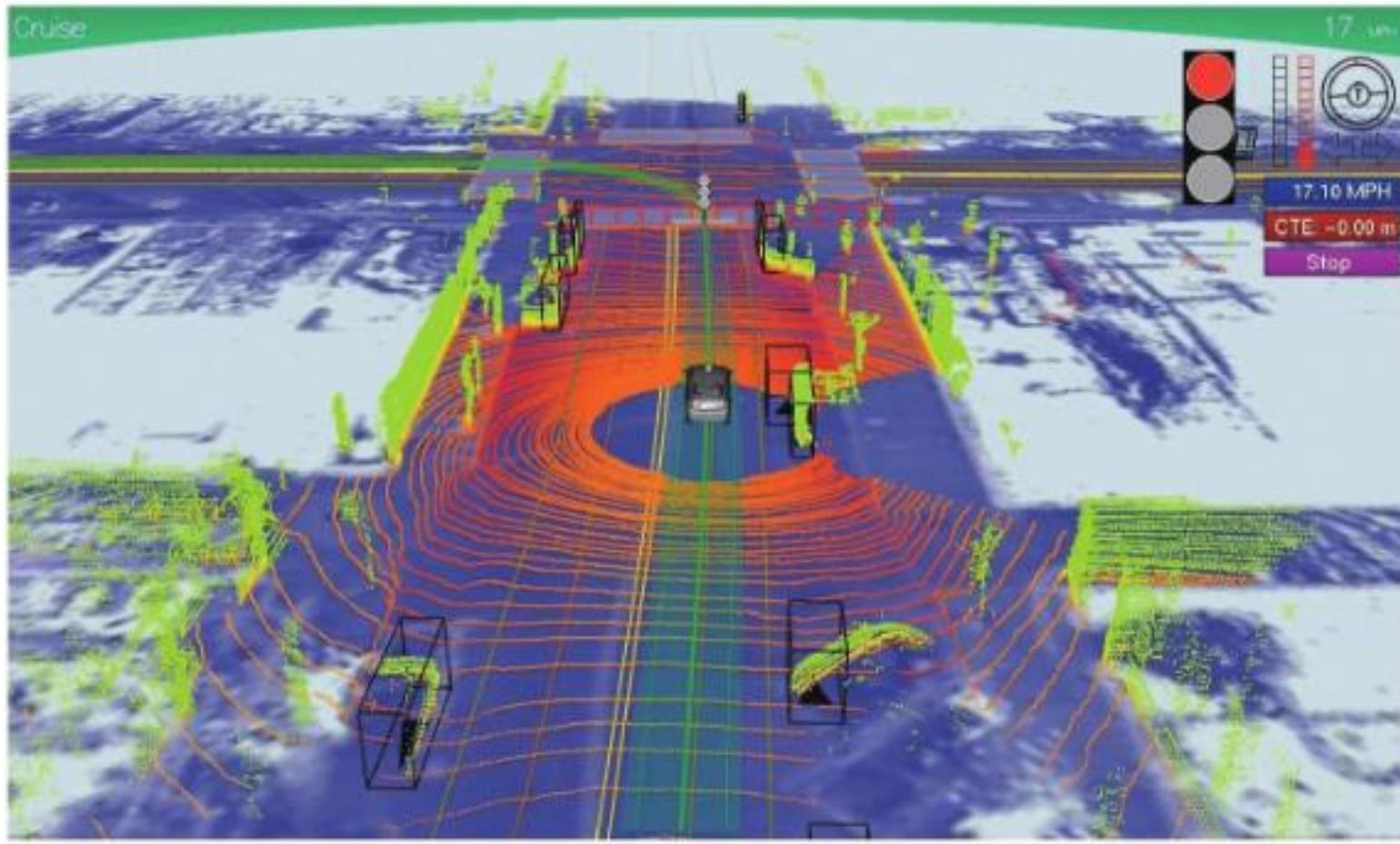


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Google翻译的中译英效果

中国科学技术大学软件学院 School of Software Engineering of USTC

无人驾驶



自动驾驶汽车的AI算法通过传感器
“看到”的实时路面情况

机器人



图13 亚马逊橙黄色的仓储机器人

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机器人



图14 DHL用于递送快递包裹的无人机



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机器人



图15 Starship Technologies的智能机器人

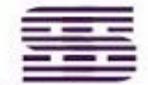
机器人



图16 奇幻工房的教育机器人达奇



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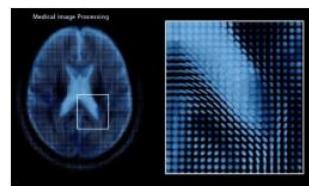
Self-driving



Surveillance detection



Translation



Medical diagnostics



Game



Personal assistant

Deep Learning

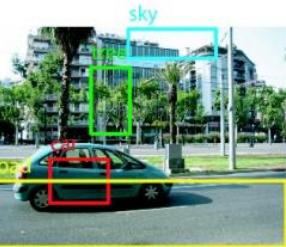
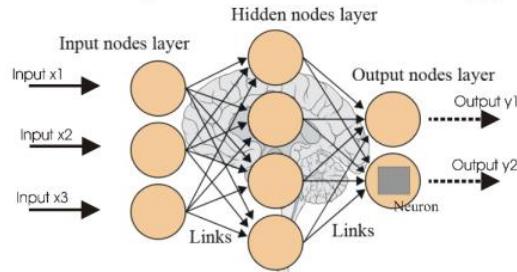


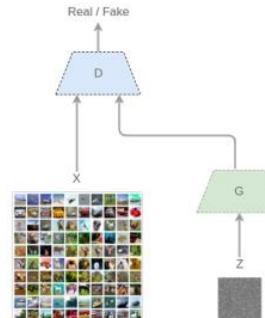
Image recognition



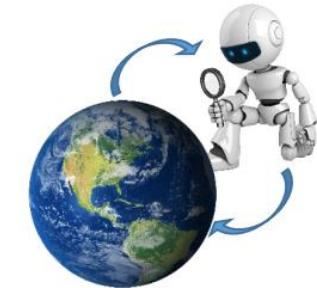
Speech recognition



Natural language



Generative model



Reinforcement learning

来自：微软亚洲研究院 周礼栋《大数据系统的演化：理论、实践和展望》报告

1.2 什么是AI?

- 人工智能就是机器展现出的智能。即只要是某种机器，具有某种或某些“智能”的特征或表现，都应该算作“人工智能”。
——维基百科
- 人工智能是数字计算机或者数字计算机控制的机器人在执行智能生物体才有的一些任务上的能力。——大英百科全书
- 人工智能是“研究、开发用于模拟、延伸和扩展人的智能的理论、方法、技术及应用系统的一门新的技术科学”，将其视为计算机科学的一个分支，指出其研究包括机器人、语言识别、图像识别、自然语言处理和专家系统等。——百度百科
- 人工智能是利用数字计算机或者数字计算机控制的机器模拟、延伸和扩展人的智能，感知环境、获取知识并使用知识获得最佳结果的理论、方法、技术及应用系统。——《人工智能标准化白皮书》2018版

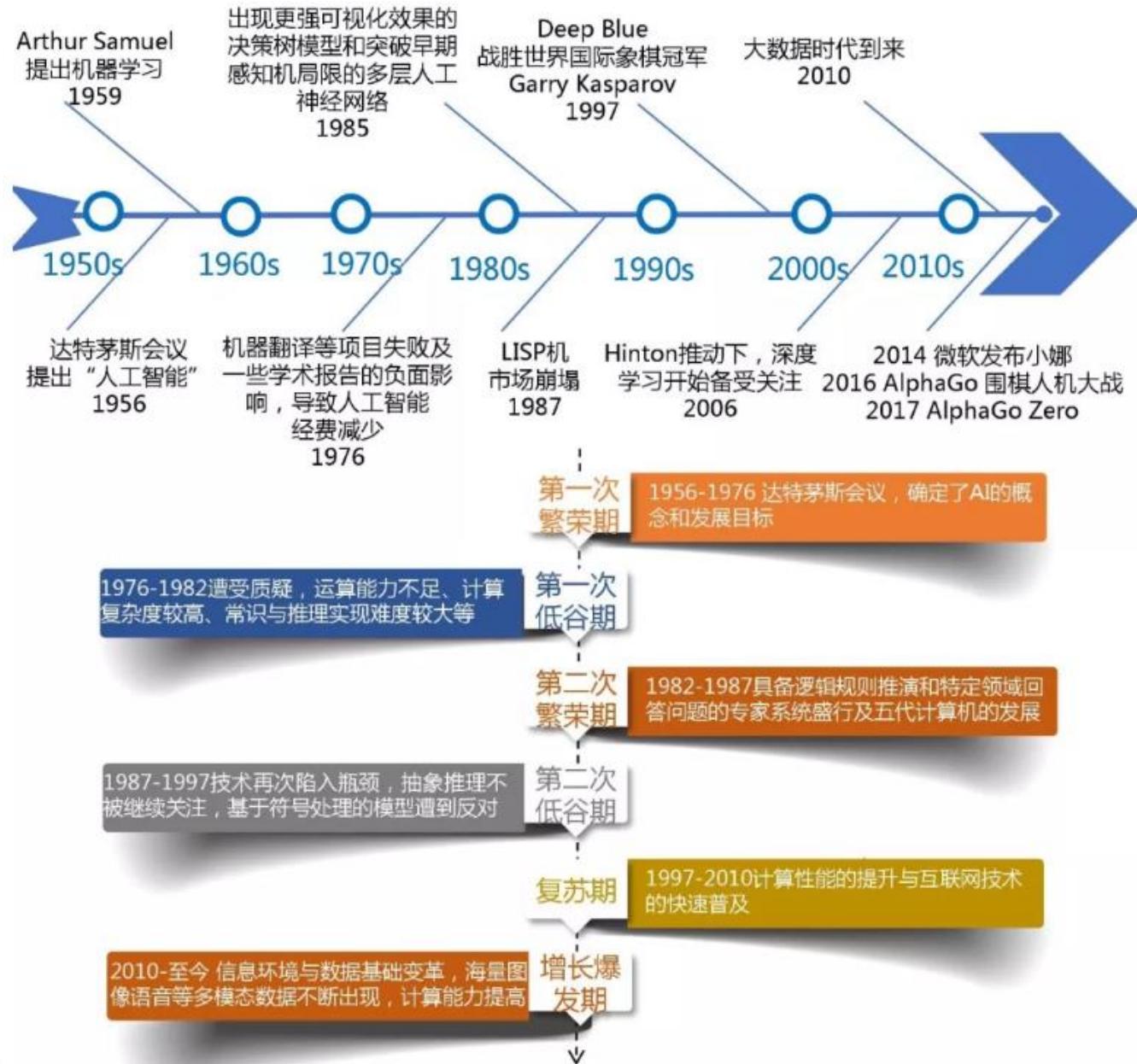


1.3 三次AI热潮

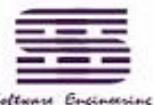
- 1962, IBM, 西洋跳棋
- 1997, IBM Deep Blue, 国际象棋
- 2016, Google AlphaGo, 围棋



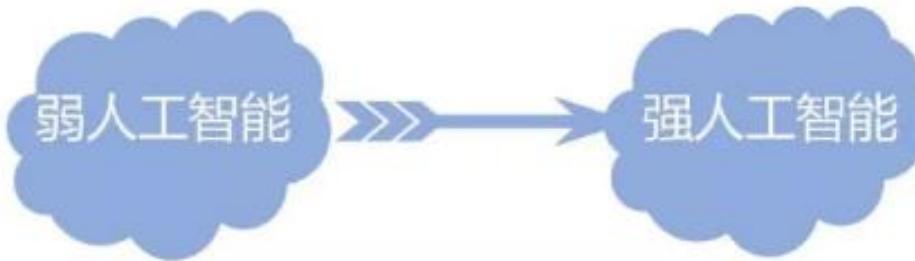
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目前发展情况

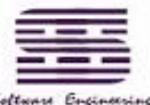


- ① 至今为止的人工智能系统都还是实现特定功能的专用智能，即目前主流研究仍然集中于弱人工智能，弱人工智能的研究已经取得了显著进步，如语音识别、图像处理和物体分割、机器翻译等方面取得了重大突破，甚至可以接近或超越人类水平。
- ② 强人工智能当前鲜有进展，美国私营部门的专家及国家科技委员会比较支持的观点是，至少在未来几十年内难以实现。

有自我意识



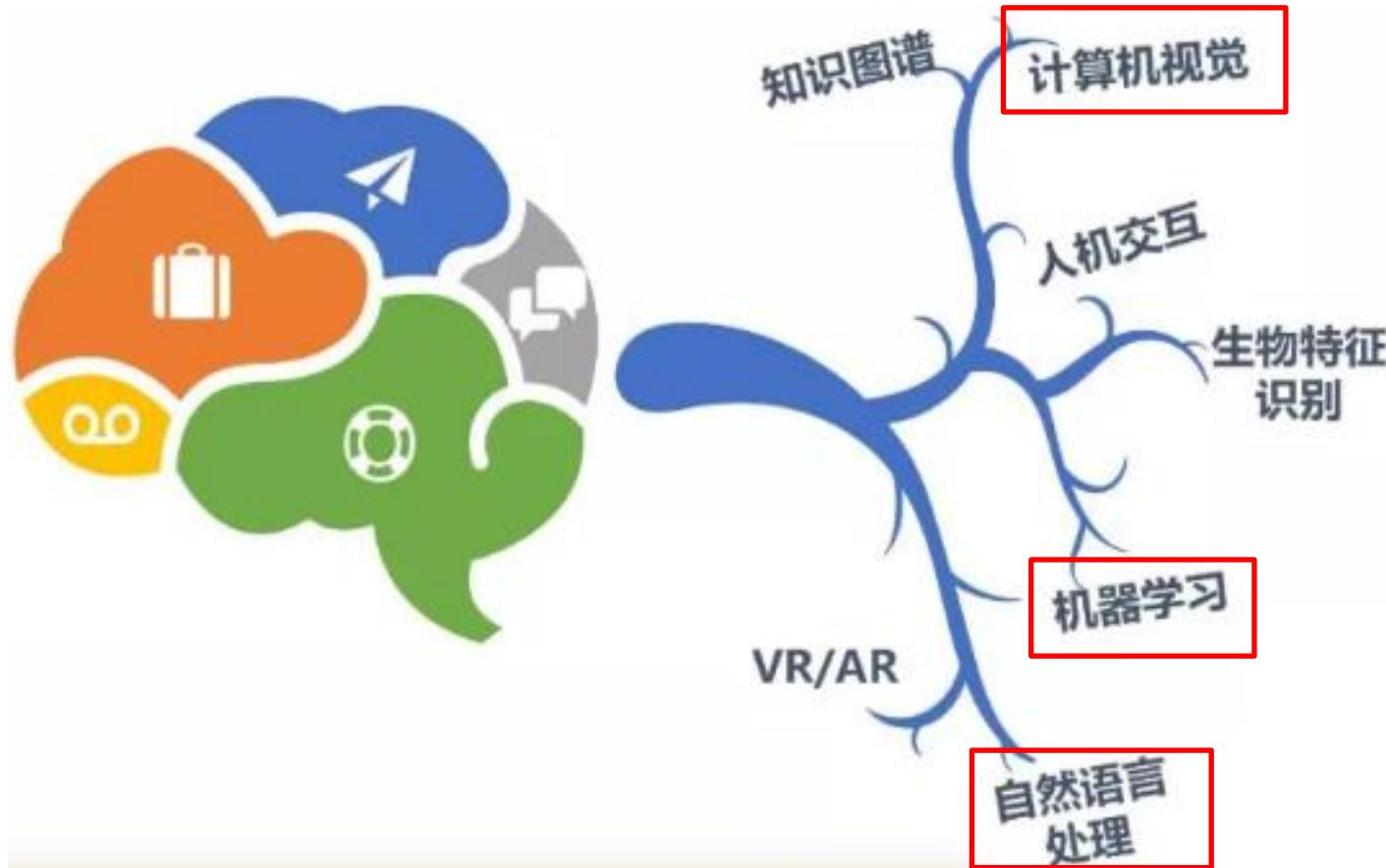
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1.4 三类AI从业者

- 学术研究者
 - 从理论上诠释机器学习的各个方面，试图找出“这样设计模型/参数为什么效果更好”，并且为其他从业者提供更优秀的模型
- ✓ 算法改进者
 - 改进现有的经典模型（根据经验或者一些灵感）
- ✓ 工业实现者
 - 掌握经典模型的结构、原理、特点和其实现
 - 能针对具体问题，选择适合的模型并做调整

1.5 AI关键技术及发展趋势



2019/9/10

技术发展趋势

技术平台开源化：开源学习框架提高开发效率，可扩大技术规模，整合技术和应用，有效布局人工智能全产业链

开源平台

专用智能向通用智能过渡：目前主要集中在专用智能方面，具有领域局限性。通用人工智能提高处理任务的普适性，将是未来的发展方向

通用智能

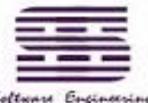
智能感知向智能认知方向迈进：当前大数据时代的人工智能是感知智能。随着类脑科技的发展，人工智能必然向认知智能时代迈进。

智能认知

人工智能标准化总体组 4



2019/9/10



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1.6 AI相关的争议性话题

- 奇点来临：AI威胁论
- AI会让人类大量失业吗？
- AI是万能的吗？



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1.7 跟上AI领域的最新进展

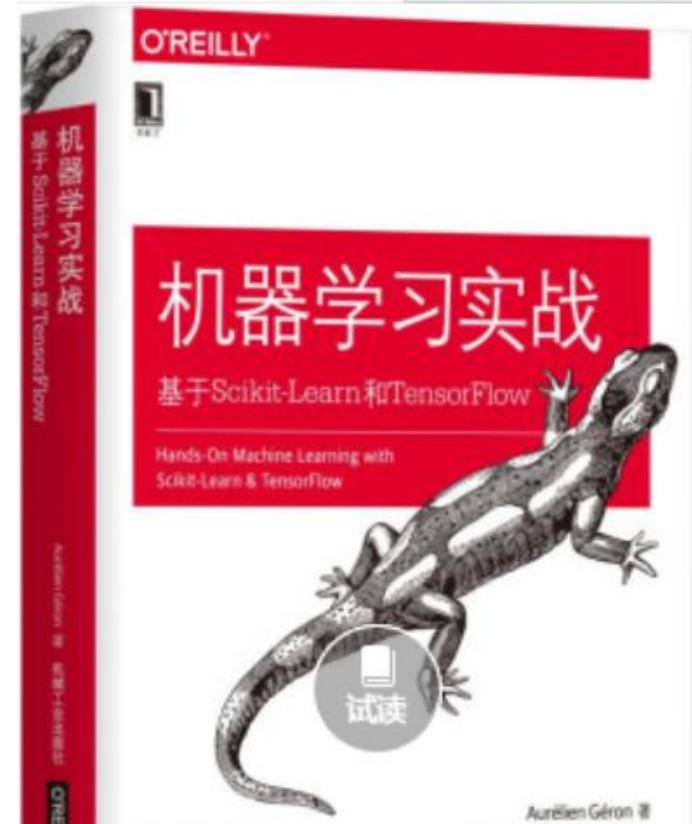
- 关注Kaggle比赛中的题目：<https://www.kaggle.com/>
 - <https://github.com/apacheCN/Interview>
 - 梯度提升机(Gradient Boosting Machine): XGBoost库：<https://xgboost.apacheCN.org/#/>
 - 深度学习：Keras库
- 在arXiv阅读最新论文进展
 - 利用辅助网站”arXiv Sanity Preserver”跟踪最新进展，筛选出最新高质量的重要论文
 - 使用谷歌学术(Google Scholar)来跟踪某学者的论文动态

1.7 跟上AI领域的最新进展

- 探索**Keras**生态系统：
 - 有大量教程、指南和相关开源项目
 - Keras博客: <https://blog.keras.io>
 - Keras的在线文档: <https://keras.io>
 - Keras的源代码: <https://github.com/keras-team/keras>
 - Keras的Slack频道:
<https://kerasteam.slack.com>

2 机器学习

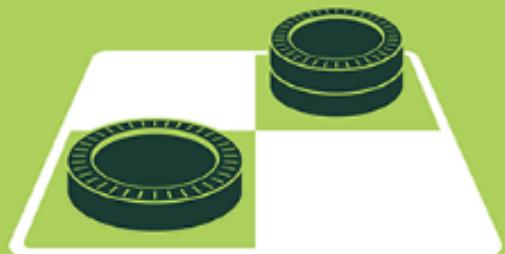
- 什么是机器学习？
- 为什么要用机器学习？
- 机器如何学习？
- 机器学习的学习路线图
- 机器学习的主要挑战
- 机器学习中的关键术语



教材代码：<https://github.com/ageron/handson-ml>

ARTIFICIAL INTELLIGENCE

Early artificial intelligence stirs excitement.



