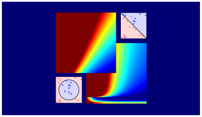
Machine Learning Foundations
(機器學習基石)



Lecture 1: The Learning Problem

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Course Design (1/2)

Machine Learning: a mixture of theoretical and practical tools

- theory oriented
  - derive everything **deeply** for solid understanding
  - less interesting to general audience
- technique**s** oriented
  - flash over the sexiest techniques **broadly** for shiny coverage
  - too many techniques, hard to choose, hard to use properly

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our approach: **foundation oriented**

Course Design (2/2)

Foundation Oriented ML Course

- mixture of philosophical illustrations, key theory, core techniques, usage in practice, and hopefully jokes **:-)**
  —what **every machine learning user** should know

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  - How Can Machines Learn **Better**? (practical + theoretical)

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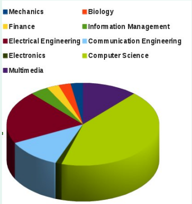
allows students to **learn 'future/untaught' techniques or study deeper theory easily**

Course History

NTU Version

- 15-17 weeks (2+ hours)
- highly-praised with **English and blackboard teaching**



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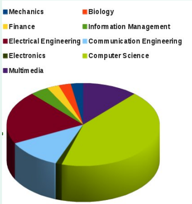

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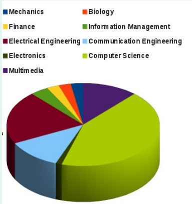

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goal: **try** making Coursera version even better than NTU version

Fun Time

Which of the following description of this course is true?

1. the course will be taught in Taiwanese
2. the course will tell me the techniques that create the android Lieutenant Commander Data in Star Trek
3. the course will be 15 weeks long
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Reference Answer: 4

1. no, my Taiwanese is unfortunately not good enough for teaching (yet)
2. no, although what we teach may serve as foundations of those (future) techniques
3. no, unless you choose to join the next course
4. yes, **let's begin the story**

Roadmap

1. **When** Can Machines Learn?

Lecture 1: The Learning Problem

- Course Introduction
- What is Machine Learning
- Applications of Machine Learning
- Components of Machine Learning
- Machine Learning and Other Fields

2. Why Can Machines Learn?
3. How Can Machines Learn?
4. How Can Machines Learn Better?

From Learning to Machine Learning

learning:

From Learning to Machine Learning

learning: acquiring skill
with experience accumulated from observations

$$\text{observations} \longrightarrow \boxed{\text{learning}} \longrightarrow \text{skill}$$

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What is skill?

A More Concrete Definition

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$\Leftrightarrow$ improve some performance measure (e.g. prediction accuracy)

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Why use machine learning?

Yet Another Application: Tree Recognition

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ML: an **alternative route** to build complicated systems

The Machine Learning Route

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Some Use Scenarios

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Give a **computer** a fish, you feed it for a day;
teach it how to fish, you feed it for a lifetime. :-)

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key essence: help decide whether to use ML

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Reference Answer: 3

1. no pattern
2. programmable definition
3. pattern: customer behavior;
   definition: not easily programmable;
   data: history of bank operation
4. arguably no (or not enough) data yet

Daily Needs: Food, Clothing, Housing, Transportation

data → ML → skill

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ML is everywhere!

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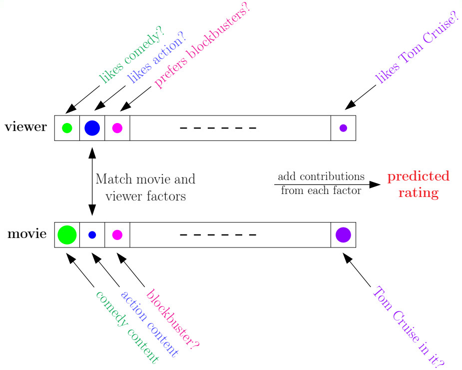
How can machines **learn our preferences**?

