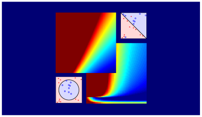
Machine Learning Foundations
(機器學習基石)



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

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

(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
$g \approx f$

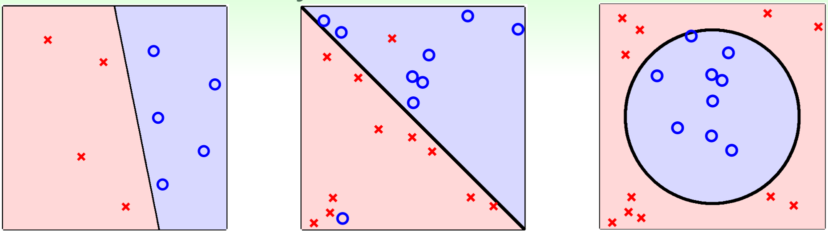
('learned' formula to be used)

hypothesis set
$\mathcal{H}$

(set of candidate formula)

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

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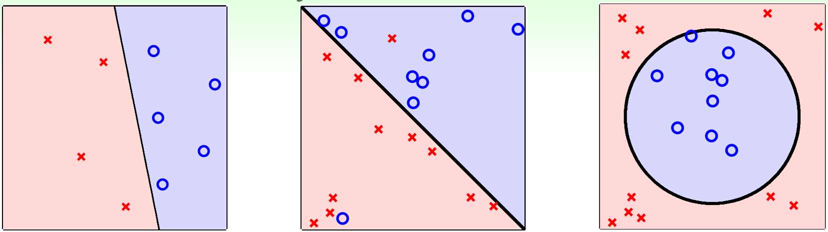

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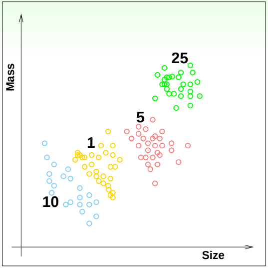
core and important problem with
many tools as **building block of other tools**

Multiclass Classification: Coin Recognition Problem



- classify US coins (1c, 5c, 10c, 25c) by (size, mass)

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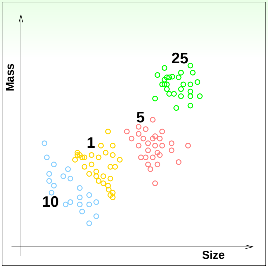

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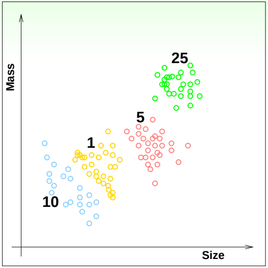

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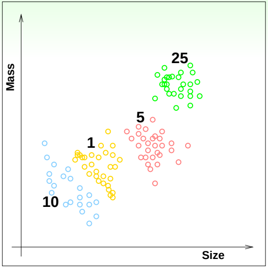

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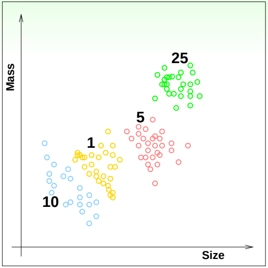
Other Multiclass Classification Problems

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

Multiclass Classification: Coin Recognition Problem



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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

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Other Regression Problems

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

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

Structured Learning: Sequence Tagging Problem

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

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

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Other Structured Learning Problems

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

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Other Structured Learning Problems

