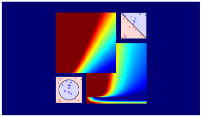
Machine Learning Foundations
(機器學習基石)



Lecture 3: Types of Learning

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Roadmap

1. **When** Can Machines Learn?

Lecture 2: Learning to Answer Yes/No

PLA $\mathcal{A}$ takes **linear separable** $\mathcal{D}$ and **perceptrons** $\mathcal{H}$ to get **hypothesis** g

Lecture 3: Types of Learning

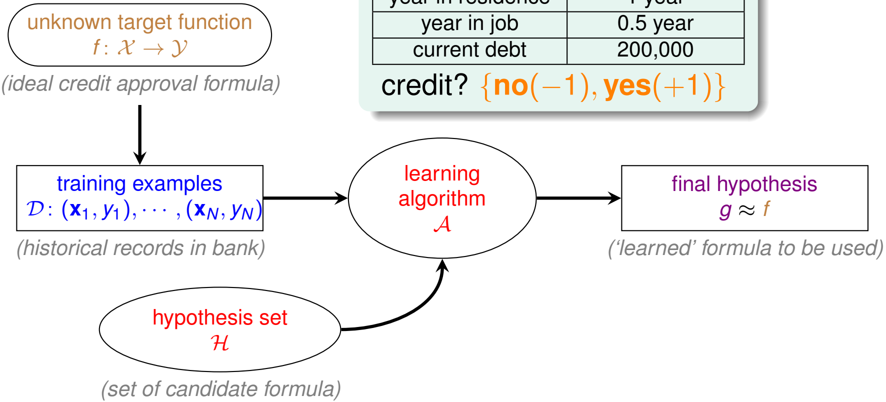
- Learning with Different Output Space $\mathcal{Y}$
- Learning with Different Data Label y_n
- Learning with Different Protocol $f \Rightarrow (\mathbf{x}_n, y_n)$
- Learning with Different Input Space $\mathcal{X}$

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

Credit Approval Problem Revisited

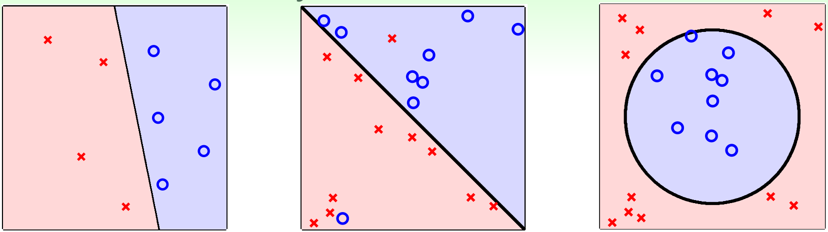
age	23 years
gender	female
annual salary	NTD 1,000,000
year in residence	1 year
year in job	0.5 year
current debt	200,000

credit? $\{\textbf{no}(-1), \textbf{yes}(+1)\}$



$\mathcal{Y} = \{-1, +1\}$: **binary classification**

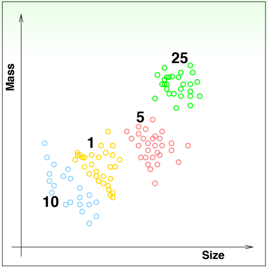
More Binary Classification Problems



- credit approve/disapprove
- email spam/non-spam
- patient sick/not sick
- ad profitable/not profitable
- answer correct/incorrect (KDDCup 2010)

core and important problem with
many tools as **building block of other tools**

Multiclass Classification: Coin Recognition Problem



- classify US coins (1c, 5c, 10c, 25c) by (size, mass)
- $\mathcal{Y} = \{1c, 5c, 10c, 25c\}$, or
  $\mathcal{Y} = \{1, 2, \cdots, K\}$ **(abstractly)**
- binary classification: special case with $K = 2$

Other Multiclass Classification Problems

- written digits $\Rightarrow 0, 1, \cdots, 9$
- pictures $\Rightarrow$ apple, orange, strawberry
- emails $\Rightarrow$ spam, primary, social, promotion, update (Google)

many applications in practice,
especially for 'recognition'