1950's

1960's

1970's

1980's

1990's

2000's

2010's

人工智能

MACHINE LEARNING

Machine learning begins to flourish.



机器学习

DEEP LEARNING

Deep learning breakthroughs drive AI boom.



深度学习

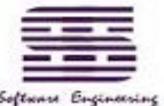
Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

思考.....

- 生物的智能从何而来?
 - 先天的本能?
 - 后天的学习?
- 机器 vs. 生物
 - 能否让机器也用类似的方式具有智能?
 - **Traditional Programs vs. Machine Learning Approaches**



2019/9/10



生物的本能



- 河狸筑水坝的能力是天生的
 - If “听到流水声”，筑水坝直到听不到流水声；
- 生物学家Lars Wilsson
 - 用扬声器播放流水声
 - 把扬声器放在水泥墙里，河狸就会用泥巴和树枝糊住墙
 - 如果把扬声器放在平地上，河狸就会把它盖住



2019/9/10



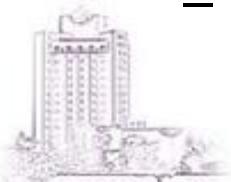
Software Engineering

43

人类设定好的天生本能

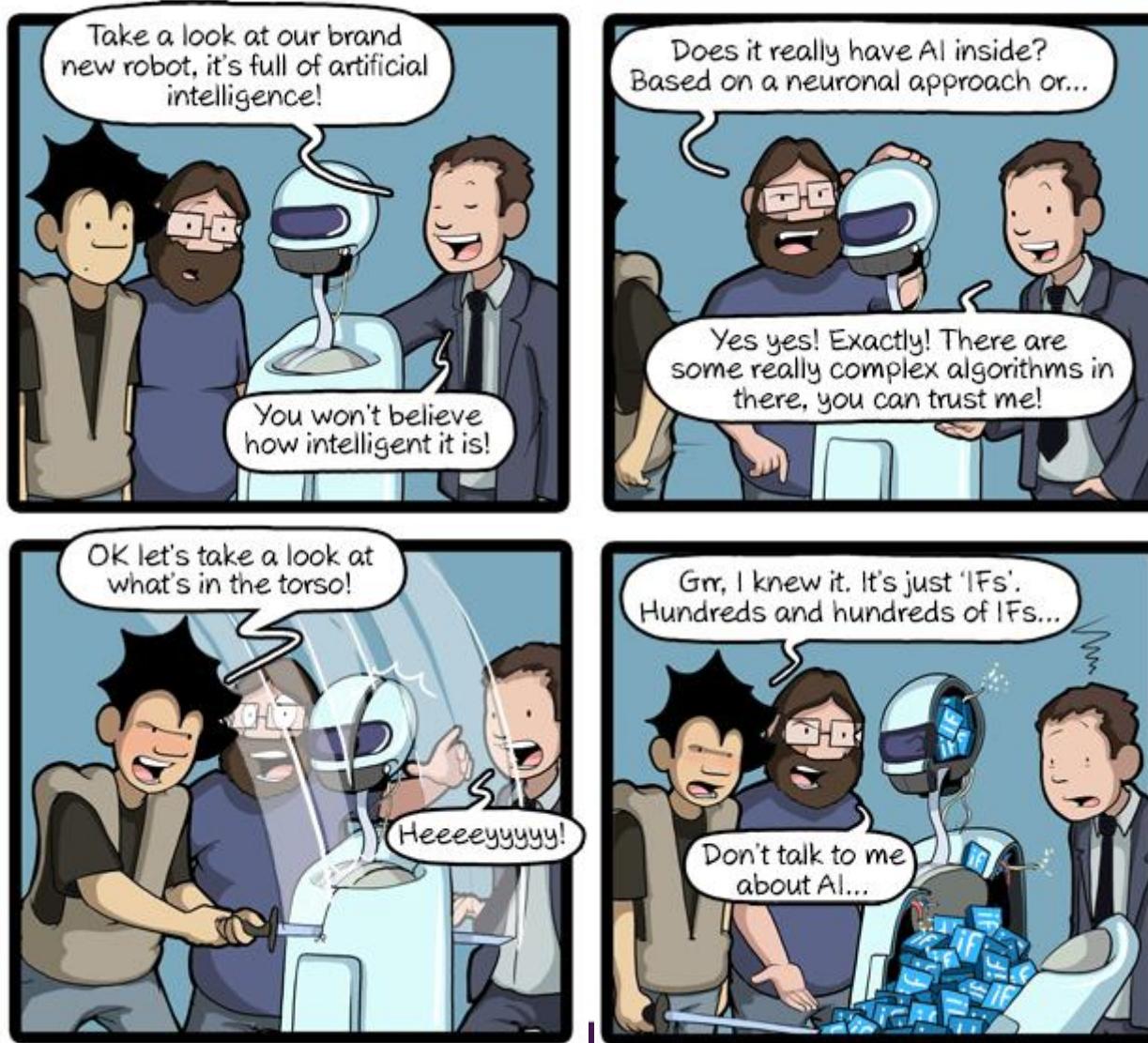


- E.g. You want to build a Chat-bot ...
 - If there is “turn off” in the input, then “turn off the music”. (hand-crafted rules)
 - You can say “Please turn off the music” or “Can you turn off the music?”. Smart?
 - What if someone says “Please don’t turn off the music”
- Weakness of hand-crafted rules
 - Hard to consider all possibilities
 - 永远无法超越创造者
 - Lots of human efforts (not suitable for small industry)



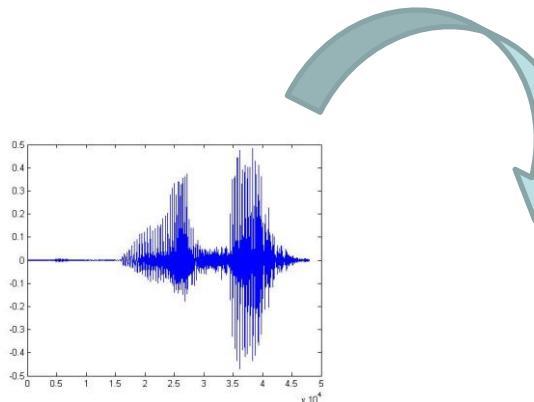
人类设定好的天生本能

AI?

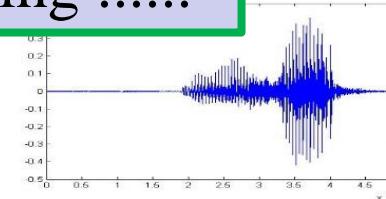


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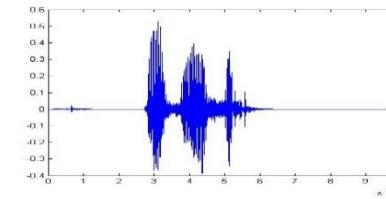
Learning Speech Recognition



Learning

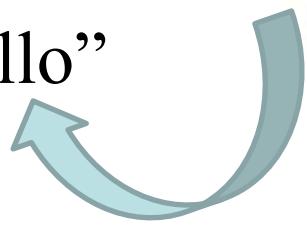


“Hi”

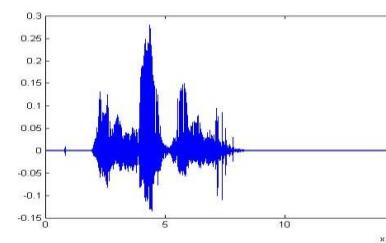


“How are you”

You said “Hello”

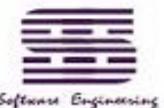


You write the program
for learning.

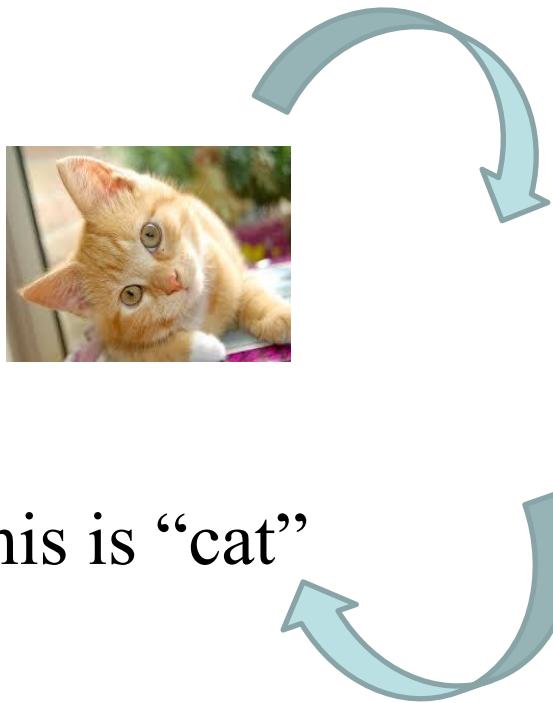


“Good bye”

A large amount of
audio data



Learning Image Recognition



This is “cat”

Learning



“monkey”



“cat”



“dog”

A large amount of
images



You write the program
for learning.



Traditional Programs



Programs can do the things you ask them to do

Program for Solving Tasks

Task: predicting positive or negative given a product review

“I love this product!” “It claims too much.” “It’s a little expensive.”

↓
program.py

+

if input contains “love”, “like”, etc.
output = positive

↓
program.py

-

if input contains “too much”, “bad”, etc.
output = negative

↓
program.py

?

Some tasks are complex, and we don't know how to write a program to solve them.



Machine Learning ≈ Looking for a Function

Task: predicting positive or negative given a product review

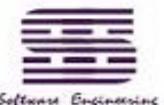
“I love this product!” “It claims too much.” “It’s a little expensive.”

↓ f
+

↓ f
-

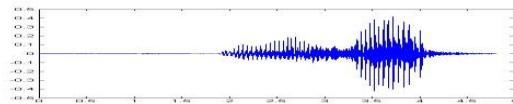
↓ f
?

Given a large amount of data, the machine learns what the function f should be.



Machine Learning ≈ Looking for a Function

- **Speech Recognition**

 $f($  $) = \text{“How are you”}$

- **Image Recognition**

 $f($  $) = \text{“Cat”}$

- **Playing Go**

 $f($  $) = \text{“5-5”}$
(next move)

- **Dialogue System**

 $f($

“Hi”

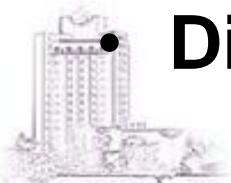
 $) =$

“Hello”



(what the user said)

(system response)

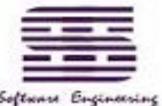


什么是机器学习？

- 更广义的概念：
 - 机器学习是让计算机具有学习的能力，无需进行明确编程。——亚瑟·萨缪尔，1959
- 工程性的概念：
 - 计算机程序利用**经验E**学习**任务T**，性能是**P**，如果针对任务**T**的**性能P**随着**经验E**不断增长，则称为机器学习。——汤姆·米切尔，1997

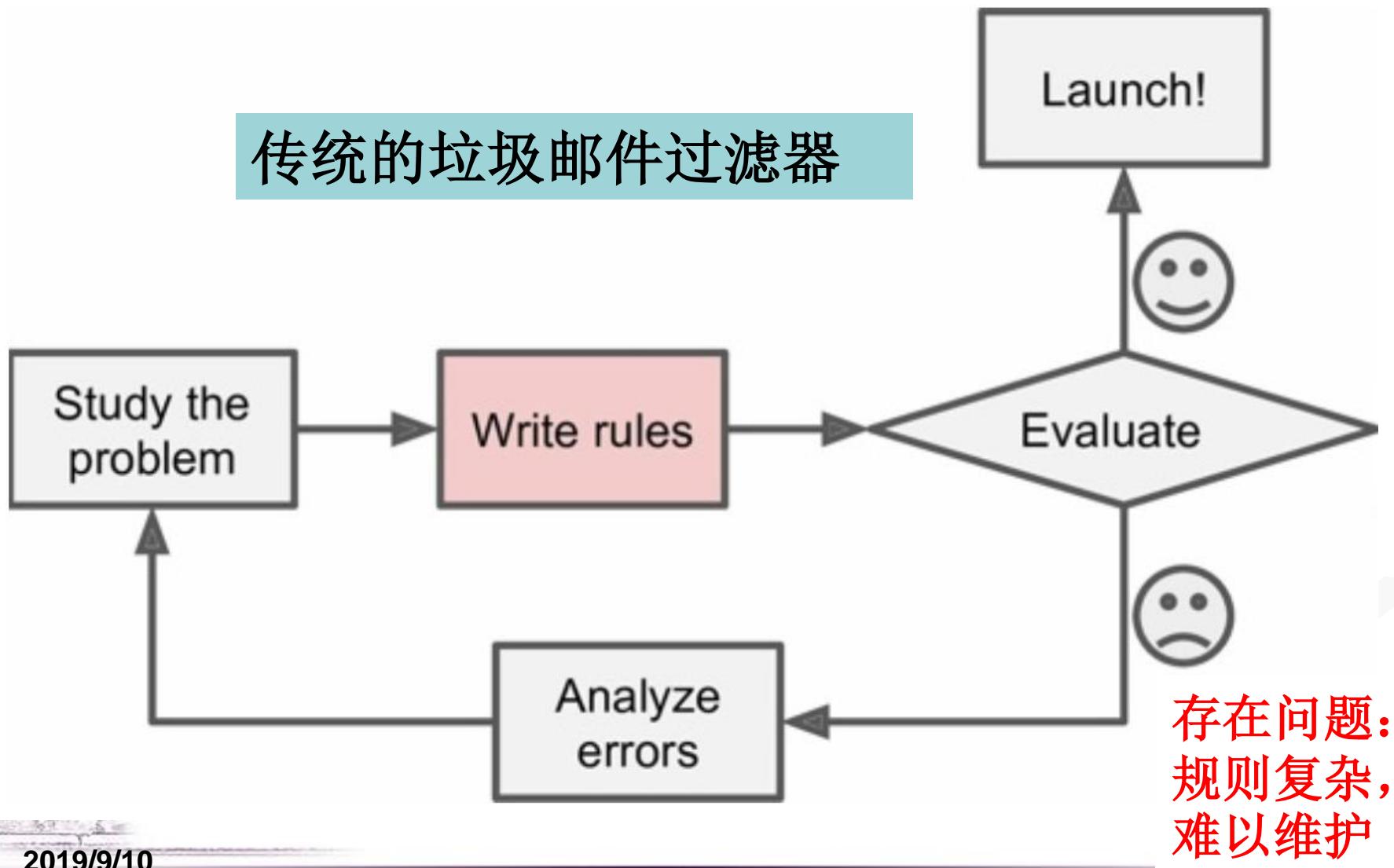


2019/9/10

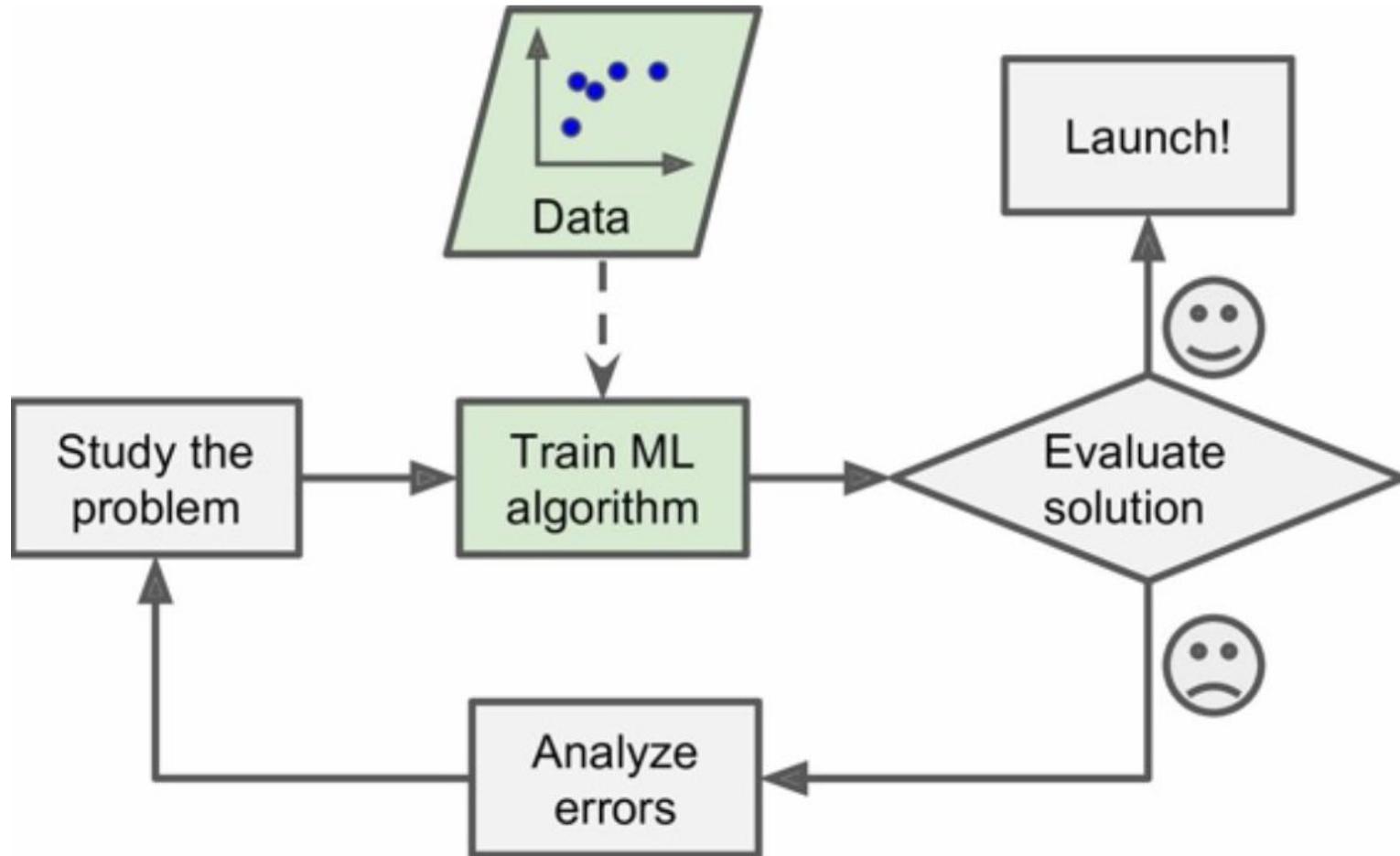


- 什么是任务T、经验E 和性能P? (示例)
 - 例如，你的垃圾邮件过滤器就是一个机器学习程序，它可以根据垃圾邮件（比如，用户标记的垃圾邮件）和普通邮件（非垃圾邮件，也称作**ham**）学习标记垃圾邮件。
 - 用来进行学习的样例称作**训练集**。每个训练样例称作训练实例（或样本）。
 - 在这个例子中，**任务T**就是标记新邮件是否是垃圾邮件，**经验E**是训练数据，**性能P**可以定义为准确率，即正确分类的比例。