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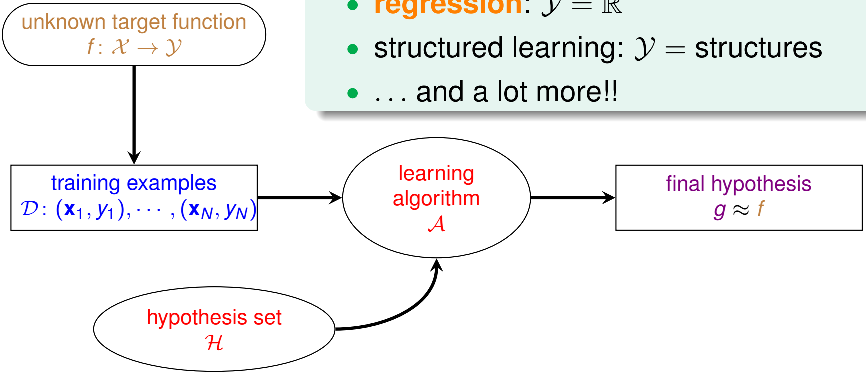
a fancy but complicated learning problem

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

Fun Time

What is this learning problem?

The entrance system of the school gym, which does automatic face recognition based on machine learning, is built to charge four different groups of users differently: Staff, Student, Professor, Other. What type of learning problem best fits the need of the system?

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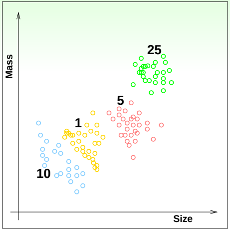
Reference Answer: 2

There is an 'explicit' $\mathcal{Y}$ that contains four classes.

Supervised: Coin Recognition Revisited



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

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

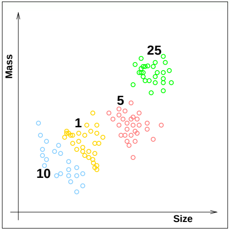
learning algorithm
$\mathcal{A}$

final hypothesis
$g \approx f$

hypothesis set
$\mathcal{H}$

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

Unsupervised: Coin Recognition without y_n



supervised multiclass classification

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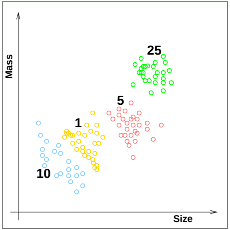

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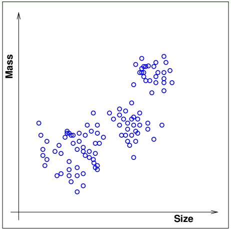

unsupervised multiclass classification
$\iff$ '**clustering**'

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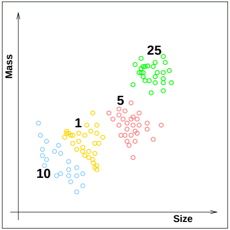

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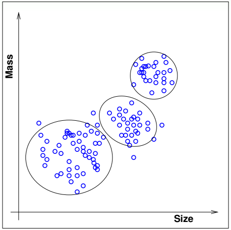

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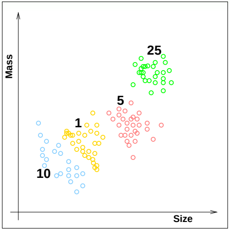

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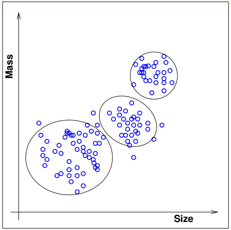

unsupervised multiclass classification
$\iff$ '**clustering**'

Other Clustering Problems

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

clustering: a challenging but useful problem

Unsupervised: Learning without y_n

Other Unsupervised Learning Problems

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

Unsupervised: Learning without y_n

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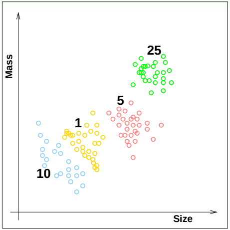
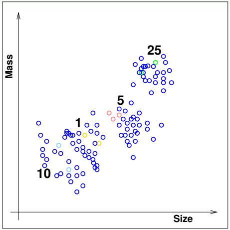
unsupervised learning: diverse, with possibly very different performance goals