Regression: Patient Recovery Prediction Problem

- binary classification: patient features $\Rightarrow$ sick or not
- multiclass classification: patient features $\Rightarrow$ which type of cancer
- regression: patient features $\Rightarrow$ **how many days before recovery**
- $\mathcal{Y} = \mathbb{R}$ or $\mathcal{Y} = [\text{lower}, \text{upper}] \subset \mathbb{R}$ (bounded regression)
  —**deeply studied in statistics**

Other Regression Problems

- company data $\Rightarrow$ stock price
- climate data $\Rightarrow$ temperature

also core and important with many 'statistical' tools as **building block of other tools**

Structured Learning: Sequence Tagging Problem

$\underbrace{\textit{I}}_{\textit{pronoun}}\ \underbrace{\textit{love}}_{\textit{verb}}\ \underbrace{\textit{ML}}_{\textit{noun}}$

- multiclass classification: word $\Rightarrow$ word class
- structured learning:
  sentence $\Rightarrow$ structure (class of each word)
- $\mathcal{Y} = \{PVN, PVP, NVN, PV, \cdots\}$, not including *VVVVV*
- huge multiclass classification problem (structure $\equiv$ hyperclass) **without 'explicit' class definition**

Other Structured Learning Problems

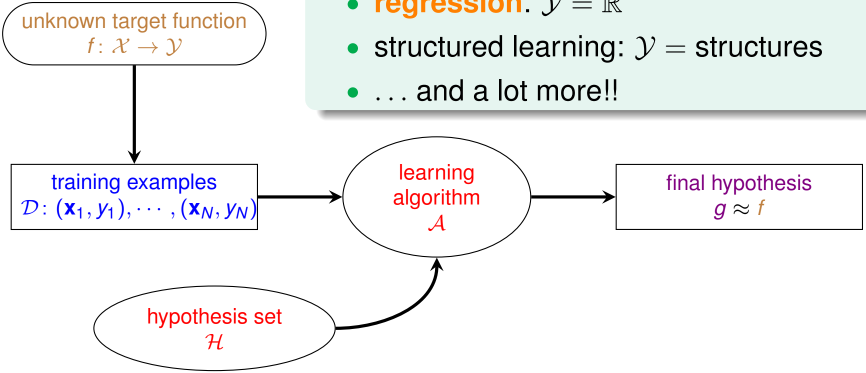
- protein data $\Rightarrow$ protein folding
- speech data $\Rightarrow$ speech parse tree

a fancy but complicated learning problem

Mini Summary

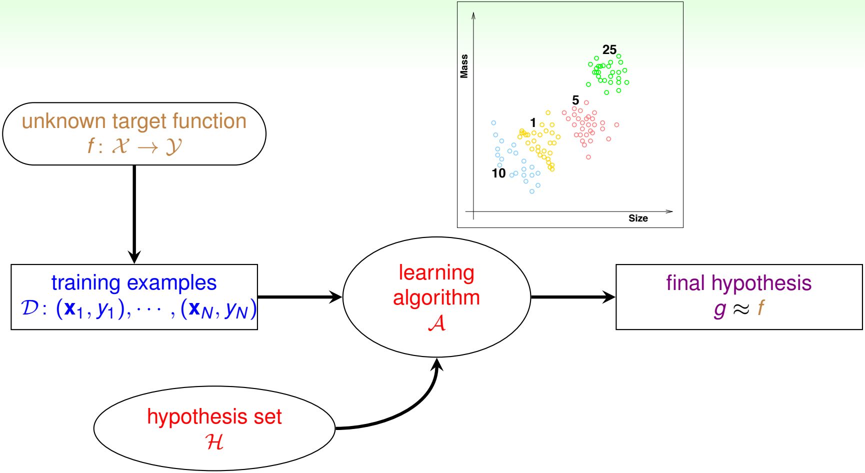
Learning with Different Output Space $\mathcal{Y}$

- **binary classification**: $\mathcal{Y} = \{-1, +1\}$
- multiclass classification: $\mathcal{Y} = \{1, 2, \cdots, K\}$
- **regression**: $\mathcal{Y} = \mathbb{R}$
- structured learning: $\mathcal{Y} =$ structures
- ... and a lot more!!