Entertainment: Recommender System (2/2)



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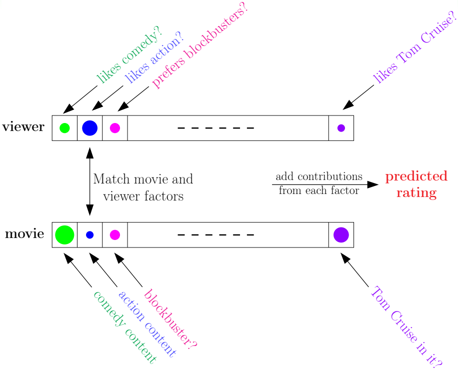

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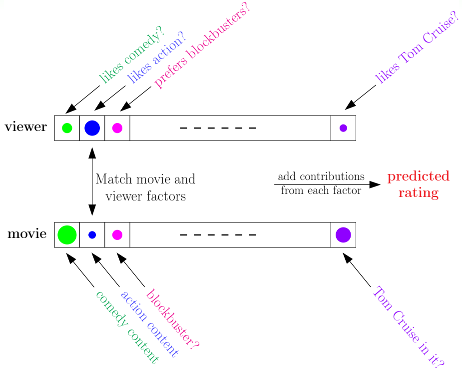

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2. Medicine
3. Law
4. none of the above

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1. predict stock price from data
2. predict medicine effect from data
3. summarize legal documents from data
4. **:-) Welcome to study this hot topic!**

Components of Learning: Metaphor Using Credit Approval

Applicant Information

age	23 years
gender	female
annual salary	NTD 1,000,000
year in residence	1 year
year in job	0.5 year
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unknown pattern to be learned:

'approve credit card good for bank?'

Formalize the Learning Problem

Basic Notations

- input: $\mathbf{x} \in \mathcal{X}$ (customer application)
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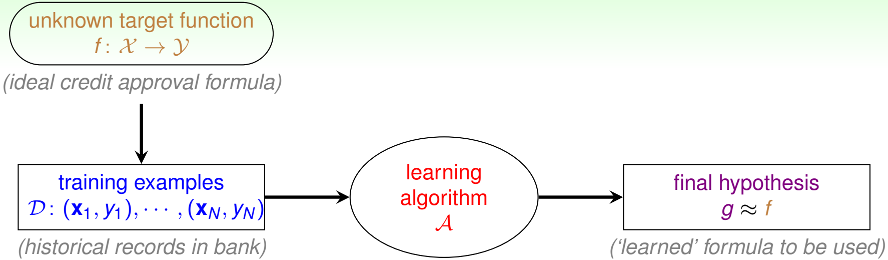
$$\{(\mathbf{x}_n, y_n)\} \text{ from } f \longrightarrow \boxed{\text{ML}} \longrightarrow g$$

Learning Flow for Credit Approval



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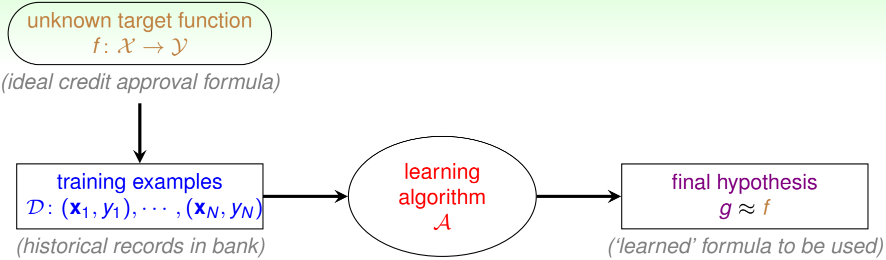