为什么使用机器学习？



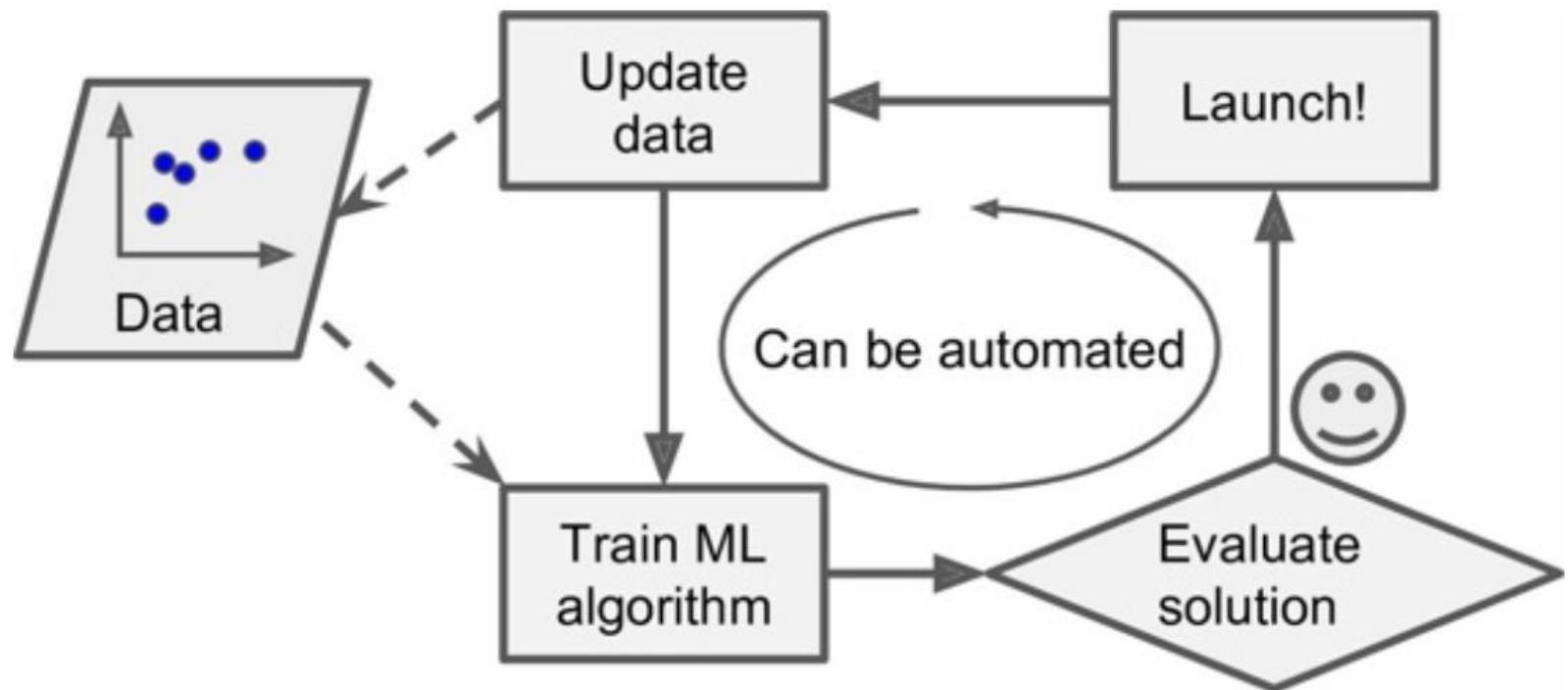
为什么使用机器学习？



基于机器学习的垃圾邮件过滤器

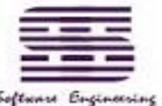
2019/9/10

为什么使用机器学习？



基于机器学习的垃圾邮件过滤器
具有数据的自适应性

2019/9/10



什么场合下需要使用机器学习？

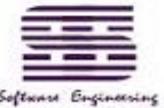
- 需要进行大量手工调整或需要拥有长串规则才能解决的问题：机器学习算法通常可以简化代码、提高性能。
- 问题复杂，传统方法难以解决：最好的机器学习方法可以找到解决方案。
- 环境有波动：机器学习算法可以适应新数据。
- 洞察复杂问题和大量数据。

机器如何学习呢？

- “三步曲”：对给定模型进行训练，找到最佳参数
 - 目标：针对给定模型，找到最佳函数（即找到模型的最佳参数）
 - 模型：可认为是函数的集合。
 - 对于给定模型，若参数的取值不同，将对应不同的函数。
 - 模型训练结果有三种情况：拟合得好、欠拟合 和 过拟合
- 欠拟合和过拟合问题：是什么？如何解决？
- 对给定的问题，可以选择那些模型来进行训练？



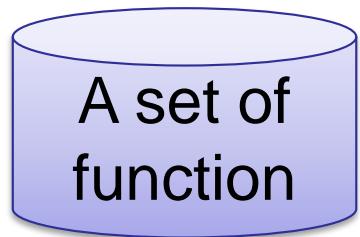
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Framework

Image Recognition:

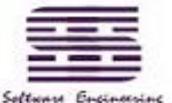
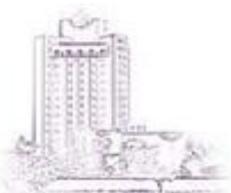
$$f\left(\begin{array}{c} \text{Image of a cat} \end{array} \right) = \text{“cat”}$$



Model

$$f_1\left(\begin{array}{c} \text{Image of a cat} \end{array} \right) = \text{“cat”} \quad f_2\left(\begin{array}{c} \text{Image of a cat} \end{array} \right) = \text{“monkey”}$$

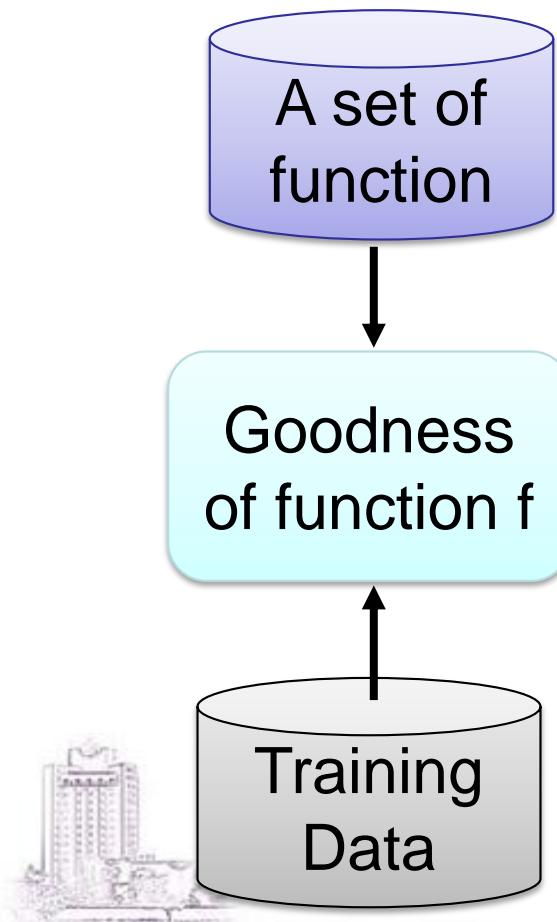
$$f_1\left(\begin{array}{c} \text{Image of a dog} \end{array} \right) = \text{“dog”} \quad f_2\left(\begin{array}{c} \text{Image of a dog} \end{array} \right) = \text{“snake”}$$



Framework

Image Recognition:

$$f(\text{cat}) = \text{"cat"}$$



$$f_1(\text{cat}) = \text{"cat"} \quad f_2(\text{monkey}) = \text{"monkey"}$$

Better!

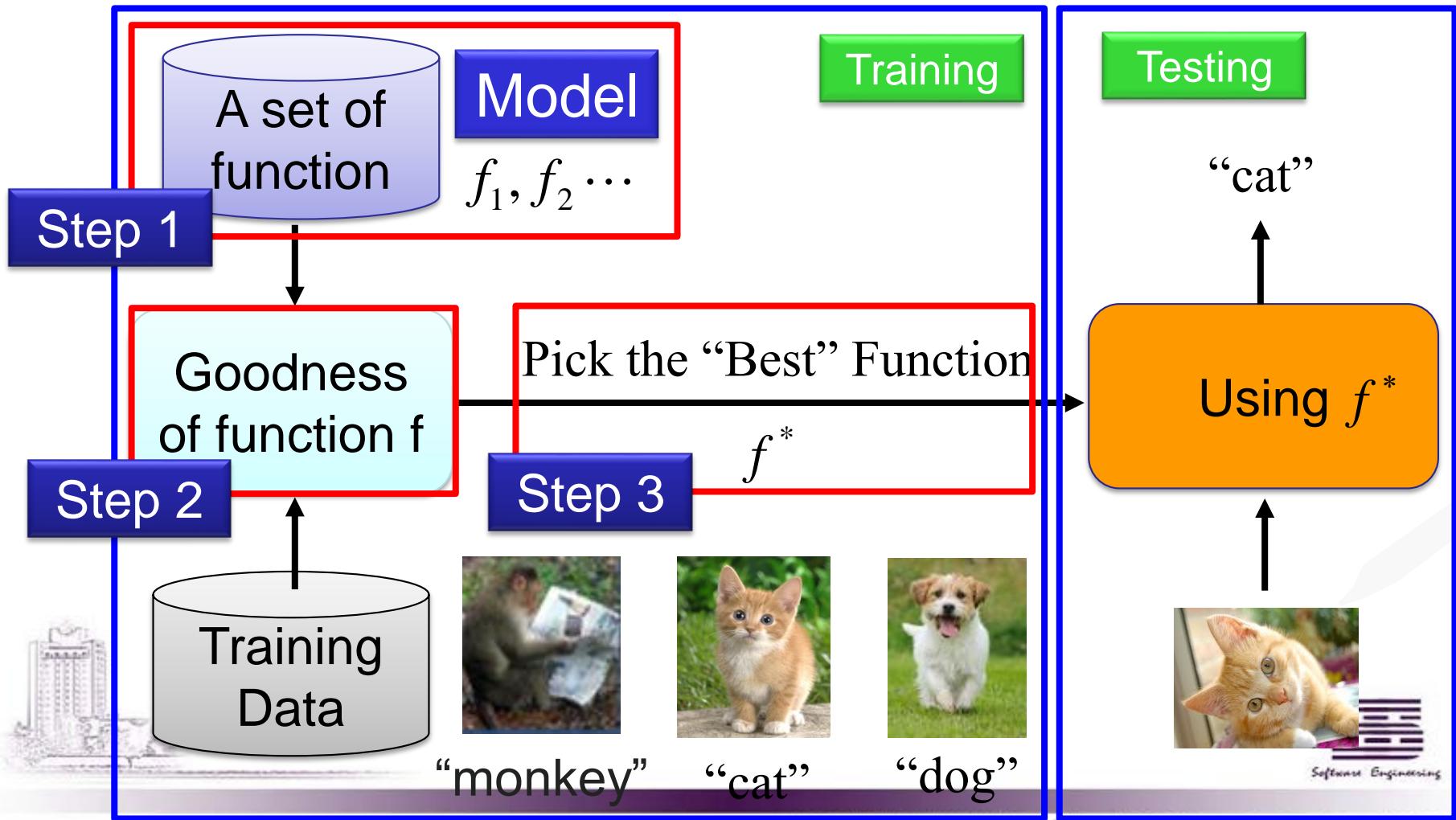
$$f_1(\text{dog}) = \text{"dog"} \quad f_2(\text{snake}) = \text{"snake"}$$



Framework

Image Recognition:

$$f(\text{cat}) = \text{"cat"}$$



Machine Learning is so simple

Step 1:
define a
set of
function

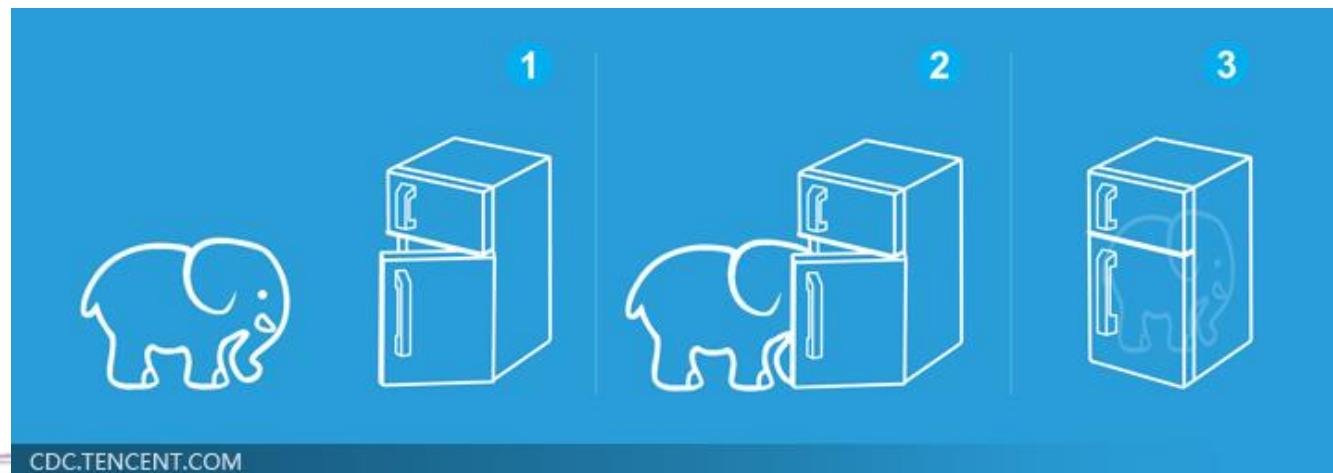


Step 2:
goodness
of function
(evaluated by
Loss Function)



Step 3:
pick the
best
function

就好像把大象放进冰箱



Recipe of Machine Learning



YES

Step 1: define a set
of function

Step 2: goodness of
function

Step 3: pick the best
function

NO

Overfitting!

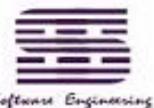
Good Results on
Testing Data?

NO

Underfitting!

Good Results on
Training Data?

the best function f^*



Recipe of Machine Learning



YES

Good Results on
Testing Data?

More data

Regularization

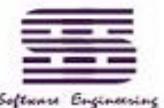
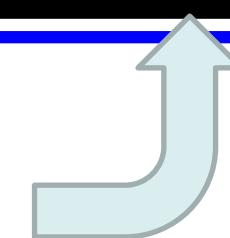
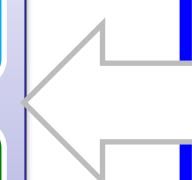


YES

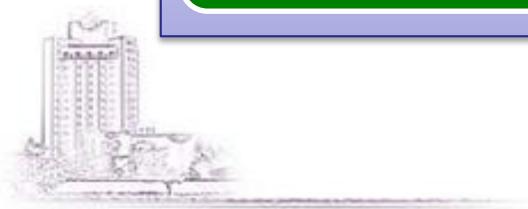
Good Results on
Training Data?

Add more features as input

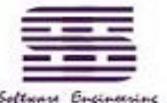
A more complex model



Software Engineering



Learning Map



Learning Map

scenario

Learning Theory

Semi-supervised Learning

Transfer Learning

Unsupervised Learning

Reinforcement Learning

Supervised Learning

Learning Map

scenario

task

Learning Theory

Regression

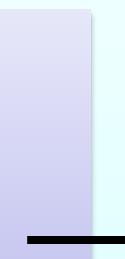
Semi-supervised Learning

Transfer Learning

Unsupervised Learning

Reinforcement Learning

Classification



Structured Learning

Classification

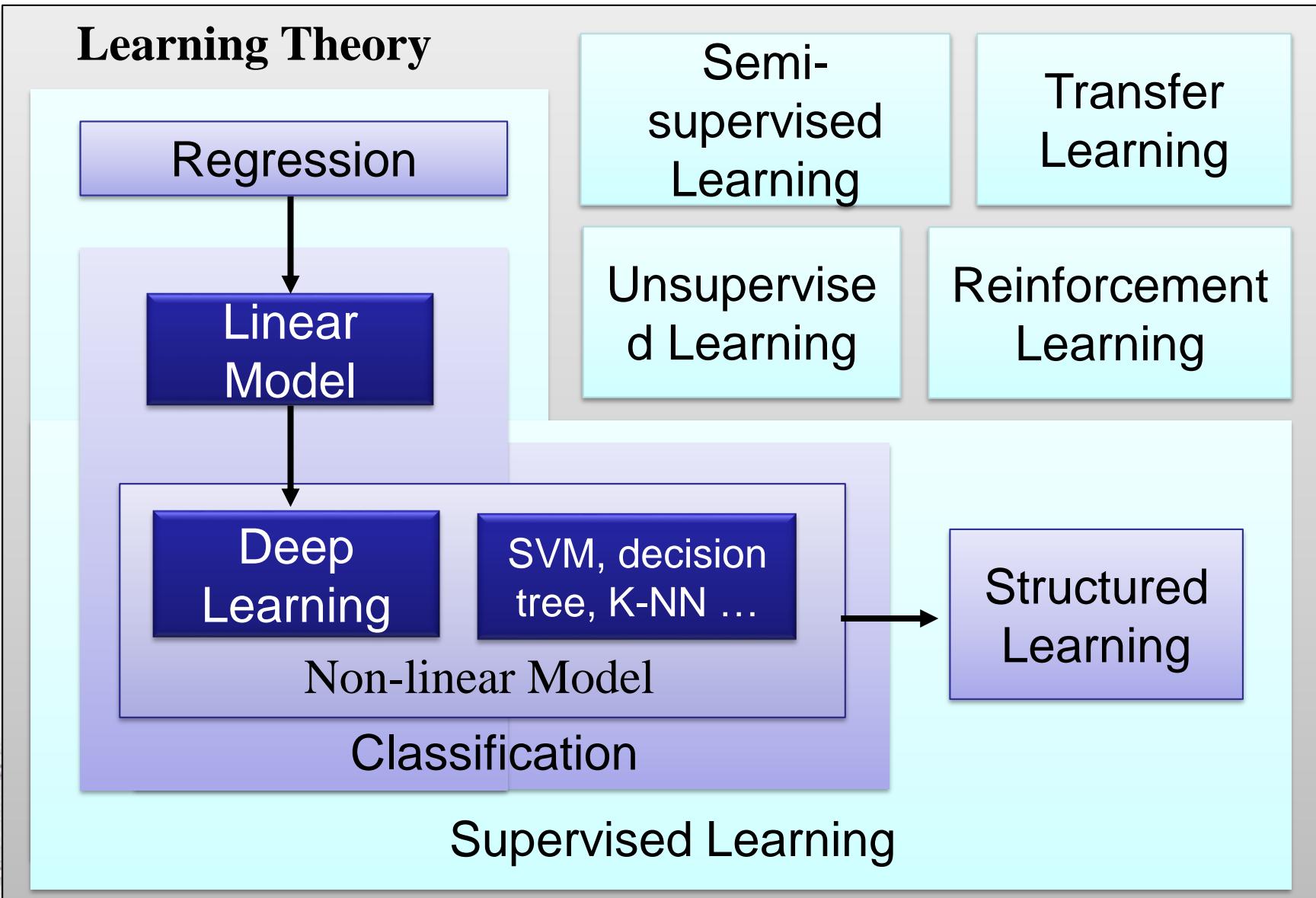
Supervised Learning

Learning Map

scenario

task

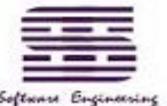
method



- 模型选择的三个维度：
 - Scenario: 数据集是否带标签？是否是强化学习？
 - Task: 要预测的值（即输出值）是否是数值类型？是否连续？
 - Method: 选择的模型



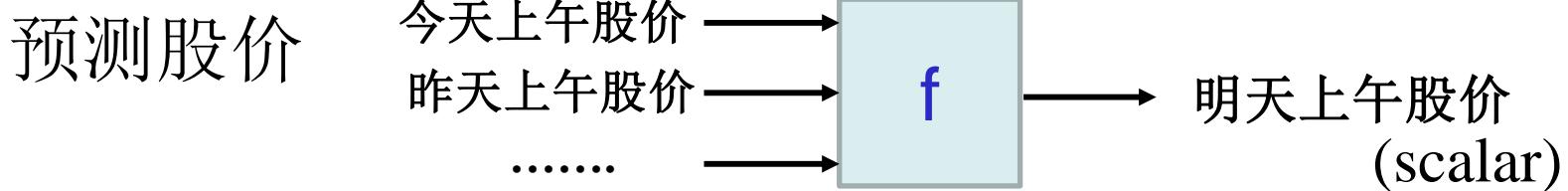
2019/9/10



Learning Map

Regression

The output of the target function f is “scalar”.