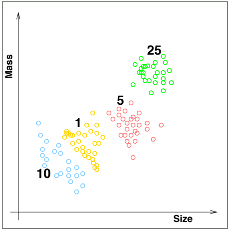
core tools: binary classification and regression

Supervised: Coin Recognition Revisited

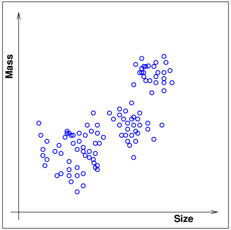


supervised learning:
every $\mathbf{x}_n$ **comes with corresponding y_n**

Unsupervised: Coin Recognition without y_n



supervised multiclass classification



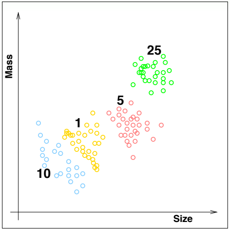
unsupervised multiclass classification
$\Longleftrightarrow$ '**clustering**'

Other Clustering Problems

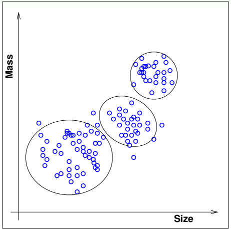
- articles $\Rightarrow$ topics
- consumer profiles $\Rightarrow$ consumer groups

clustering: a challenging but useful problem

Unsupervised: Coin Recognition without y_n



supervised multiclass classification



unsupervised multiclass classification
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Other Clustering Problems

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clustering: a challenging but useful problem

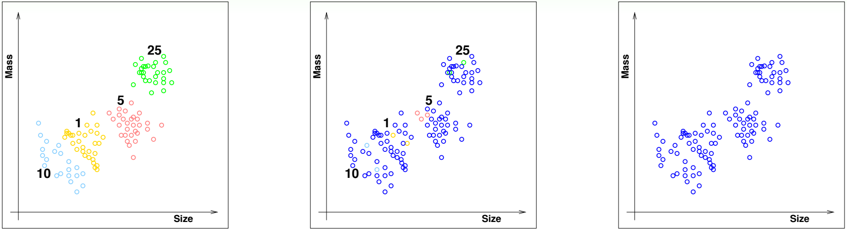
Unsupervised: Learning without y_n

Other Unsupervised Learning Problems

- clustering: $\{\mathbf{x}_n\} \Rightarrow \text{cluster}(\mathbf{x})$
  (≈ 'unsupervised multiclass classification')
  —i.e. articles ⇒ topics
- **density estimation**: $\{\mathbf{x}_n\} \Rightarrow \text{density}(\mathbf{x})$
  (≈ 'unsupervised bounded regression')
  —i.e. traffic reports with location ⇒ dangerous areas
- **outlier detection**: $\{\mathbf{x}_n\} \Rightarrow \text{unusual}(\mathbf{x})$
  (≈ extreme 'unsupervised binary classification')
  —i.e. Internet logs ⇒ intrusion alert
- . . . and a lot more!!

unsupervised learning: diverse, with possibly very different performance goals

Semi-supervised: Coin Recognition with Some y_n



supervised — **semi-supervised** — unsupervised (clustering)

Other Semi-supervised Learning Problems

- face images with a few labeled $\Rightarrow$ face identifier (Facebook)
- medicine data with a few labeled $\Rightarrow$ medicine effect predictor

semi-supervised learning: leverage unlabeled data to avoid 'expensive' labeling

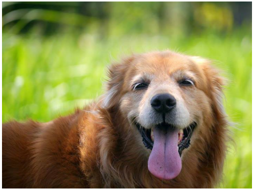
Reinforcement Learning

a 'very different' but natural way of learning

Teach Your Dog: Say 'Sit Down'

The dog pees on the ground.
BAD DOG. THAT'S A VERY WRONG ACTION.