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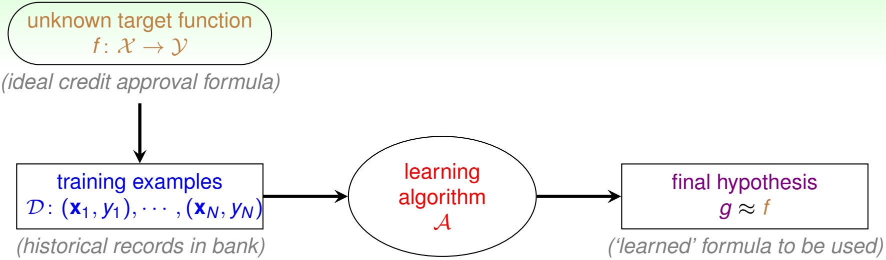

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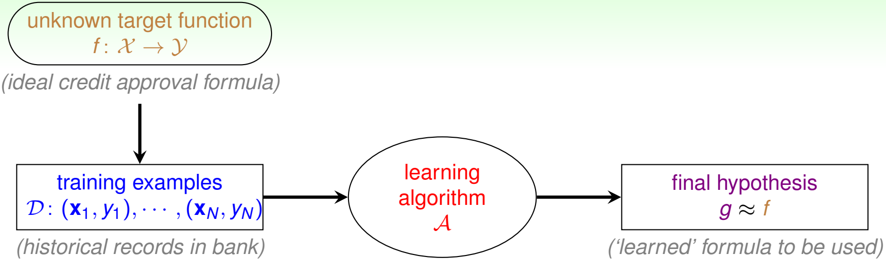

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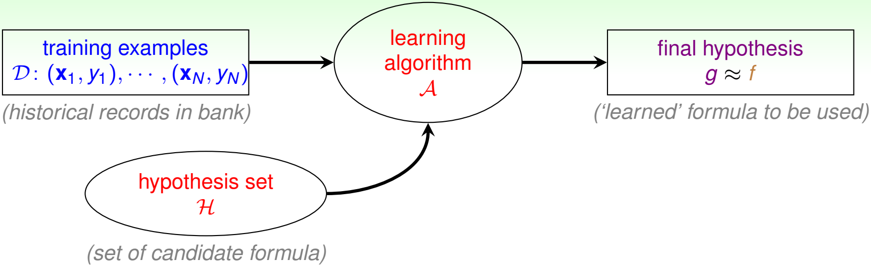
What does g look like?

The Learning Model



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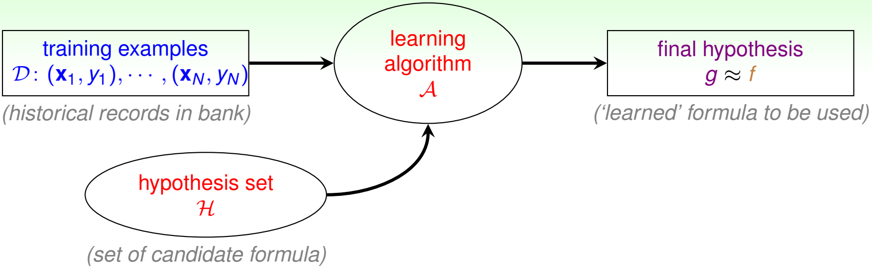

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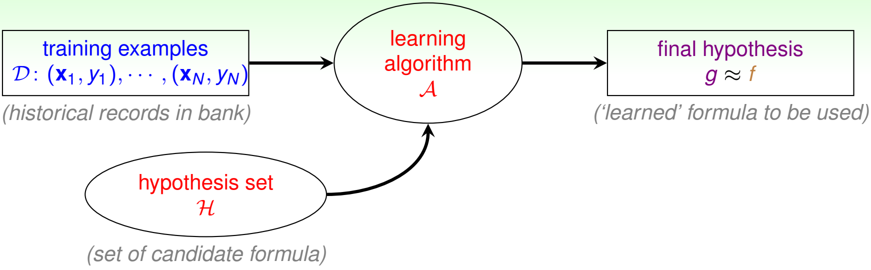

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  - up to $\mathcal{A}$ to pick the 'best' one as g