Training Data:

Input:

9/01 上午股价=85 9/02 上午股价=80

Output:

9/03 上午 股价 = 100

Input:

9/12 上午 股价=30 9/13 上午 股价 = 25

Output:

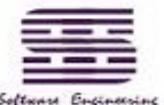
9/14 上午 股价 = 20

Learning Map

Regression

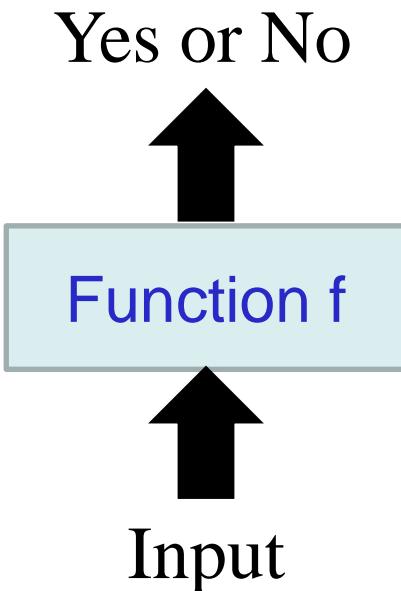


Classification

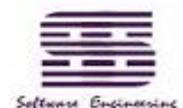
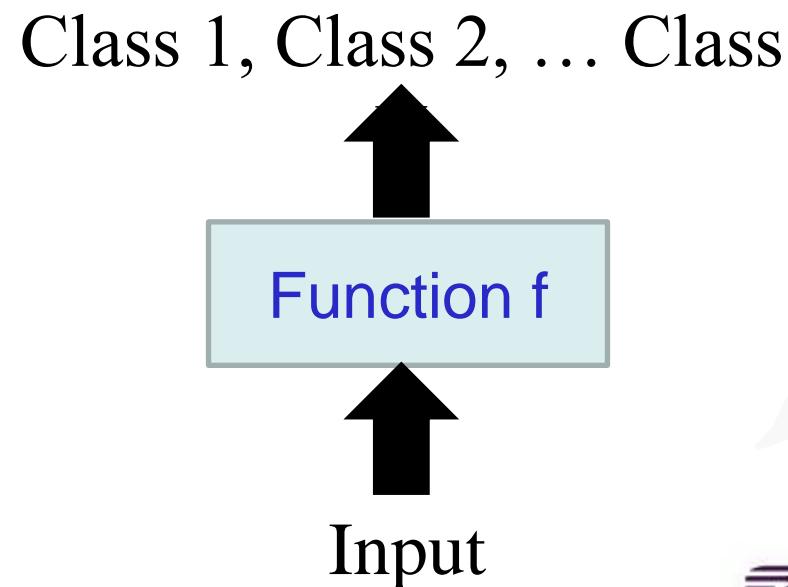


Classification

- **Binary Classification**

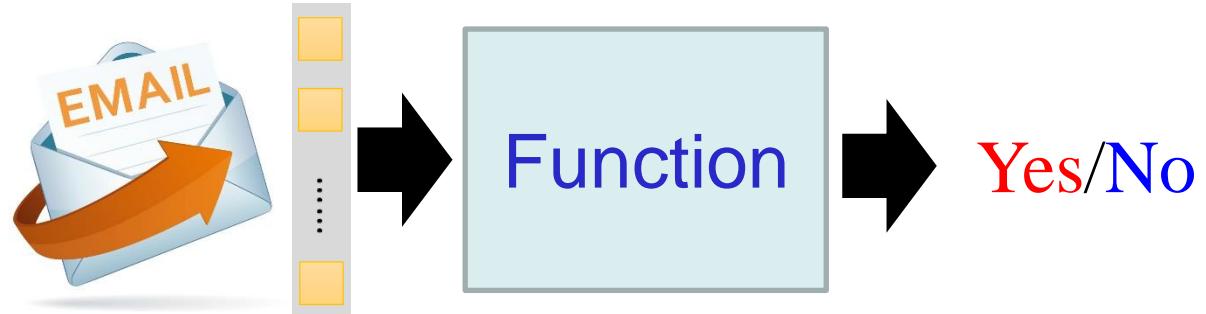


- **Multi-class Classification**

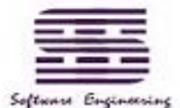


Binary Classification

Spam
filtering

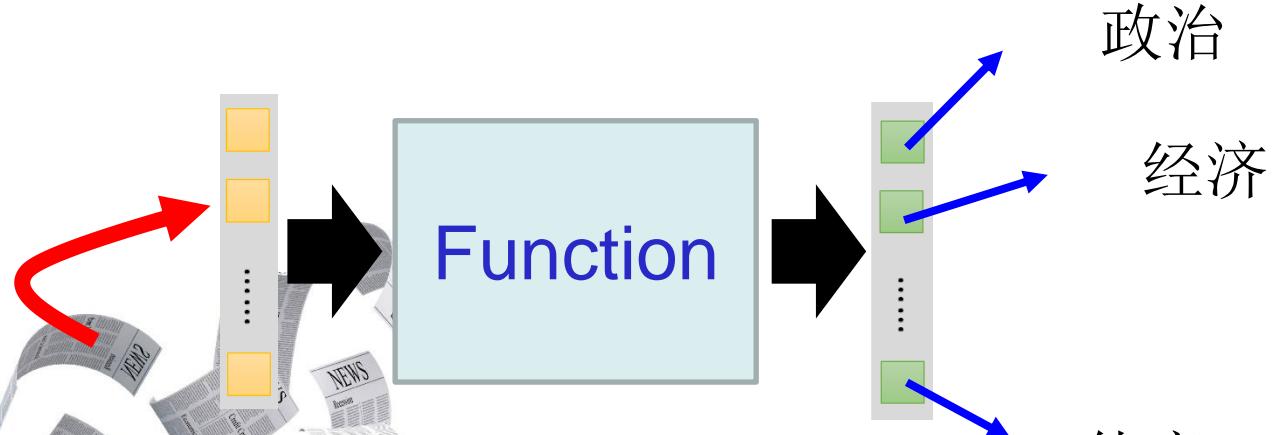


Training
Data

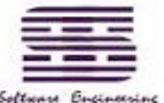
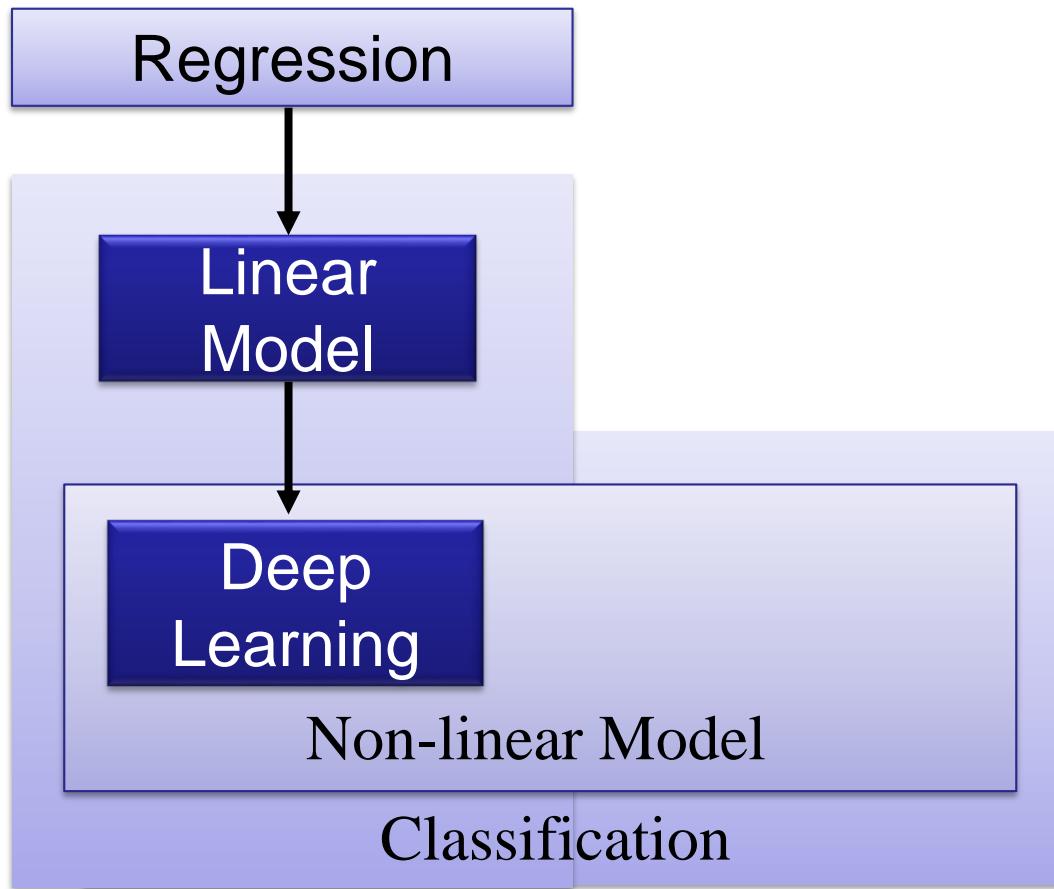


Multi-class Classification

Document Classification

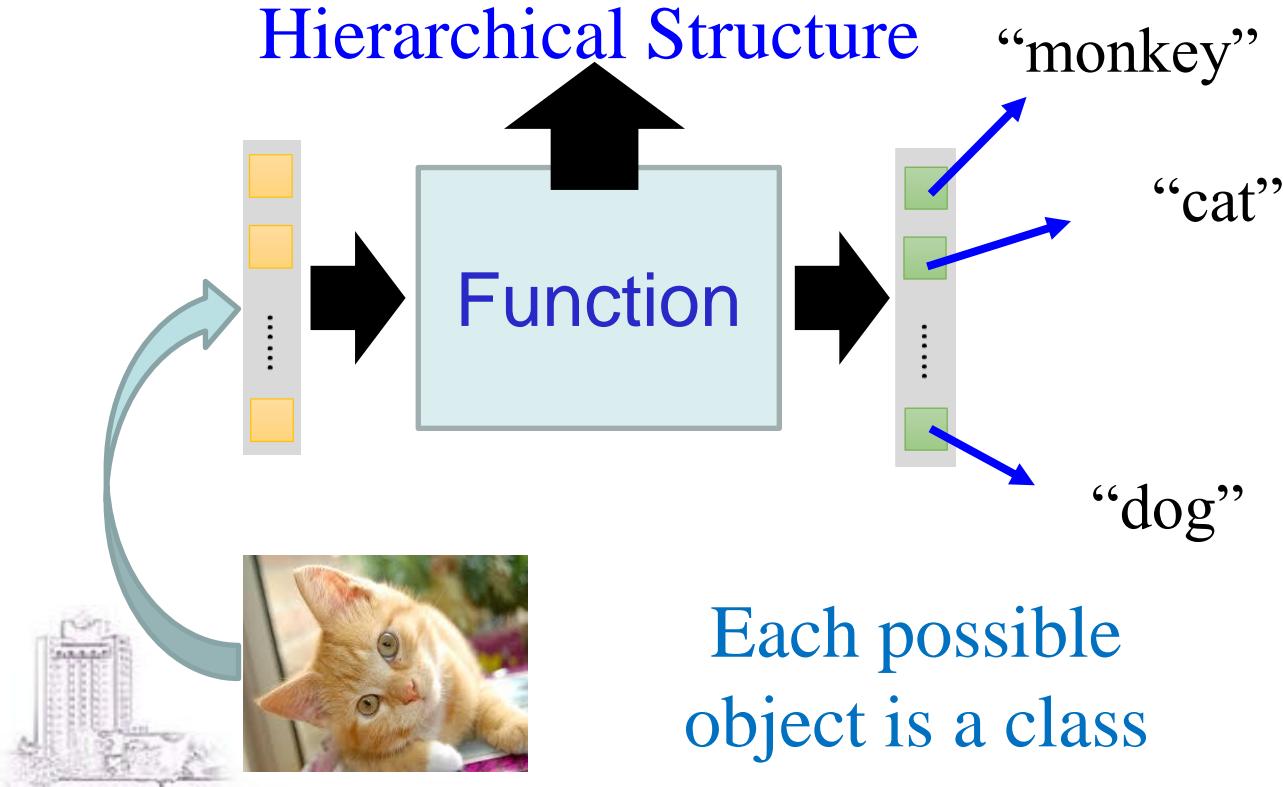


Learning Map

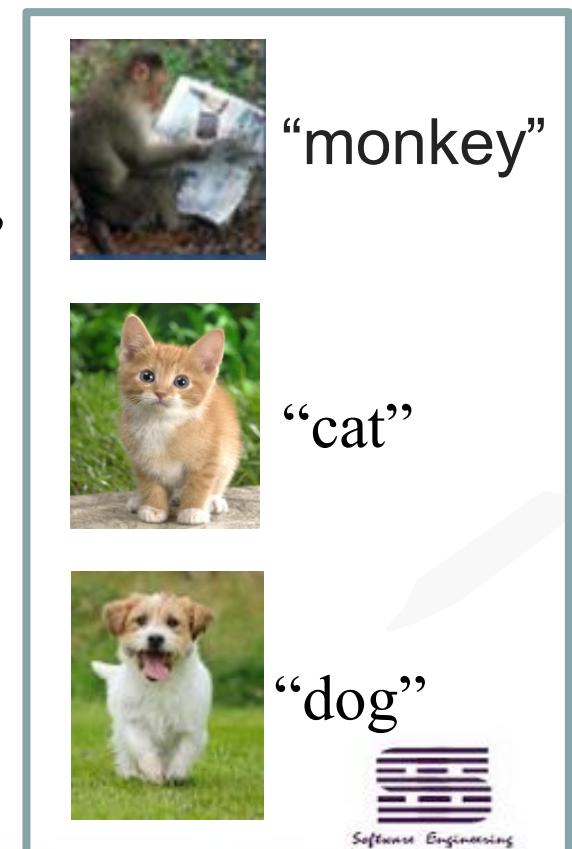


Classification - Deep Learning

- Image Recognition

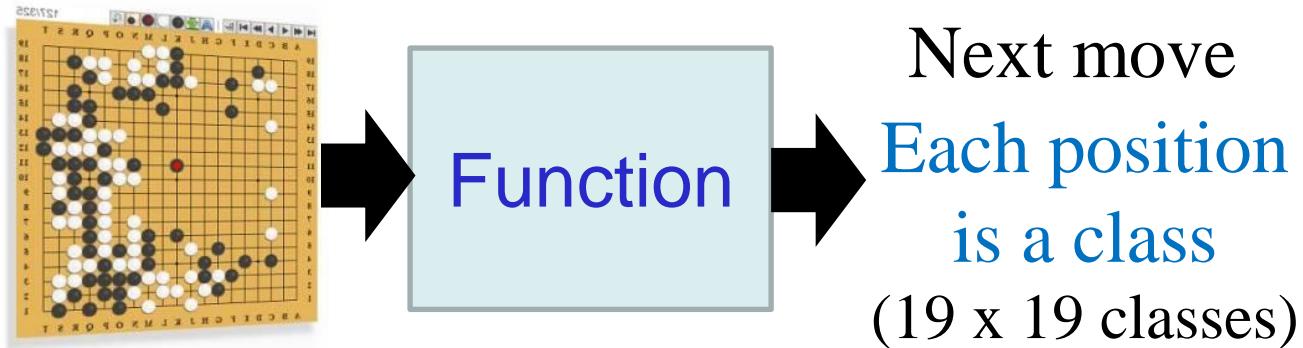


Training Data

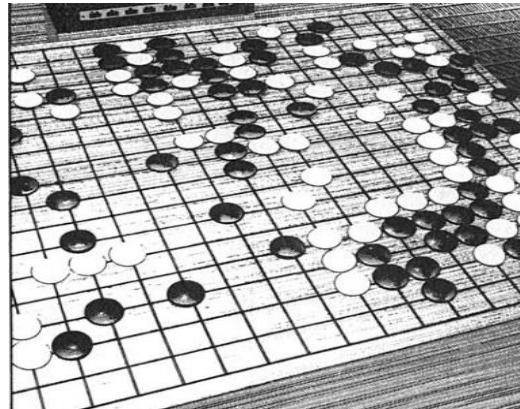


Classification - Deep Learning

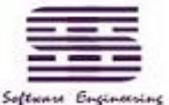
- Playing GO



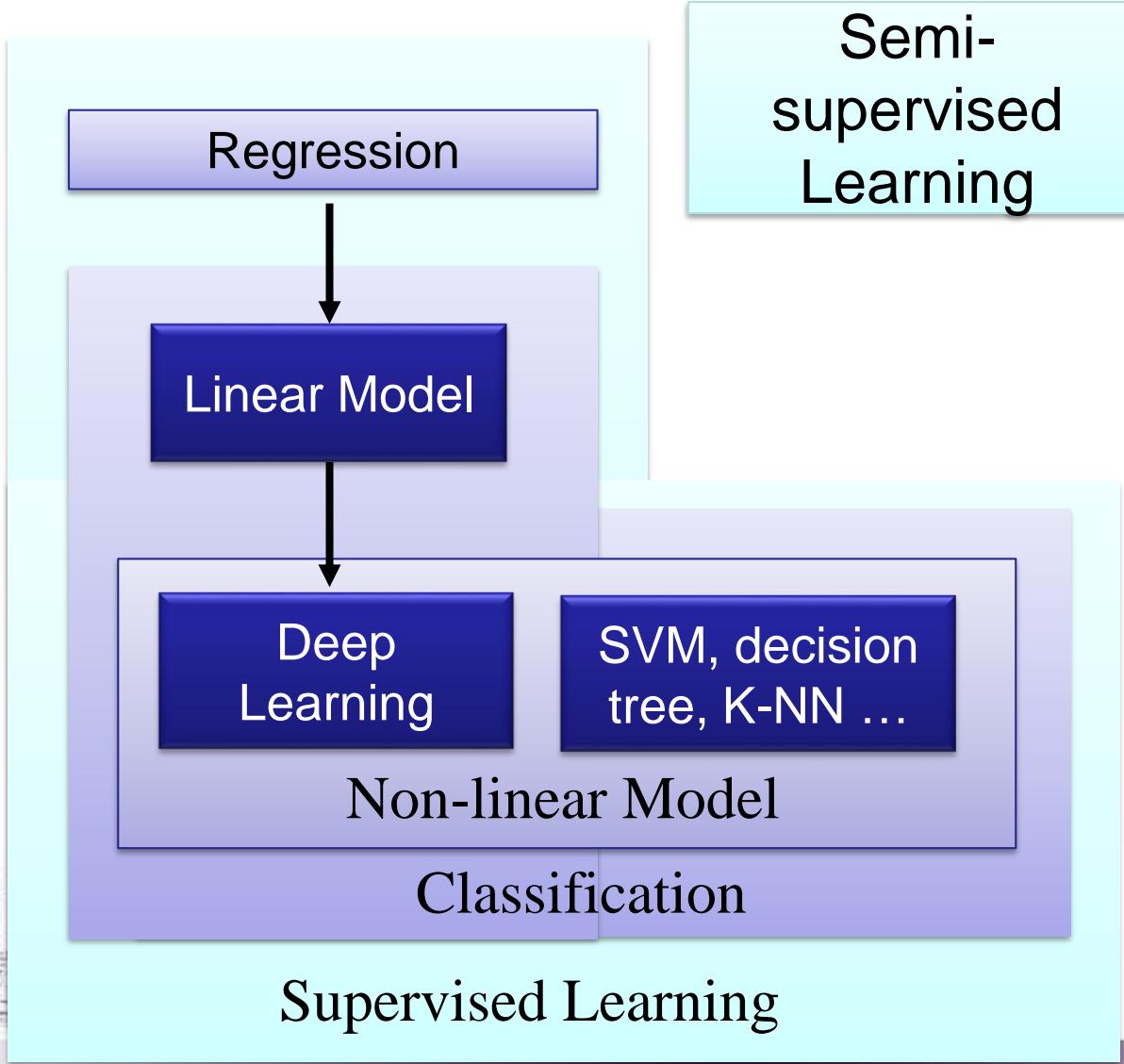
Training Data



一堆棋谱



Learning Map



Hard to collect a large amount of labelled data

Semi-supervised Learning

Training Data:
Input/output pair
of target function

Function output
= label



Semi-supervised Learning

For example, recognizing cats and dogs

Labelled
data



cat

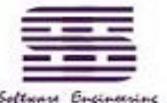


dog

Unlabeled
data

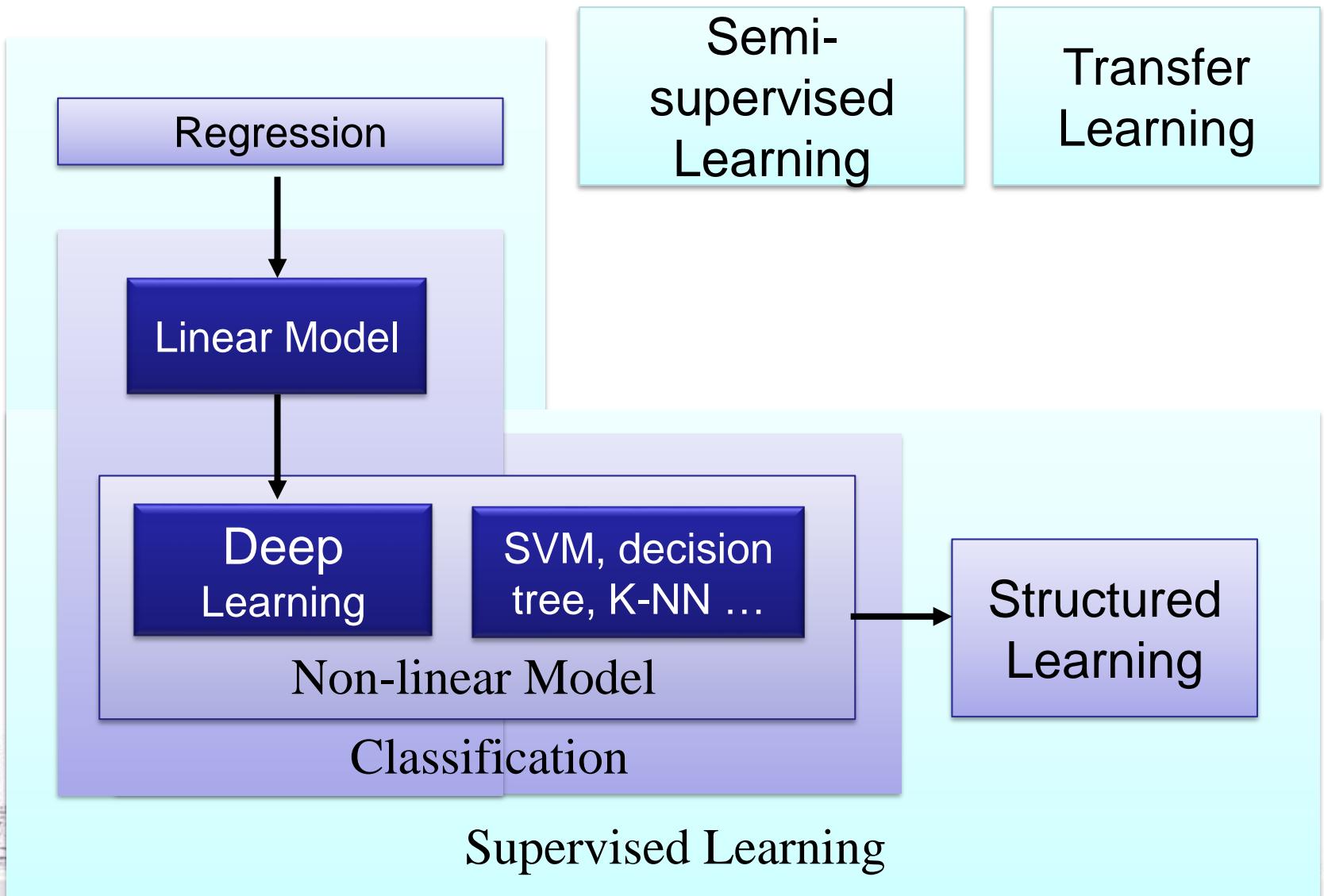


(Images of cats and dogs)