- cannot easily show the dog that y_n = sit when $\mathbf{x}_n$ = 'sit down'
- but can 'punish' to say $\tilde{y}_n$ = pee is wrong



Other Reinforcement Learning Problems Using $(\mathbf{x}, \tilde{y}, \text{goodness})$

- (customer, ad choice, ad click earning) $\Rightarrow$ ad system
- (cards, strategy, winning amount) $\Rightarrow$ black jack agent

reinforcement: learn with **'partial/implicit information'** (often sequentially)

Reinforcement Learning

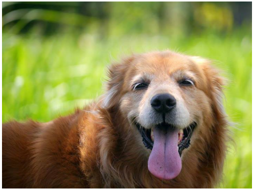
a 'very different' but natural way of learning

Teach Your Dog: Say 'Sit Down'

The dog sits down.

Good Dog. Let me give you some cookies.

- still cannot show y_n = sit when $\mathbf{x}_n$ = 'sit down'
- but can 'reward' to say $\tilde{y}_n$ = sit is good



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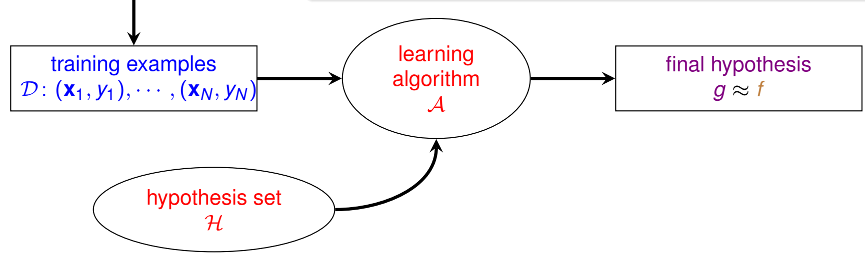
reinforcement: learn with **'partial/implicit information'** (often sequentially)

Mini Summary

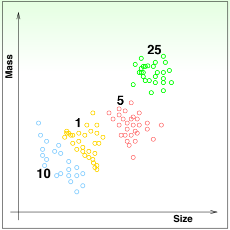
Learning with Different Data Label y_n

- **supervised**: all y_n
- unsupervised: no y_n
- semi-supervised: some y_n
- reinforcement: implicit y_n by goodness($\tilde{y}_n$)
- . . . and more!!



core tool: supervised learning

Batch Learning: Coin Recognition Revisited



unknown target function
$f\colon \mathcal{X} \to \mathcal{Y}$

training examples
$\mathcal{D}\colon (\mathbf{x}_1, y_1), \cdots, (\mathbf{x}_N, y_N)$

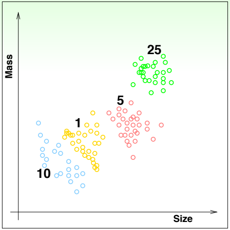
learning algorithm
$\mathcal{A}$

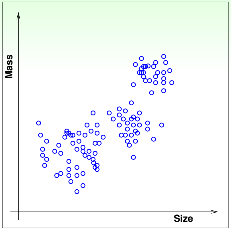
final hypothesis
$g \approx f$

hypothesis set
$\mathcal{H}$

batch supervised multiclass classification:
learn from **all known** data

More Batch Learning Problems





- batch of (email, spam?) $\Rightarrow$ spam filter
- batch of (patient, cancer) $\Rightarrow$ cancer classifier
- batch of patient data $\Rightarrow$ group of patients

batch learning: **a very common protocol**

Online: Spam Filter that 'Improves'

- batch spam filter:
  learn with known (email, spam?) pairs, and predict with fixed g
- **online** spam filter, which **sequentially**:
  1. observe an email $\mathbf{x}_t$
  2. predict spam status with current $g_t(\mathbf{x}_t)$
  3. receive 'desired label' y_t from user, and then update g_t with $(\mathbf{x}_t, y_t)$