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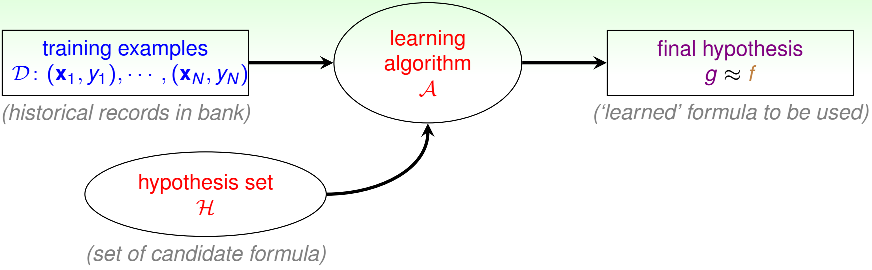

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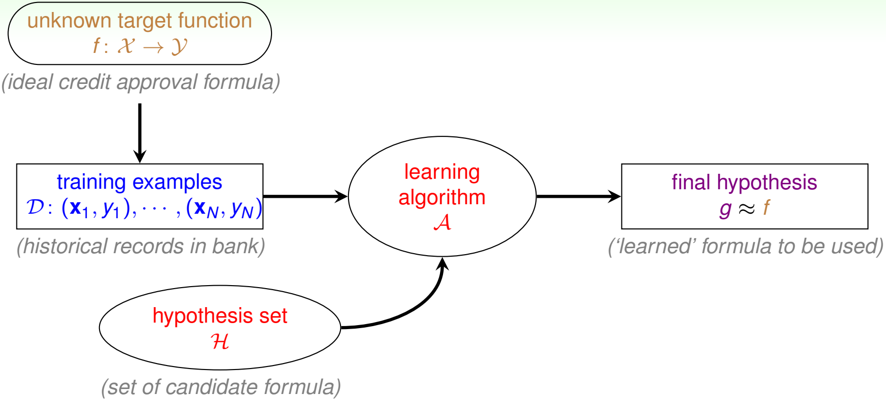
  - h_2: debt > NTD 100,000 (really?)
  - h_3: year in job ≤ 2 (really?)
- hypothesis set $\mathcal{H}$:
  - can contain **good or bad hypotheses**
  - up to $\mathcal{A}$ to pick the 'best' one as g

learning model = $\mathcal{A}$ and $\mathcal{H}$

Practical Definition of Machine Learning



machine learning:
use data to compute hypothesis g
that approximates target f

Fun Time

How to use the four sets below to form a learning problem for song recommendation?

$$\begin{aligned}
\mathcal{S}_1 &= [0, 100] \\
\mathcal{S}_2 &= \text{all possible (userid, songid) pairs} \\
\mathcal{S}_3 &= \text{all formula that `multiplies' user factors \& song factors,} \\
&\quad\ \text{indexed by all possible combinations of such factors} \\
\mathcal{S}_4 &= \text{1,000,000 pairs of ((userid, songid), rating)}
\end{aligned}$$

1. $\mathcal{S}_1 = \mathcal{X}, \mathcal{S}_2 = \mathcal{Y}, \mathcal{S}_3 = \mathcal{H}, \mathcal{S}_4 = \mathcal{D}$
2. $\mathcal{S}_1 = \mathcal{Y}, \mathcal{S}_2 = \mathcal{X}, \mathcal{S}_3 = \mathcal{H}, \mathcal{S}_4 = \mathcal{D}$
3. $\mathcal{S}_1 = \mathcal{D}, \mathcal{S}_2 = \mathcal{H}, \mathcal{S}_3 = \mathcal{Y}, \mathcal{S}_4 = \mathcal{X}$
4. $\mathcal{S}_1 = \mathcal{X}, \mathcal{S}_2 = \mathcal{D}, \mathcal{S}_3 = \mathcal{Y}, \mathcal{S}_4 = \mathcal{H}$

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How to use the four sets below to form a learning problem for song recommendation?