Learning Map

scenario task method



Transfer Learning

For example, recognizing cats and dogs

Labelled
data



cat



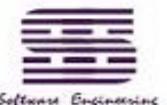
dog



elephant



Data not related to the task considered (can be either labeled or unlabeled)



Learning Map



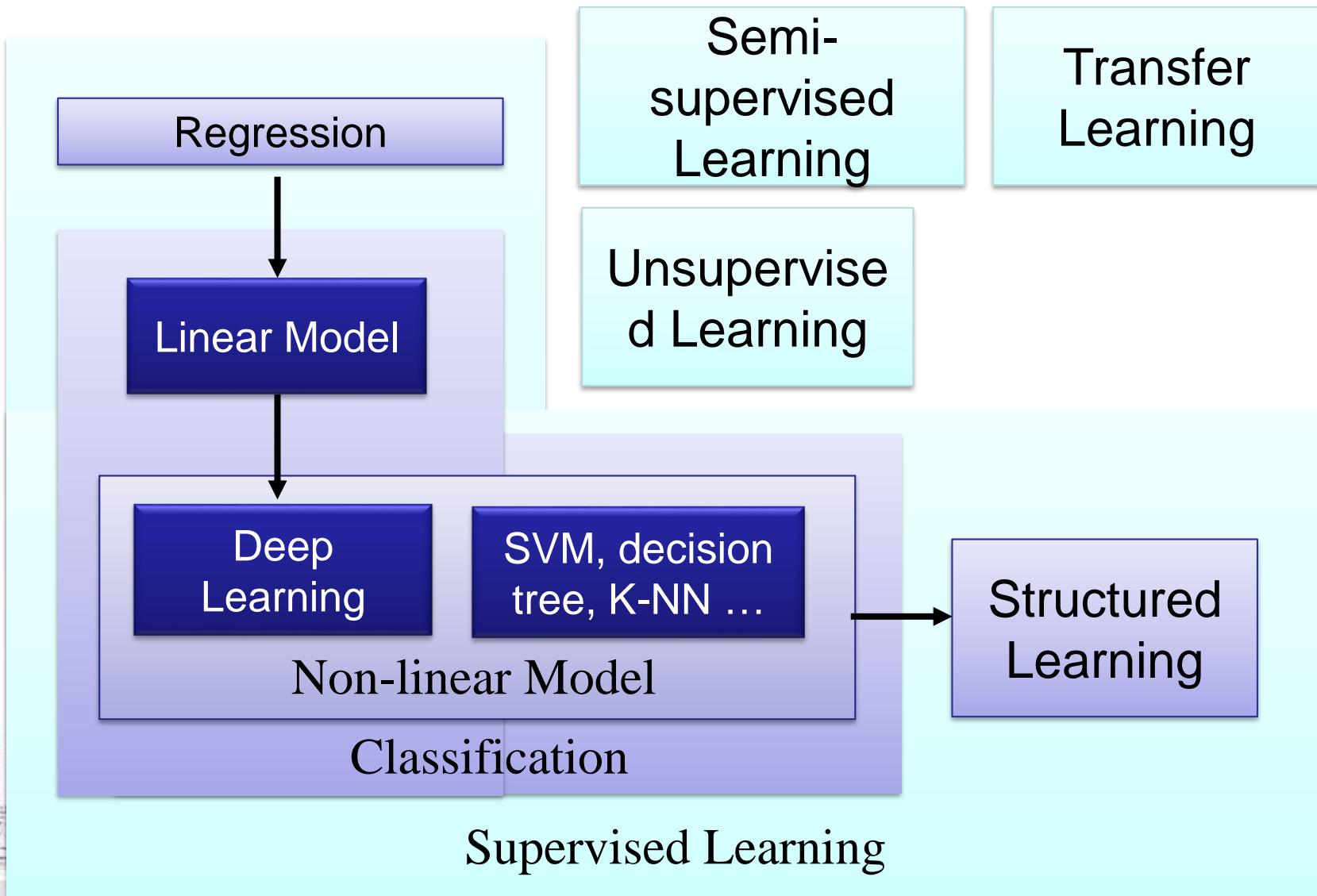
scenario



task

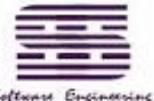
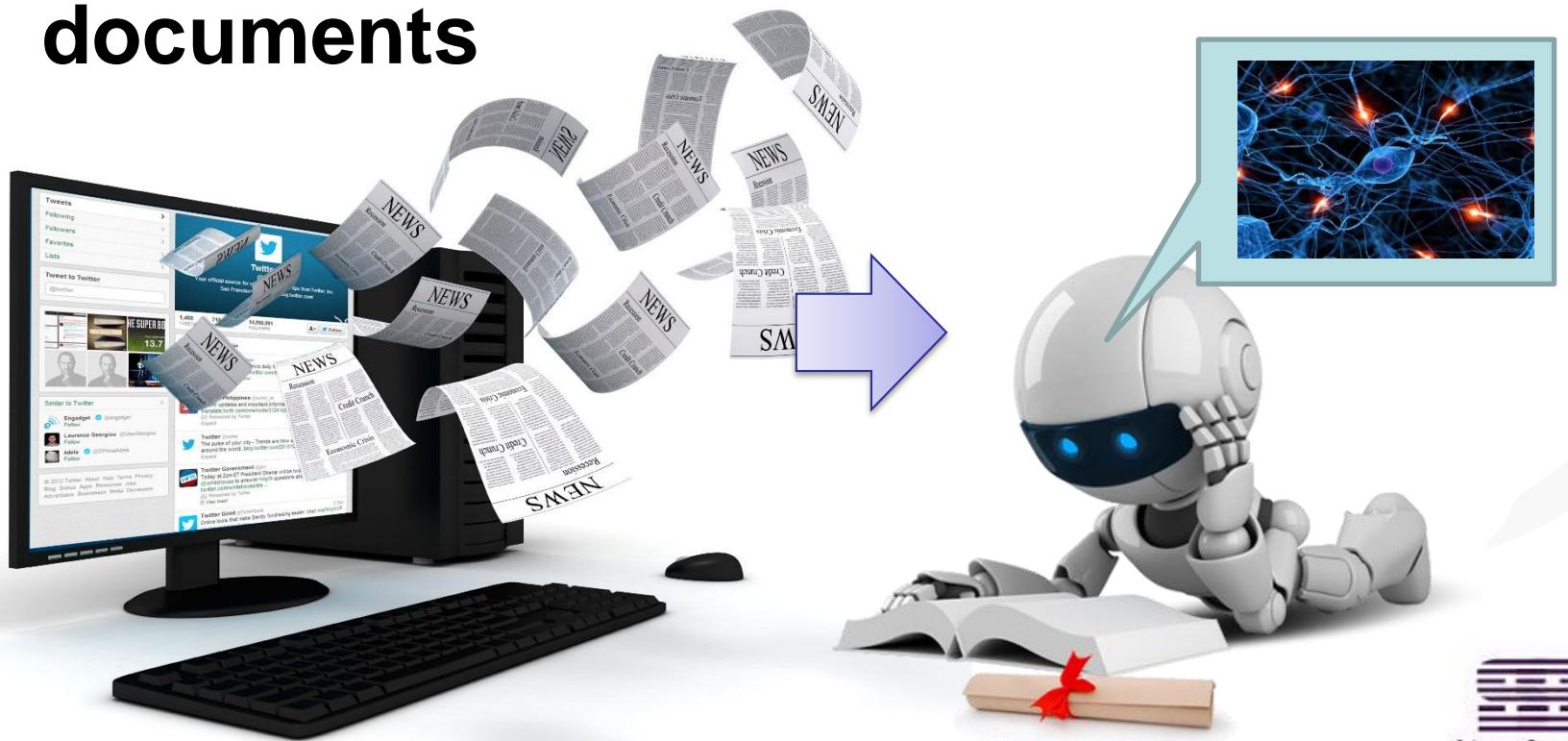


method



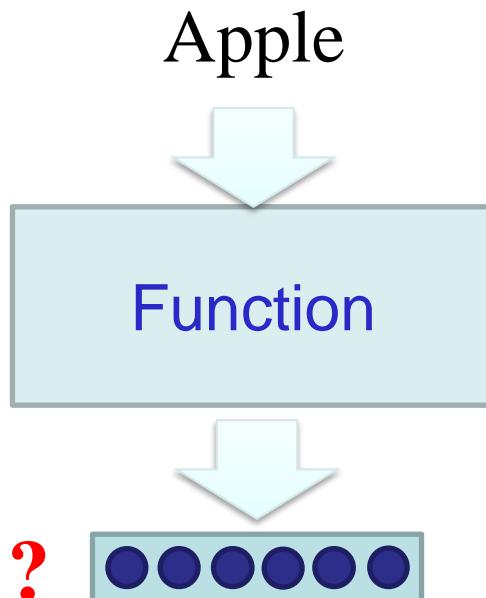
Unsupervised Learning

- **Machine Reading:** Machine learns the meaning of words from reading a lot of documents

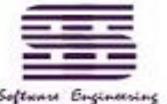


Unsupervised Learning

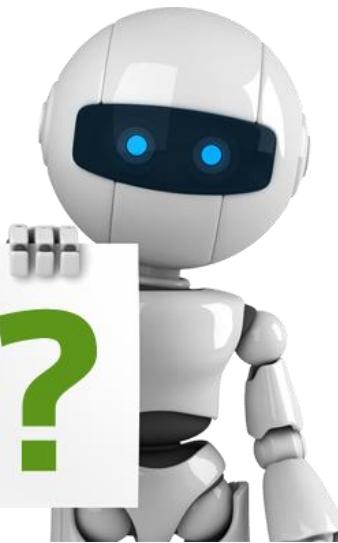
- **Machine Reading: Machine learns the meaning of words from reading a lot of documents**



Training data is a lot of text



Unsupervised Learning



Draw something!

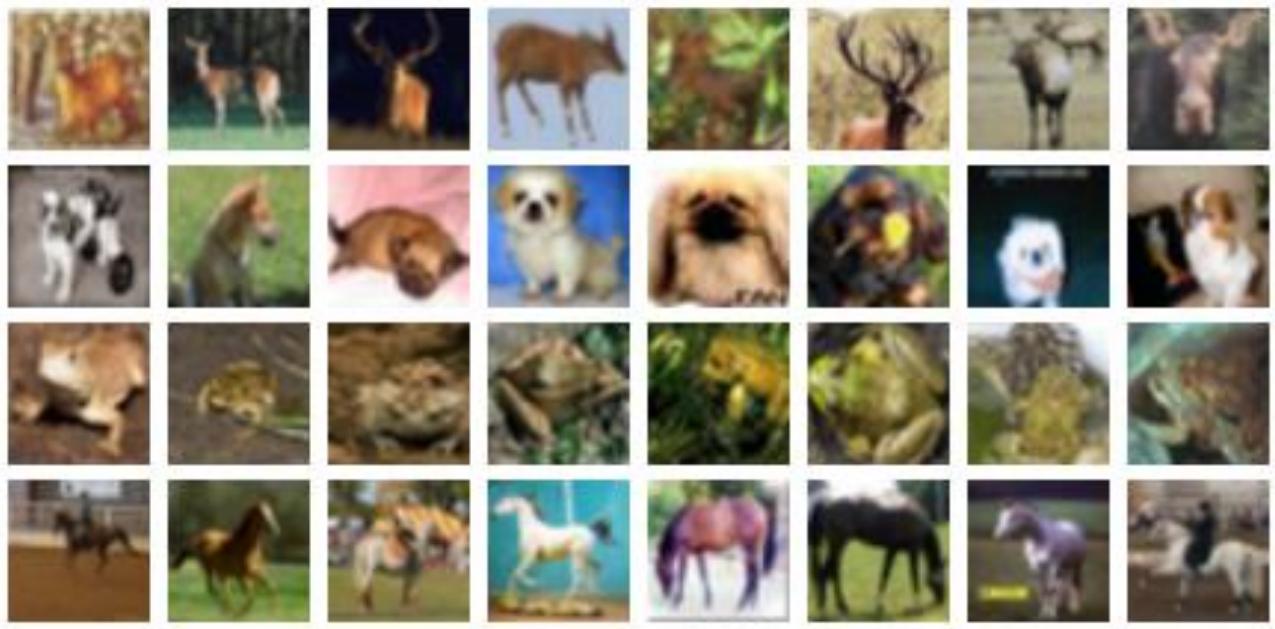


Unsupervised Learning

- Machine Drawing



Training data is a lot of images



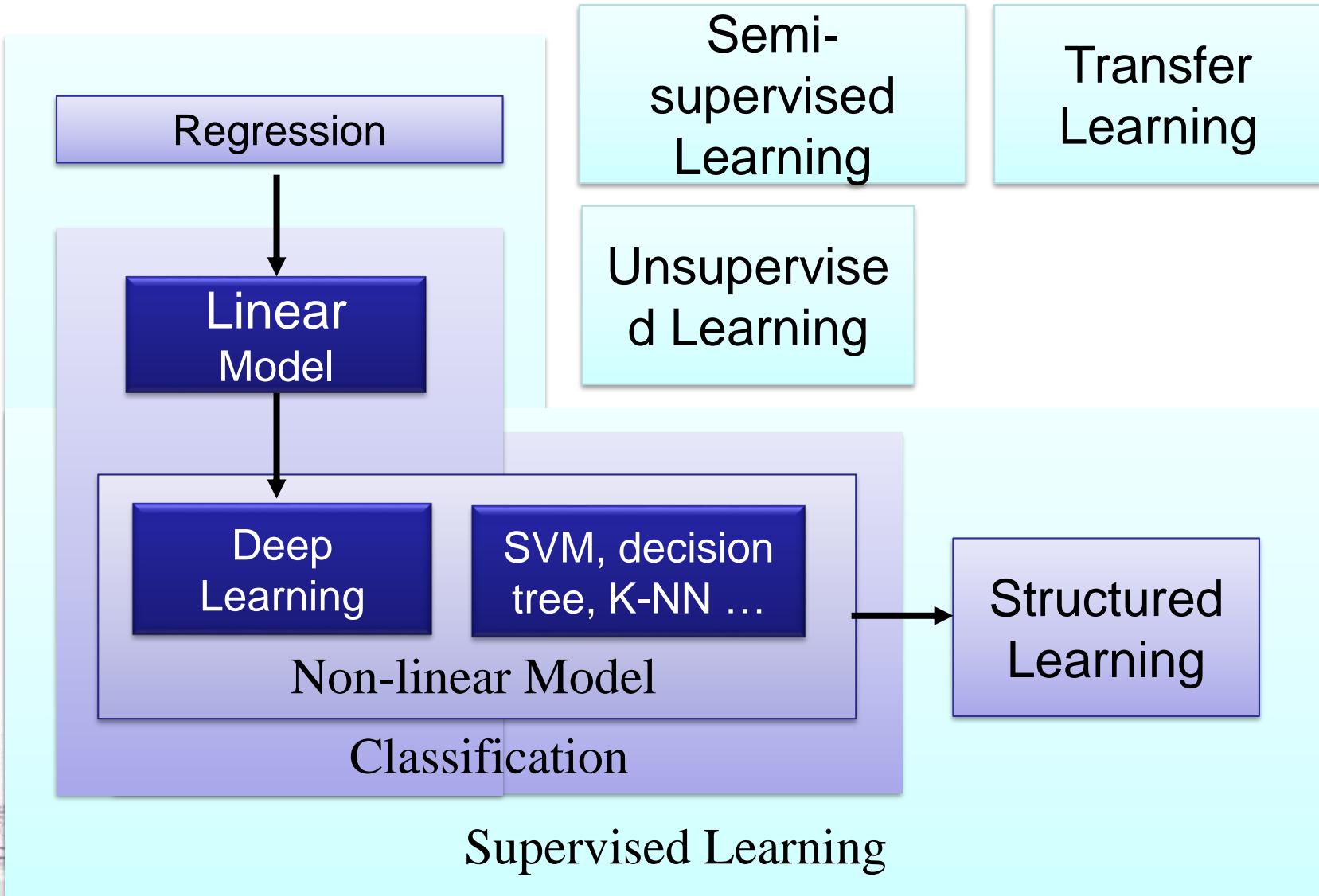
Software Engineering

Learning Map

scenario

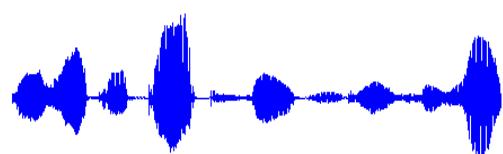
task

method



Structured Learning

- Beyond Classification



Speech Recognition

“大家好，欢迎大家来修人工智能”

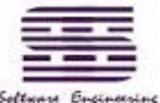
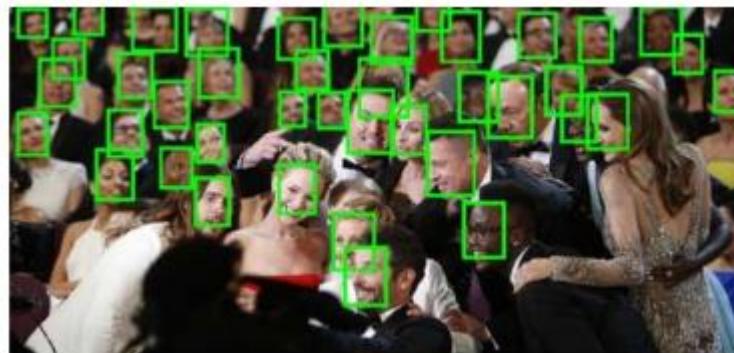
“人工智能”



“Artificial Intelligence”