Connection to What We Have Learned

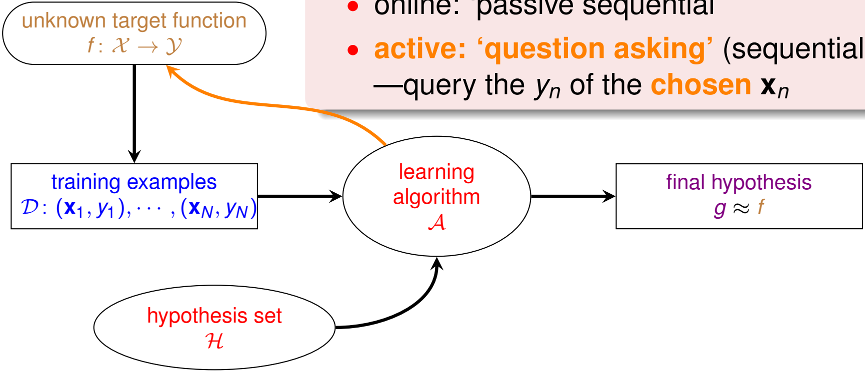
- PLA can be easily adapted to online protocol (how?)
- reinforcement learning is often done online (why?)

online: hypothesis 'improves' through receiving data instances **sequentially**

Active Learning: Learning by ‘Asking’

Protocol ⇔ Learning Philosophy

- batch: ‘duck feeding’
- online: ‘passive sequential’
- **active: ‘question asking’** (sequentially) —query the y_n of the **chosen** $\mathbf{x}_n$

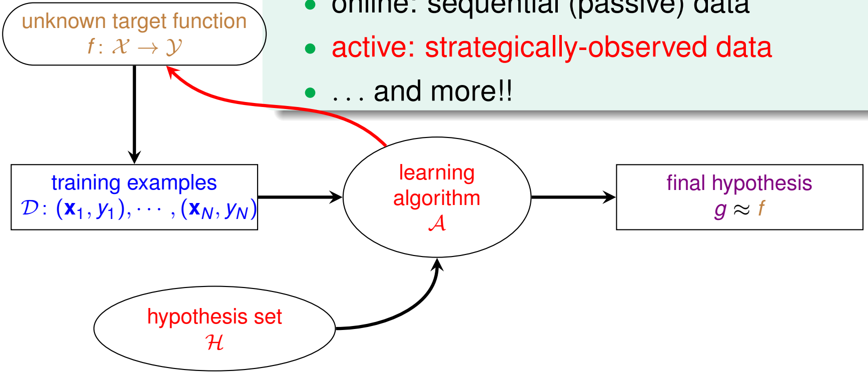


active: improve hypothesis with fewer labels (hopefully) by asking questions **strategically**

Mini Summary

Learning with Different Protocol $f \Rightarrow (\mathbf{x}_n, y_n)$

- **batch**: all known data
- online: sequential (passive) data
- active: strategically-observed data
- . . . and more!!



core protocol: batch

Credit Approval Problem Revisited

age	23 years
gender	female
annual salary	NTD 1,000,000
year in residence	1 year
year in job	0.5 year
current debt	200,000

unknown target function
$f : \mathcal{X} \rightarrow \mathcal{Y}$

(ideal credit approval formula)

training examples
$\mathcal{D} : (\mathbf{x}_1, y_1), \cdots, (\mathbf{x}_N, y_N)$

(historical records in bank)

learning algorithm
$\mathcal{A}$

final hypothesis
$g \approx f$

('learned' formula to be used)

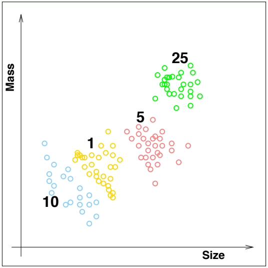
hypothesis set
$\mathcal{H}$

(set of candidate formula)

concrete features: each dimension of $\mathcal{X} \subseteq \mathbb{R}^d$ represents 'sophisticated physical meaning'