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4. $\mathcal{S}_1 = \mathcal{X}, \mathcal{S}_2 = \mathcal{D}, \mathcal{S}_3 = \mathcal{Y}, \mathcal{S}_4 = \mathcal{H}$

Reference Answer: 2

$$\mathcal{S}_4 \xrightarrow{\mathcal{A} \text{ on } \mathcal{S}_3} (g\colon \mathcal{S}_2 \to \mathcal{S}_1)$$

Machine Learning and Data Mining

Machine Learning

use data to compute hypothesis g that approximates target f

Data Mining

use **(huge)** data to **find property** that is interesting

Machine Learning and Data Mining

Machine Learning

use data to compute hypothesis g that approximates target f

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use **(huge)** data to **find property** that is interesting

- if 'interesting property' **same as** 'hypothesis that approximate target'

Machine Learning and Data Mining

Machine Learning	Data Mining
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  —**ML = DM** (usually what KDDCup does)

Machine Learning and Data Mining

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difficult to distinguish ML and DM in reality

Machine Learning and Artificial Intelligence

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Artificial Intelligence

compute **something that shows intelligent behavior**

Machine Learning and Artificial Intelligence

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- $g \approx f$ is something that shows intelligent behavior

Machine Learning and Artificial Intelligence

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Machine Learning and Artificial Intelligence

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Artificial Intelligence

compute **something that shows intelligent behavior**

- $g \approx f$ is something that shows intelligent behavior —**ML can realize AI**, among other routes
- e.g. chess playing
  - traditional AI: game tree
  - ML for AI: 'learning from board data'

Machine Learning and Artificial Intelligence

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—**ML can realize AI**, among other routes
- e.g. chess playing
  - traditional AI: game tree
  - ML for AI: ‘learning from board data’

ML is one possible route to realize AI

Machine Learning and Statistics

Machine Learning

use data to compute hypothesis g that approximates target f

Statistics

use data to **make inference about an unknown process**

Machine Learning and Statistics

Machine Learning

use data to compute hypothesis g that approximates target f

Statistics

use data to **make inference about an unknown process**

- g is an inference outcome; f is something unknown

Machine Learning and Statistics

Machine Learning

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Statistics

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- g is an inference outcome; f is something unknown —statistics **can be used to achieve ML**

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- traditional statistics also focus on **provable results with math assumptions**, and care less about computation

Machine Learning and Statistics

Machine Learning

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Statistics

use data to **make inference about an unknown process**

- g is an inference outcome; f is something unknown —statistics **can be used to achieve ML**
- traditional statistics also focus on **provable results with math assumptions**, and care less about computation

statistics: many useful tools for ML

Fun Time

Which of the following claim is not totally true?

1. machine learning is a route to realize artificial intelligence
2. machine learning, data mining and statistics all need data
3. data mining is just another name for machine learning
4. statistics can be used for data mining

Fun Time

Which of the following claim is not totally true?

1. machine learning is a route to realize artificial intelligence
2. machine learning, data mining and statistics all need data
3. data mining is just another name for machine learning
4. statistics can be used for data mining

Reference Answer: 3

While data mining and machine learning do share a huge overlap, they are arguably not equivalent because of the difference of focus.

Summary

1. **When** Can Machines Learn?

Lecture 1: The Learning Problem

- Course Introduction
  foundation oriented and story-like
- What is Machine Learning
  use data to approximate target
- Applications of Machine Learning
  almost everywhere
- Components of Machine Learning
  $\mathcal{A}$ **takes** $\mathcal{D}$ **and** $\mathcal{H}$ **to get** g
- Machine Learning and Other Fields
  related to DM, AI and Stats

- **next: a simple and yet useful learning model (**$\mathcal{H}$ **and** $\mathcal{A}$**)**

2. Why Can Machines Learn?
3. How Can Machines Learn?
4. How Can Machines Learn Better?