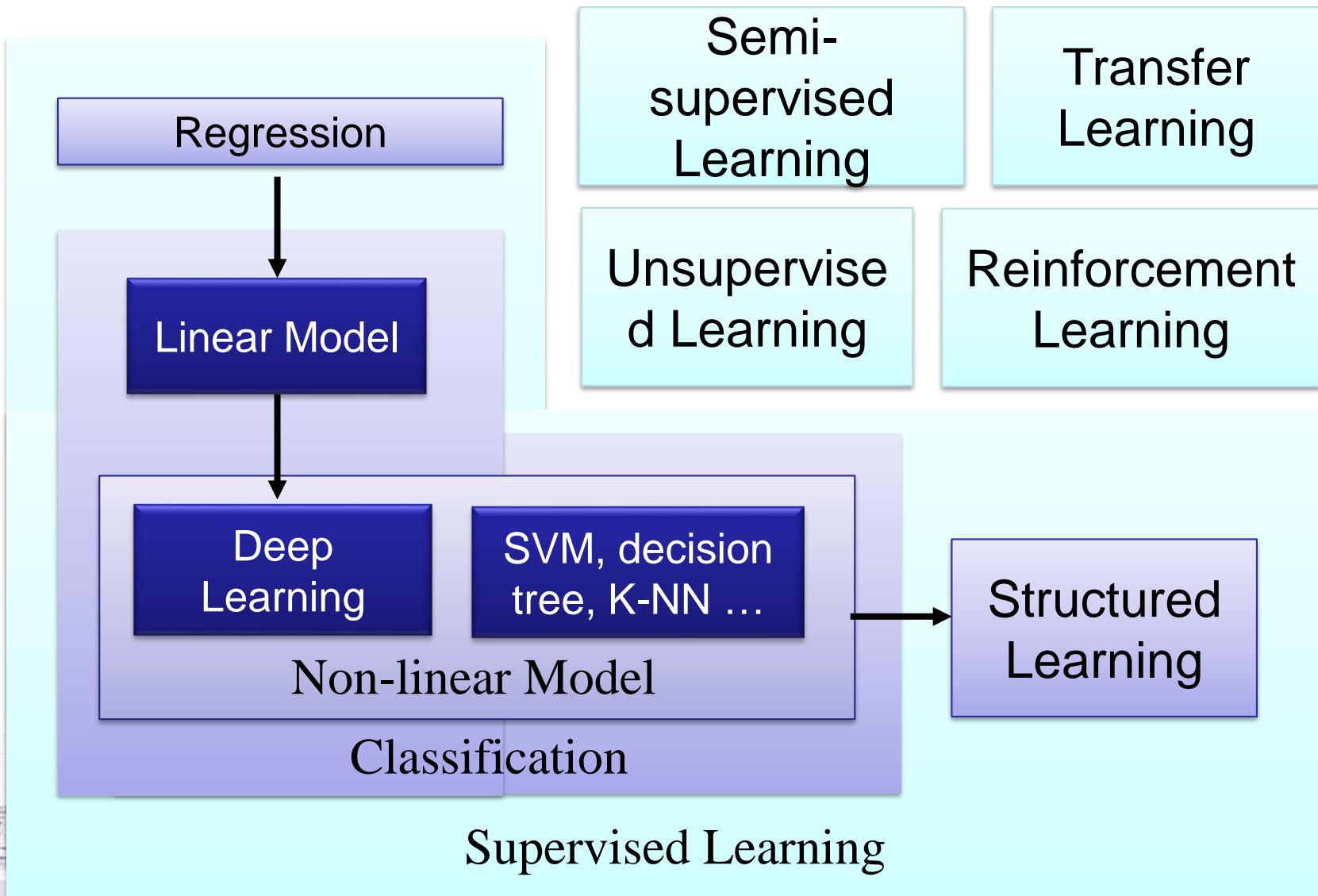
Machine Translation

人脸识别



Learning Map

scenario task method



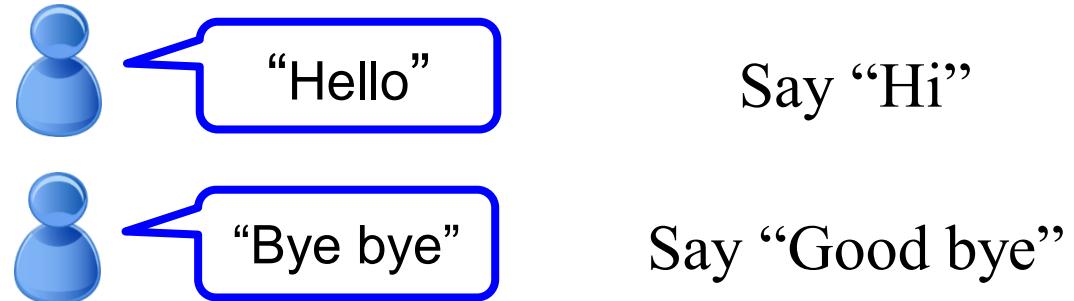
Reinforcement Learning



Supervised v.s. Reinforcement

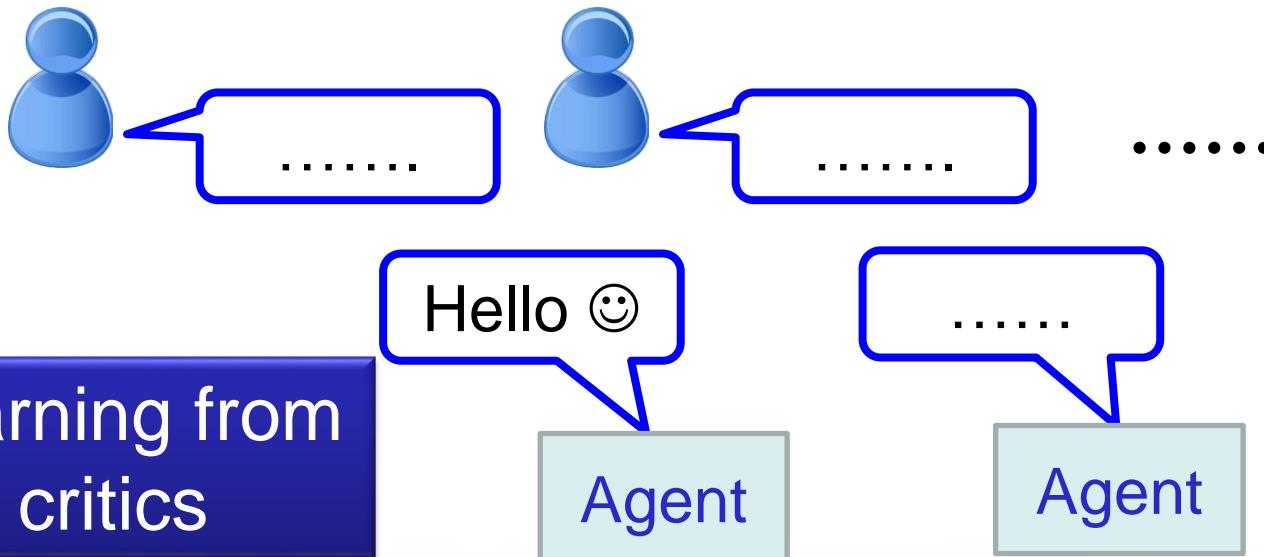
- **Supervised**

Learning from teacher

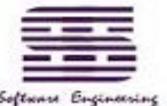


- **Reinforcement**

Learning from critics



Bad



Supervised v.s. Reinforcement

- **Supervised:**



Next move:
“5-5”



Next move:
“3-3”

- **Reinforcement Learning**

First move → many moves → Win!



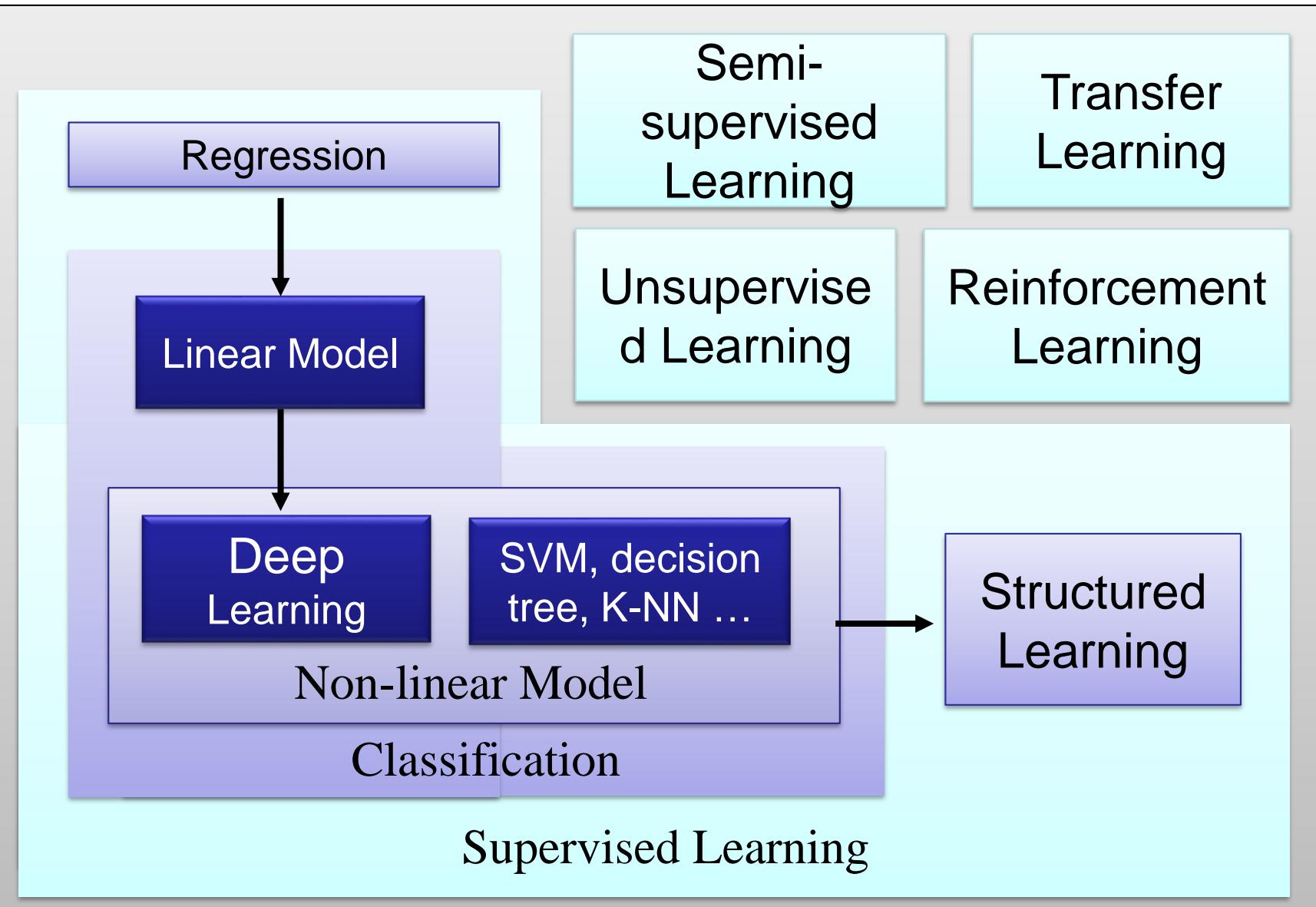
Alpha Go is supervised learning + reinforcement learning.

Relation between Terminology

scenario

task

method



机器学习的主要挑战

- 训练数据量不足
- 训练数据不具代表性
- 质量差的数据
- 无关特征
- 训练数据过度拟合
- 训练数据拟合不足
- 测试与验证

2019/9/10

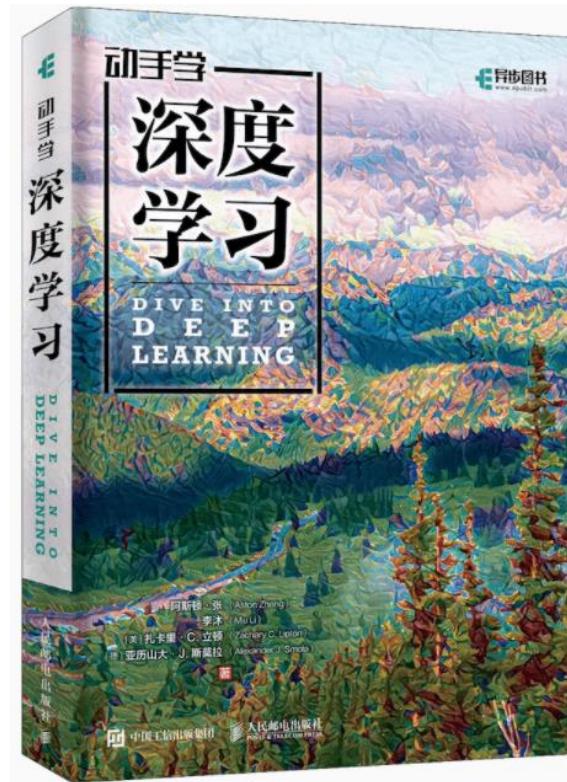
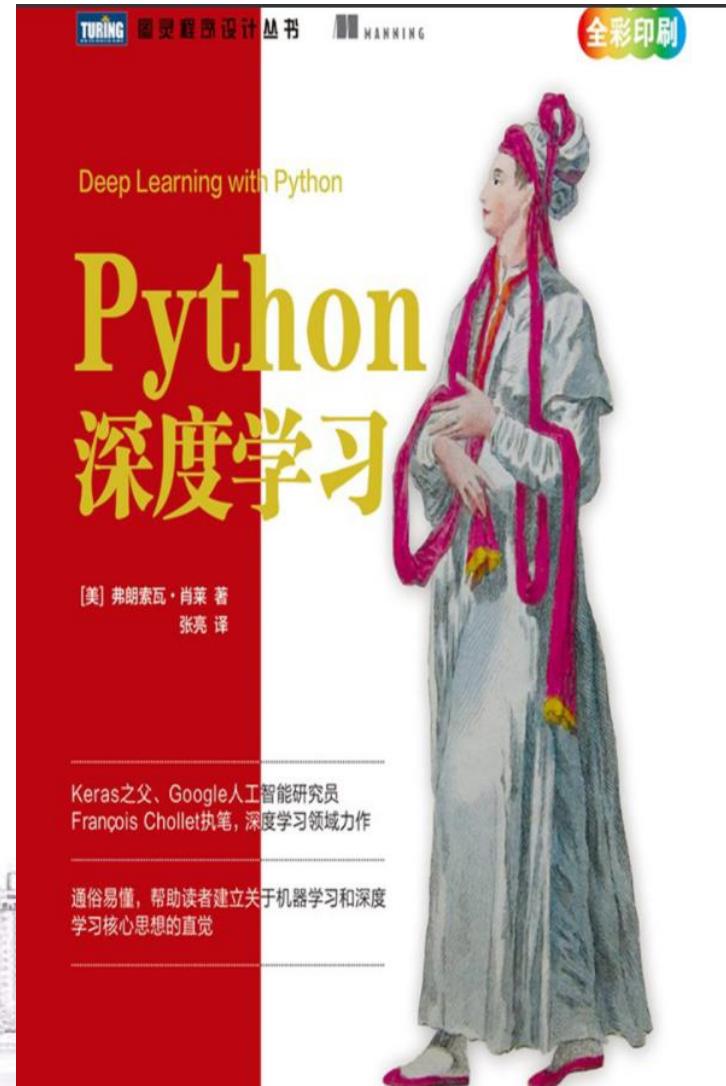
机器学习中的关键术语

- 数据：
 - 3类数据集：训练集（用于训练模型），验证集（用于选择超参数）和测试集（用于评估模型的泛化性能）
 - 样本：（输入，输出），一条数据为一个样本
 - 标签/标注：样本数据中的输出项
- 2个计算过程：
 - 学习/训练：目标是找到最佳函数来表达输入输出之间的关系
 - 推理/预测：将找到的最佳函数应用到测试数据/真实数据上，做出推理/预测。
- 机器学习中模型的种类：(从应用场景的角度划分)
 - 监督学习、非监督学习、半监督学习、强化学习、迁移学习

机器学习中的关键术语

- 两类函数：
 - 最佳函数：（模型训练的终极目标是找到这个函数）
 - 成本/代价/损失函数：用来定义训练过程中找到的函数的好坏程度
- 两类参数：
 - 参数：模型训练过程中自动找到
 - 超参数：程序员来选择/指定
 - 半自动：网格搜索、随机搜索
 - 手动：程序员设定
- 两个评价指标：
 - 模型评估标准（在训练数据集和验证数据集上）：用于模型选择
 - 模型测试标准（在测试集上）：用于测试模型的泛化性能