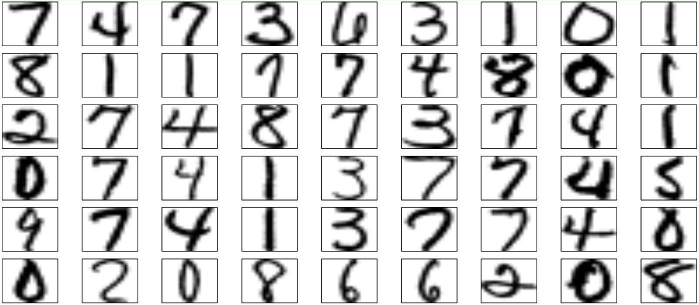
More on Concrete Features

- **(size, mass)** for coin classification
- **customer info** for credit approval
- **patient info** for cancer diagnosis
- often including 'human intelligence' on the learning task



concrete features: the 'easy' ones for ML

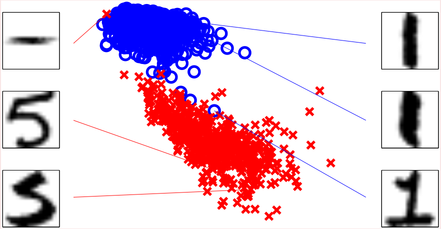
Raw Features: Digit Recognition Problem (1/2)



- digit recognition problem: features $\Rightarrow$ meaning of digit
- a typical supervised multiclass classification problem

Raw Features: Digit Recognition Problem (2/2)

by Concrete Features



$\mathbf{x}$ =(symmetry, density)

by Raw Features

- 16 by 16 gray image $\mathbf{x} \equiv (0, 0, 0.9, 0.6, \cdots) \in \mathbb{R}^{256}$
- '**simple** physical meaning'; thus more difficult for ML than concrete features

Other Problems with Raw Features

- image pixels, speech signal, etc.

raw features: often need human or machines to **convert to concrete ones**

Abstract Features: Rating Prediction Problem

Rating Prediction Problem (KDDCup 2011)

- given previous (userid, itemid, rating) tuples, predict the rating that some userid would give to itemid?
- a regression problem with $\mathcal{Y} \subseteq \mathbb{R}$ as rating and $\mathcal{X} \subseteq \mathbb{N} \times \mathbb{N}$ **as (userid, itemid)**
- '**no** physical meaning'; thus even more difficult for ML

Other Problems with Abstract Features

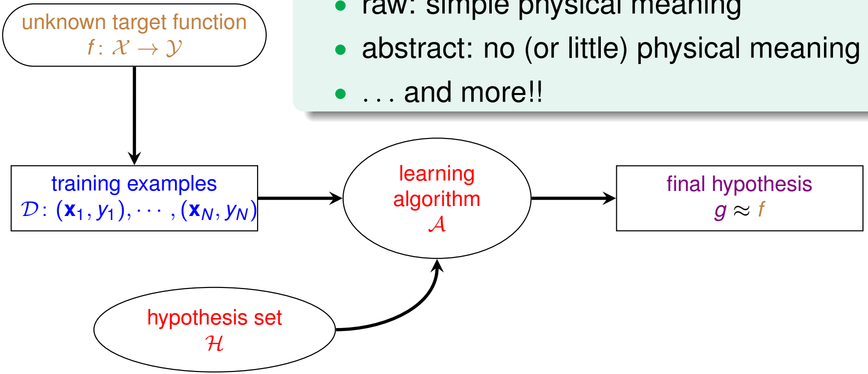
- student ID in online tutoring system (KDDCup 2010)
- advertisement ID in online ad system

abstract: again need '**feature conversion**/extraction/construction'

Mini Summary

Learning with Different Input Space $\mathcal{X}$

- **concrete**: sophisticated (and related) physical meaning
- raw: simple physical meaning
- abstract: no (or little) physical meaning
- ... and more!!



'easy' input: concrete

Summary

1. **When** Can Machines Learn?

Lecture 2: Learning to Answer Yes/No

Lecture 3: Types of Learning

- Learning with Different Output Space $\mathcal{Y}$
  [classification], [regression], structured
- Learning with Different Data Label y_n
  [supervised], un/semi-supervised, reinforcement
- Learning with Different Protocol $f \Rightarrow (\mathbf{x}_n, y_n)$
  [batch], online, active
- Learning with Different Input Space $\mathcal{X}$
  [concrete], raw, abstract

- **next: learning is impossible?!**

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