3 深度学习



基于MXNet开源深度学习框架
<https://zh.d2l.ai/>

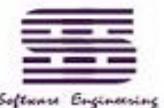


Deep Learning

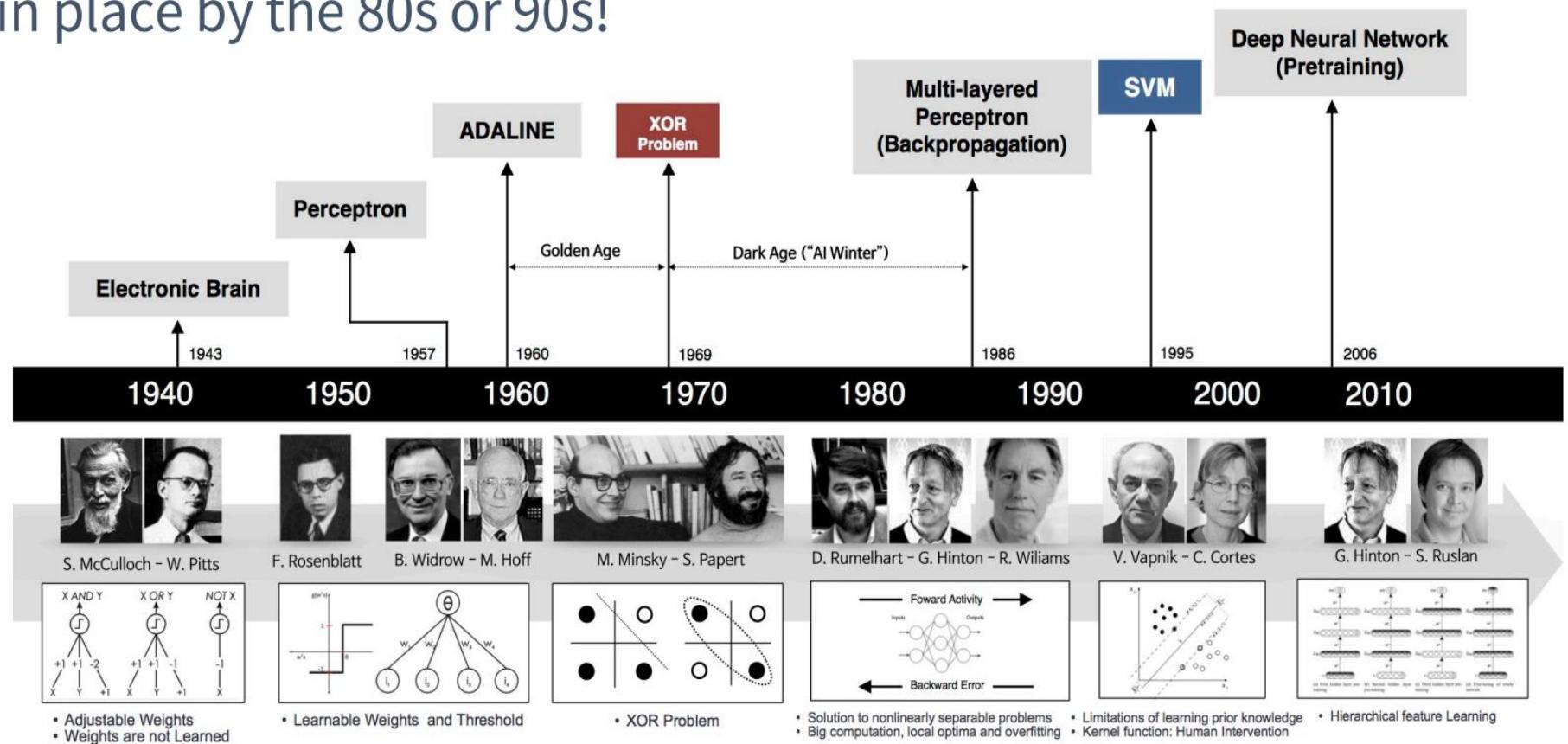
A subfield of machine learning



2019/9/10



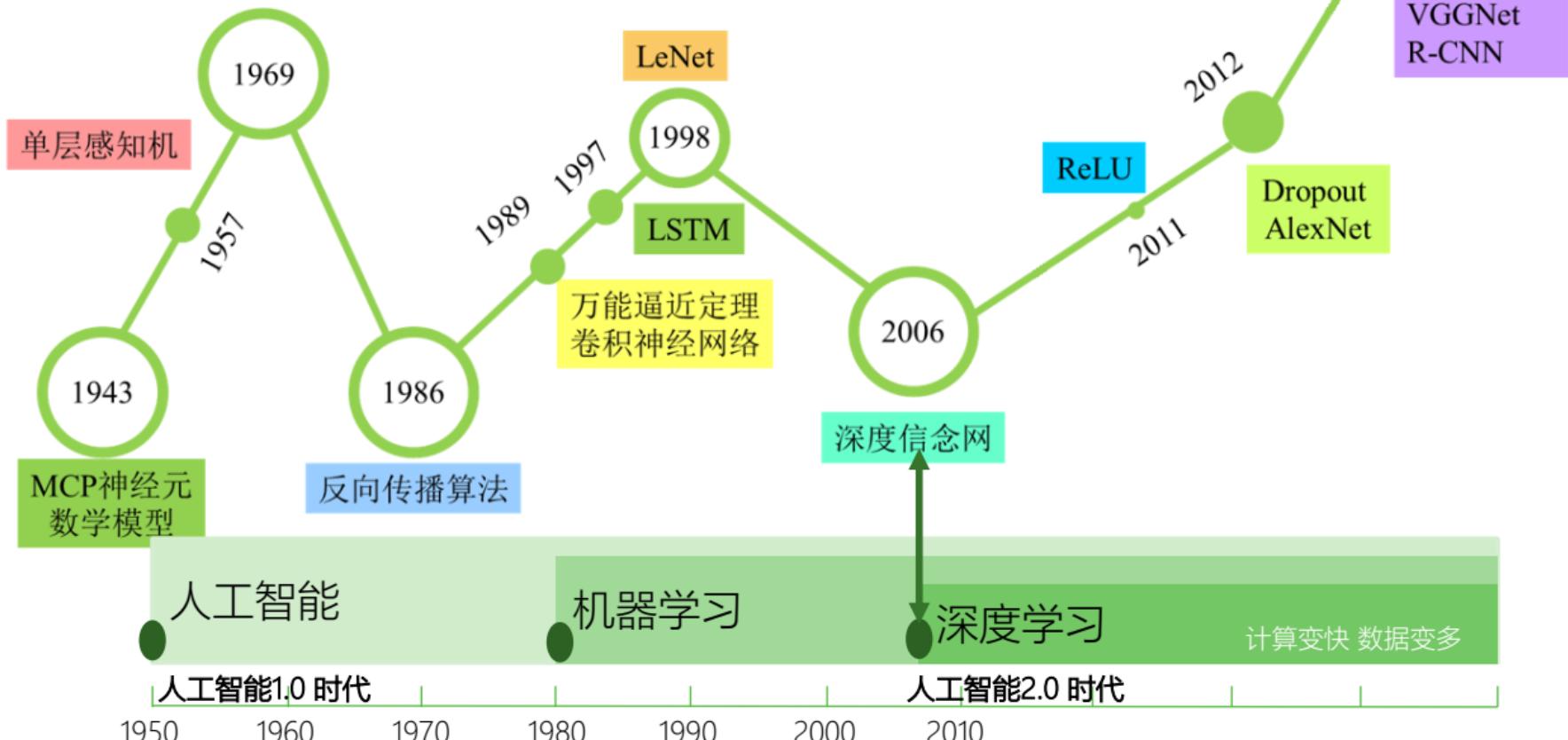
Many core concepts of deep learning were in place by the 80s or 90s!



来自：微软亚洲研究院 周礼栋《大数据系统的演化：理论、实践和展望》报告

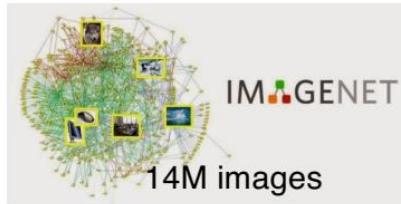
深度学习里程碑

Minsky和Seymour Papert专著Perceptron
：单层感知机不能解决XOR问题

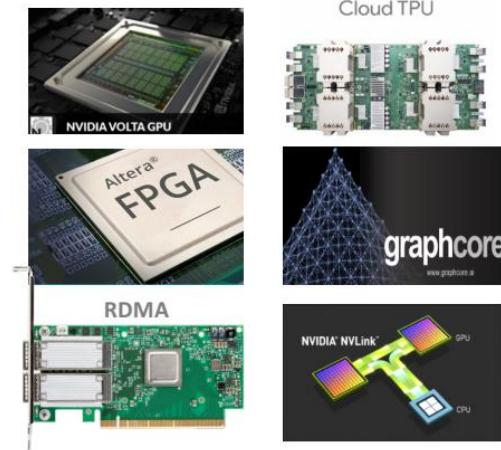


引自Prof. Meina Kan, PHD Student Xin Liu and Shuzhe Wu 5

What Makes Deep Learning Succeed?



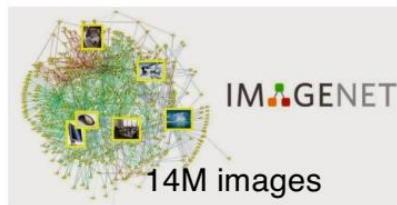
- Massive labeled datasets



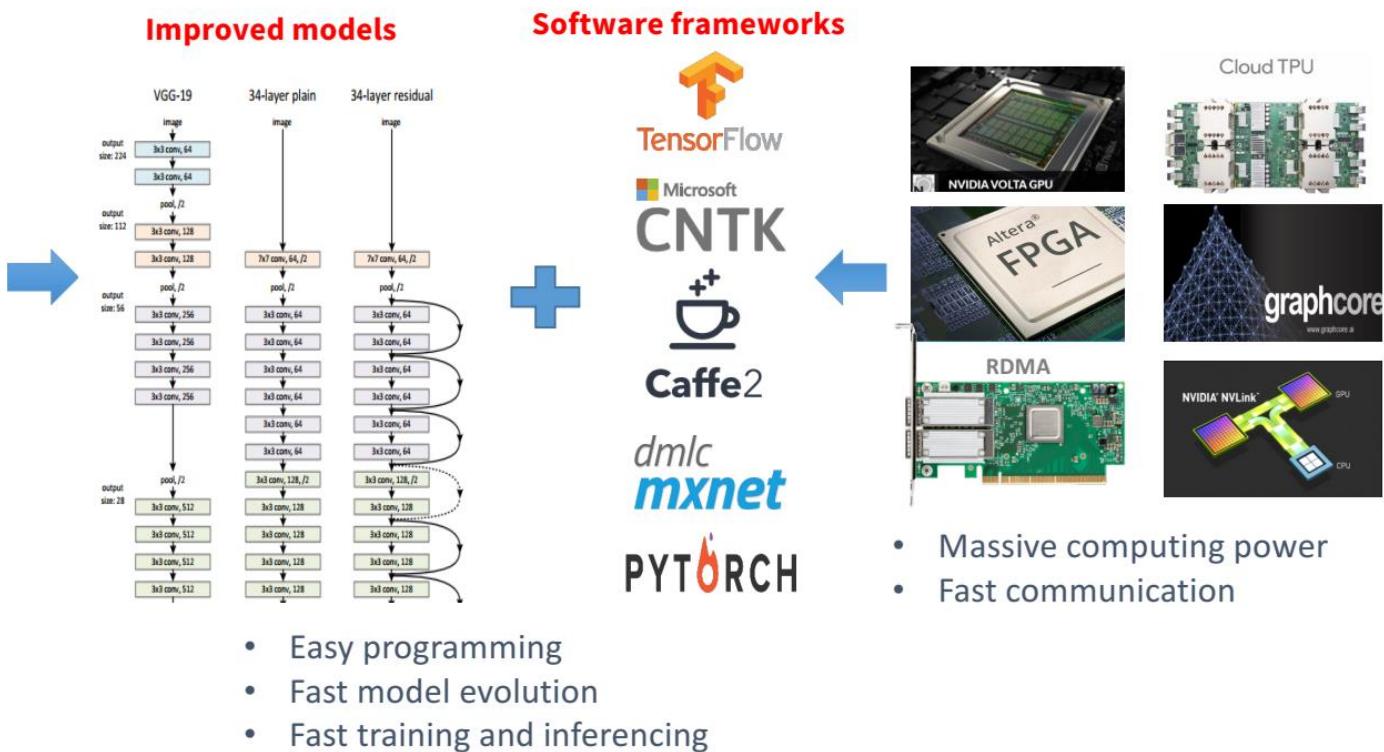
- Massive computing power
- Fast communication

来自：微软亚洲研究院 周礼栋《大数据系统的演化：理论、实践和展望》报告

What Makes Deep Learning Succeed?

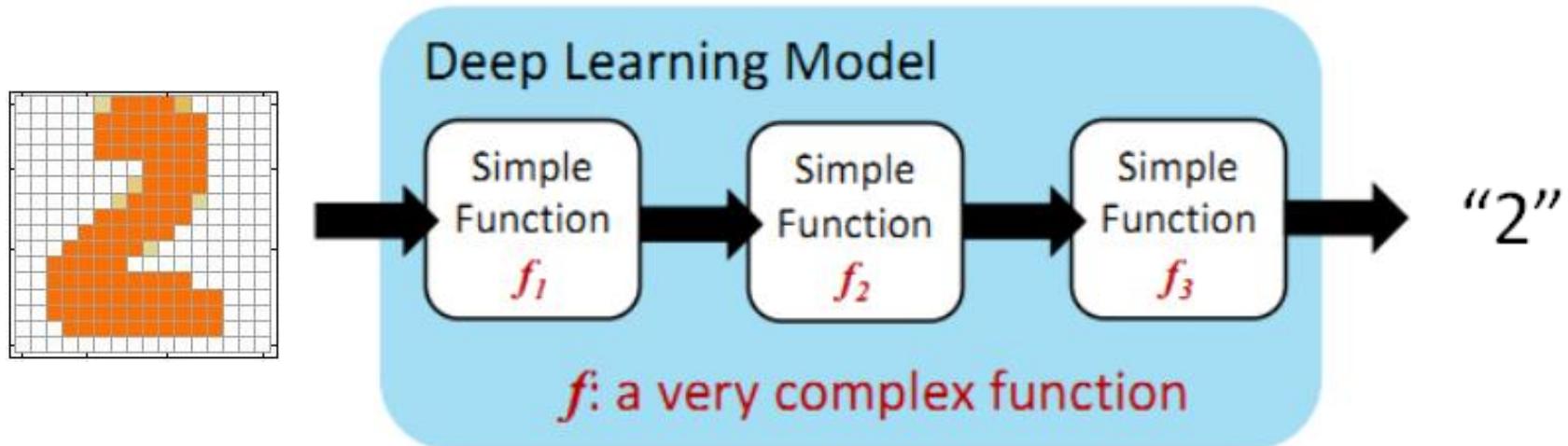


- Massive labeled datasets



来自：微软亚洲研究院 周礼栋《大数据系统的演化：理论、实践和展望》报告

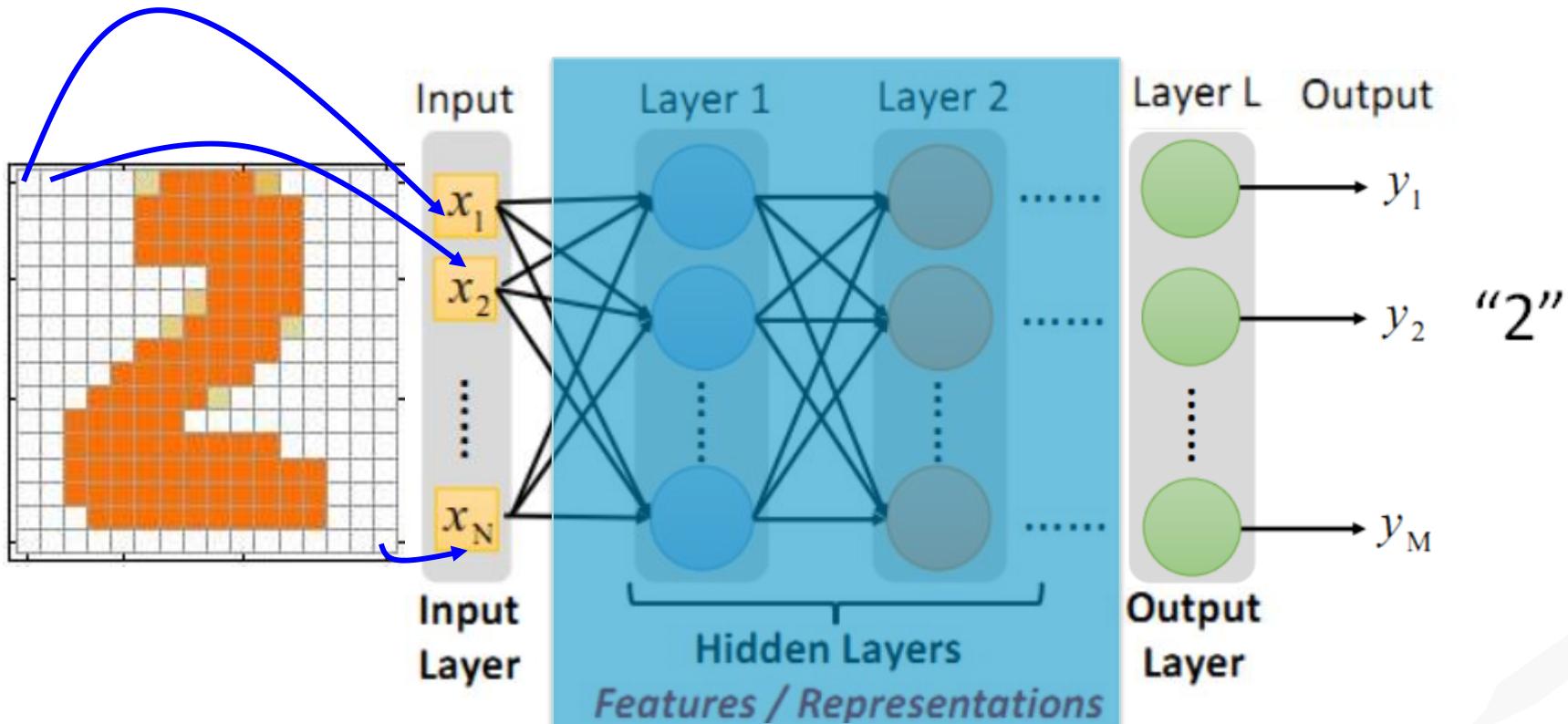
Stacked Functions Learned by Machine



End-to-end training: what each function should do is learned automatically

Deep learning usually refers to neural network based model

Stacked Functions Learned by Machine

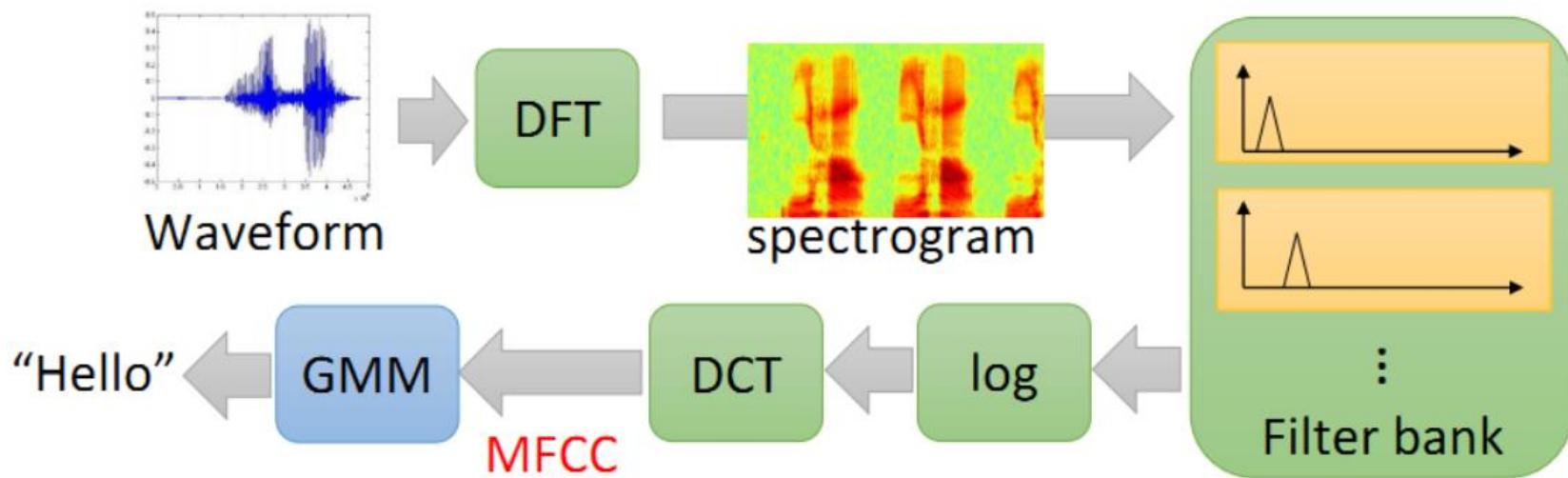


Representation Learning attempts to learn good features/representations

Deep Learning attempts to learn (multiple levels of) representations and an output

Deep v.s. Shallow – Speech Recognition

Shallow Model



Each box is a simple function in the production line:



:hand-crafted

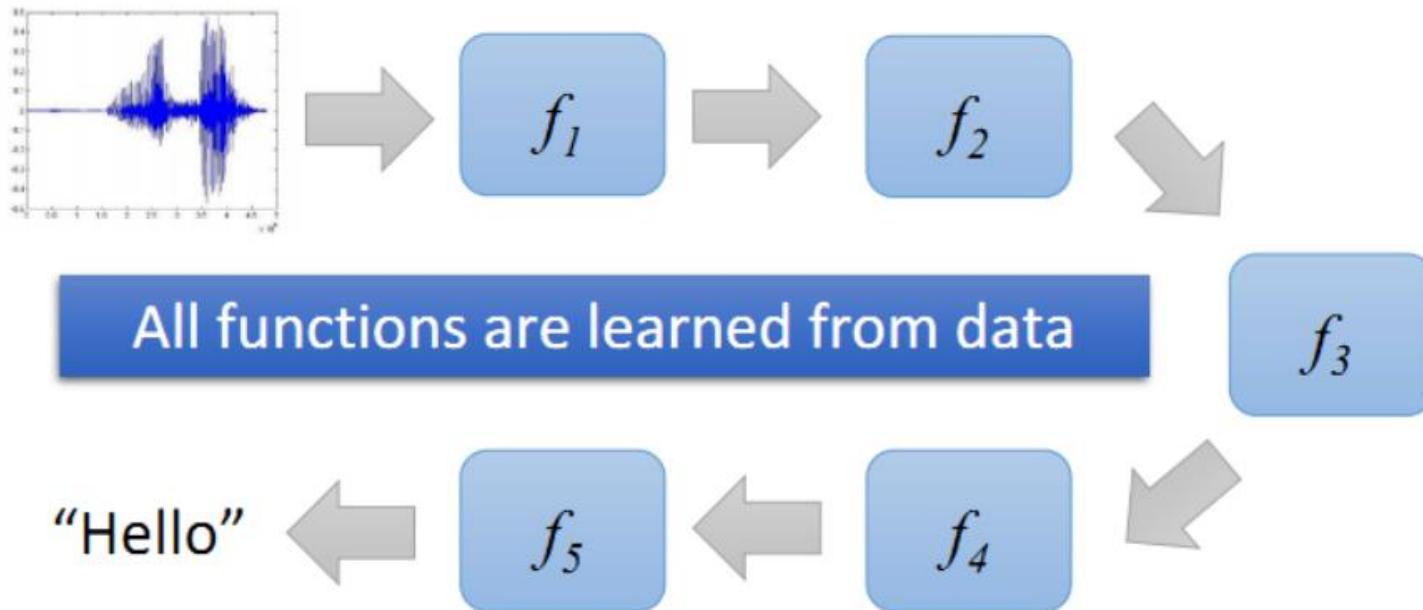


:learned from data



Deep v.s. Shallow – Speech Recognition

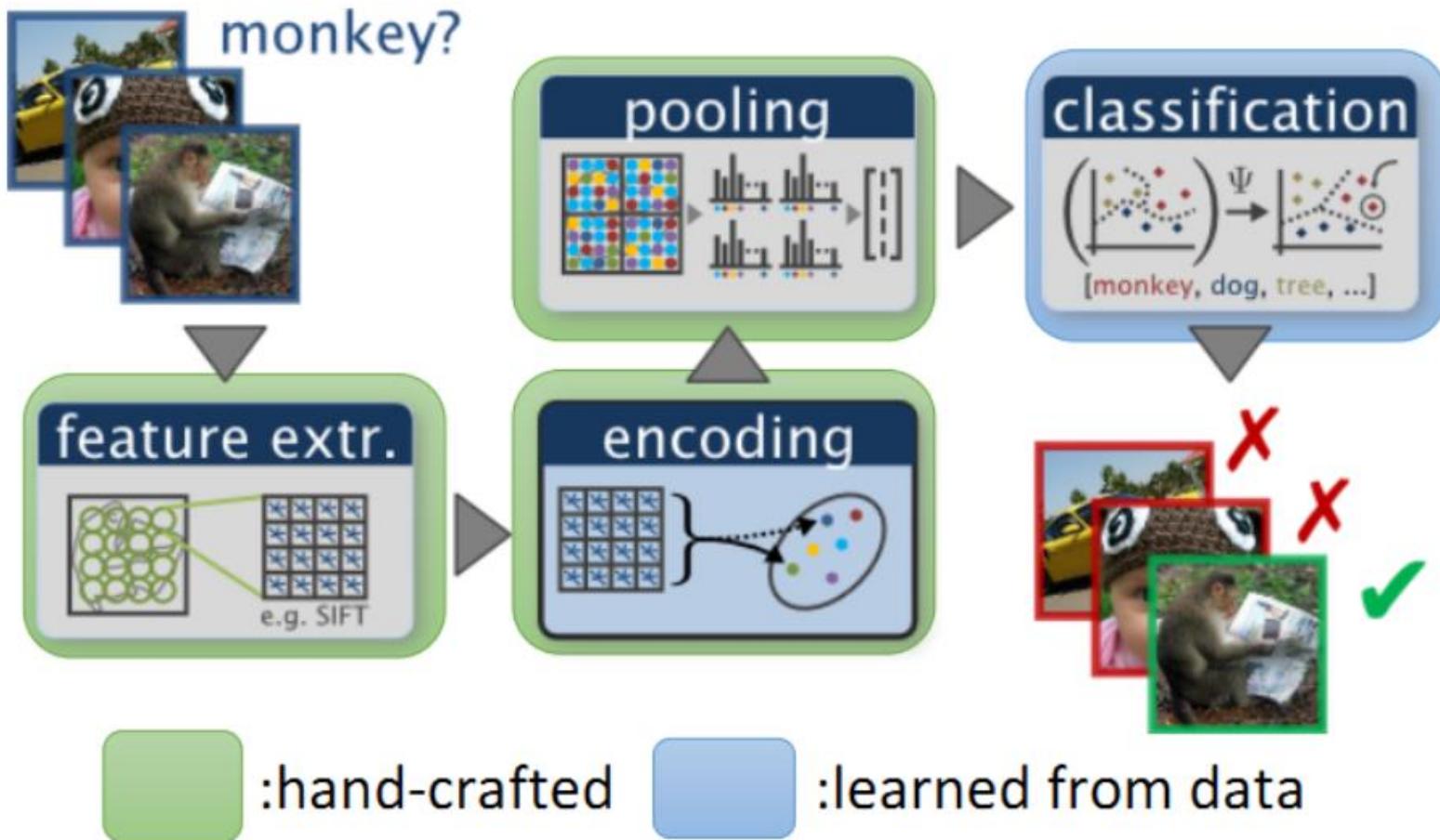
Deep model



Less engineering labor, but machine learns more

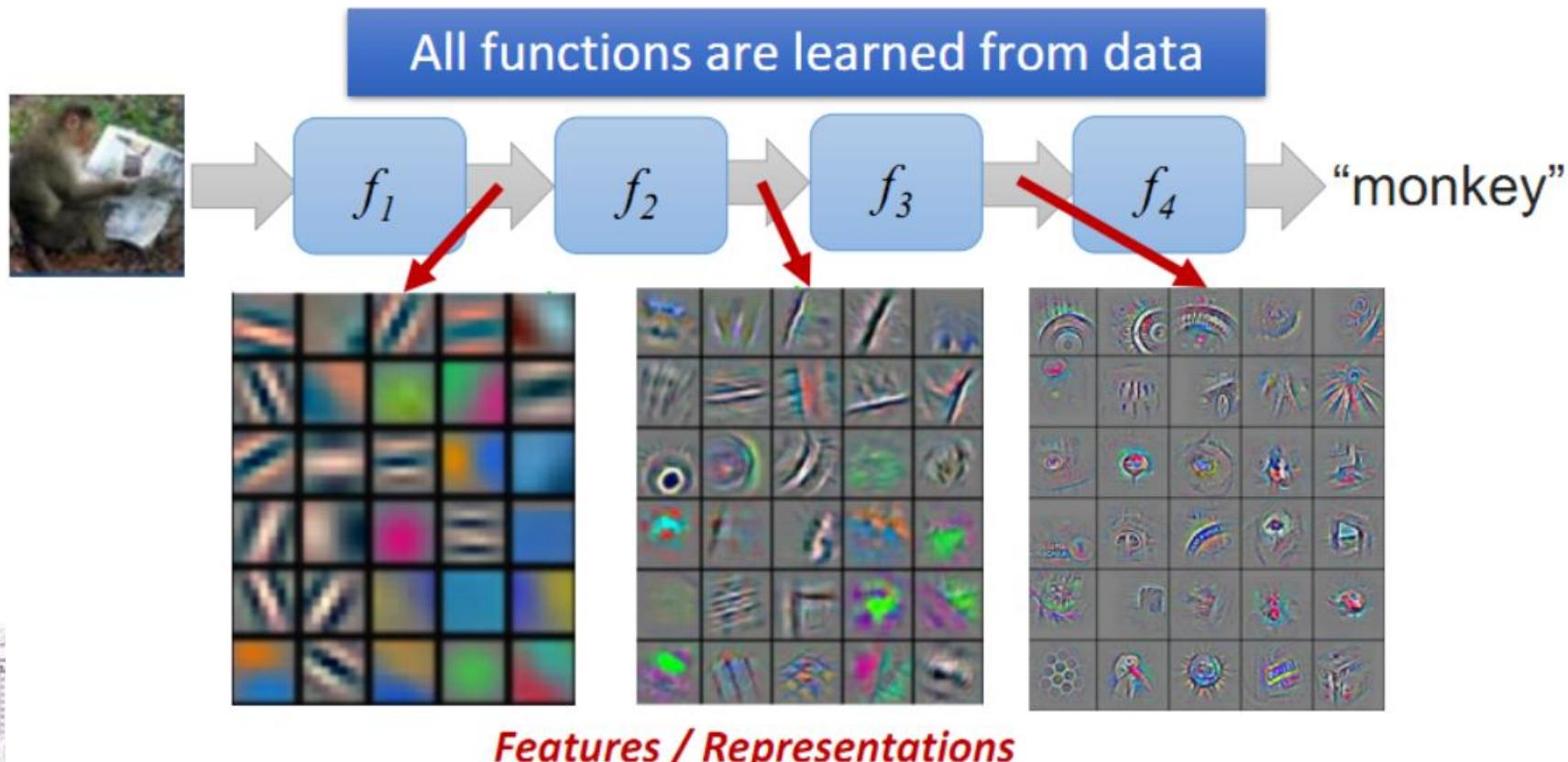
Deep v.s. Shallow – Image Recognition

Shallow Model



Deep v.s. Shallow – Image Recognition

Deep Model



Machine Learning v.s. Deep Learning

Machine Learning

describing your data
with features a
computer can
understand

function/method

Deep Learning

function(NN based)

automatically learn
Features/representations

optimizing the weights
on features

:hand-crafted

:learned from data



ImageNet 2010

Locality constrained linear coding + SVM	NEC & UIUC
Fisher kernel + SVM	Xerox Research Center Europe
SIFT features + LI2C	Nanyang Technological Institute
SIFT features + k-Nearest Neighbors	Laboratoire d'Informatique de Grenoble
Color features + canonical correlation analysis	National Institute of Informatics, Tokyo

ImageNet 2011

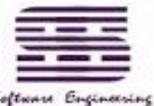
Compressed Fisher kernel + SVM	Xerox Research Center Europe
SIFT bag-of-words + VQ + SVM	University of Amsterdam & University of
SIFT + ?	ISI Lab, Tokyo University

ImageNet 2012

Deep convolutional neural network	University of Toronto
Discriminatively trained DPMs	University of Oxford
Fisher-based SIFT features + SVM	ISI Lab, Tokyo University



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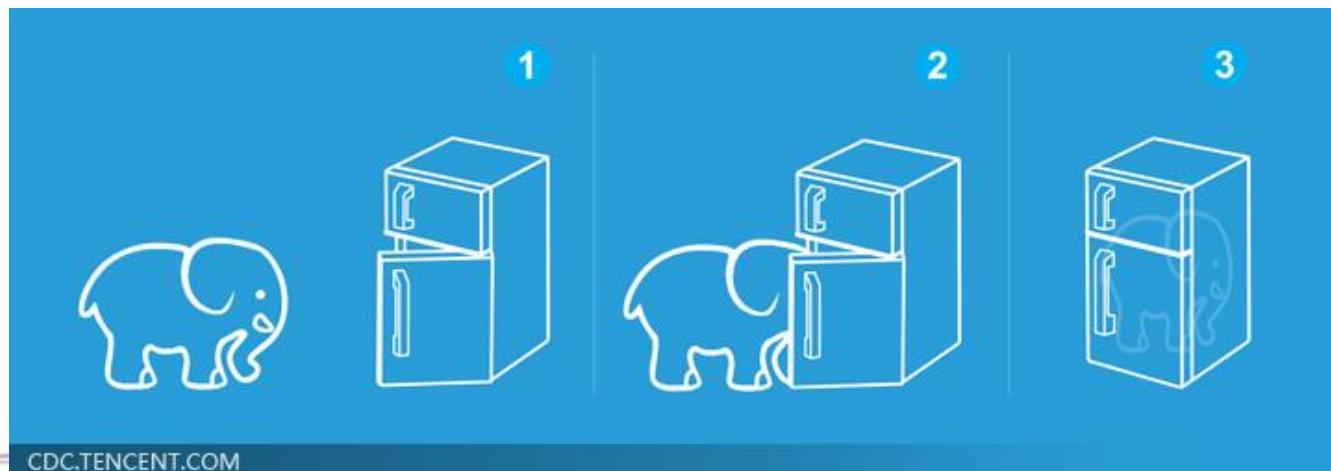


Software Engineering

Three Steps for Deep Learning

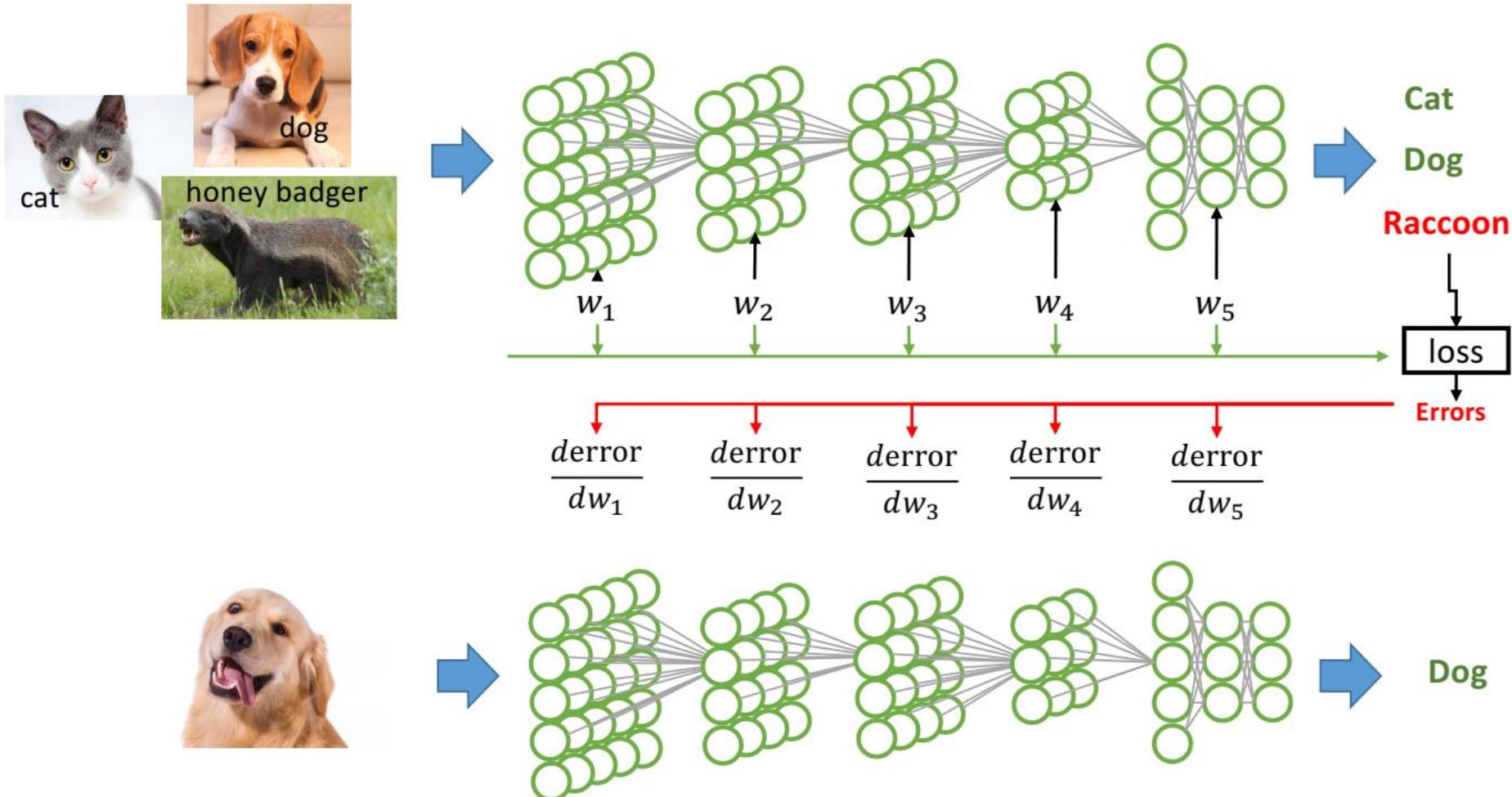


就好像把大象放进冰箱



CDC.TENCENT.COM

Deep Learning Approach

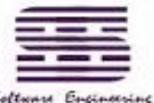
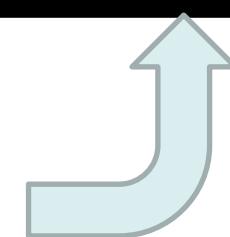
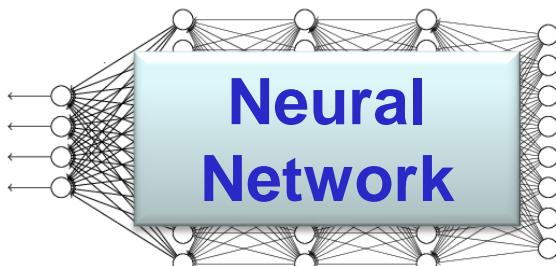
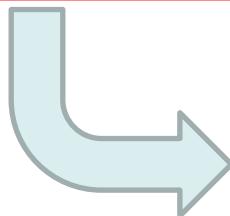
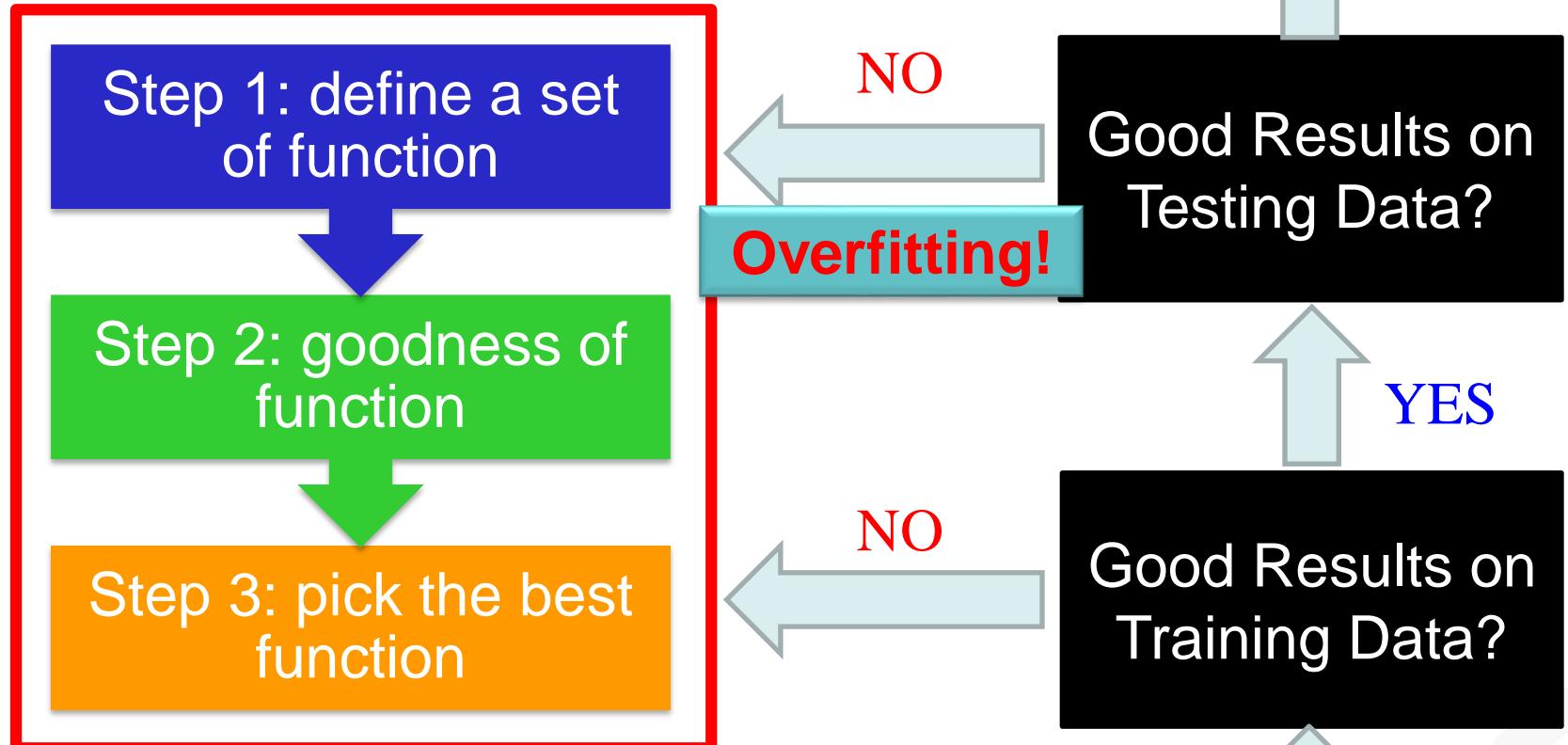


来自：微软亚洲研究院 周礼栋《大数据系统的演化：理论、实践和展望》报告

Recipe of Deep Learning



YES



Software Engineering

Recipe of Deep Learning

重点



YES

Early Stopping 提前停止

Regularization 正则化

Dropout 丢弃

New activation function

Adaptive Learning Rate

Good Results on
Testing Data?

Good Results on
Training Data?



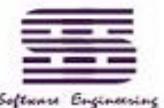
Software Engineering

Assignment #1

- 从下列两个方向中选出一个作为调研方向，写一篇调研报告。
 - 机器学习（不涵盖DNN）
 - CV
 - NLP
- 提示：可以从研发团队（大学、重点实验室、企业）、经典模型算法、应用场景、资源获取方式（比如微信公众号，官网地址，博客）、课程、相关开源数据集等多个角度进行充分调研。



2019/9/10



谢谢！



2019/9/10