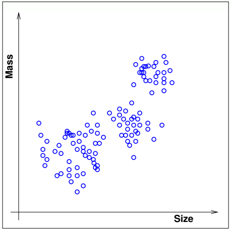
Semi-supervised: Coin Recognition with Some y_n



supervised



semi-supervised

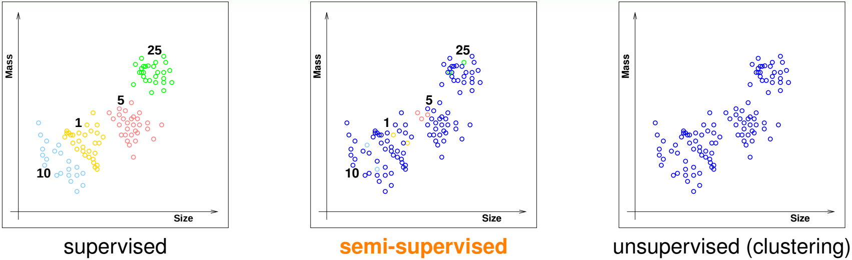


unsupervised (clustering)

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: Coin Recognition with Some y_n



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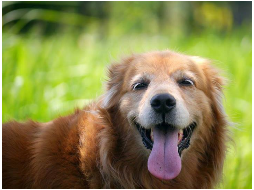
semi-supervised learning: leverage unlabeled data to avoid 'expensive' labeling

Reinforcement Learning

a 'very different' but natural way of learning



Reinforcement Learning

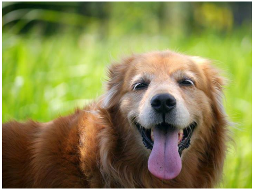
a 'very different' but natural way of learning

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



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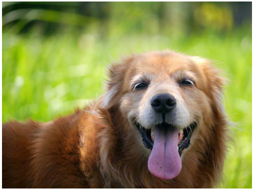
The dog sits down.

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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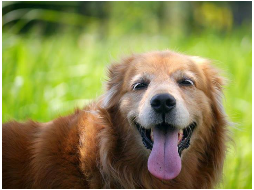

Other Reinforcement Learning Problems Using $(\mathbf{x}, \tilde{y}, \text{goodness})$

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

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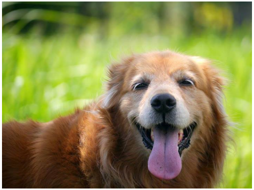

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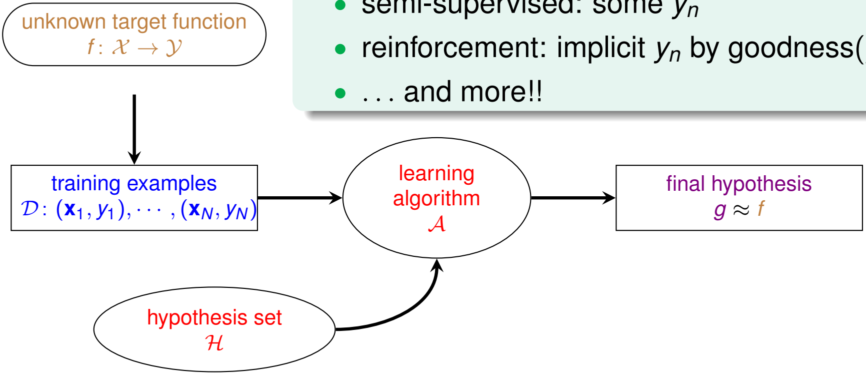
reinforcement: learn with **'partial/implicit information'** (often sequentially)

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

Fun Time

What is this learning problem?

To build a tree recognition system, a company decides to gather one million of pictures on the Internet. Then, it asks each of the 10 company members to view 100 pictures and record whether each picture contains a tree. The pictures and records are then fed to a learning algorithm to build the system. What type of learning problem does the algorithm need to solve?

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1. supervised
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3. semi-supervised
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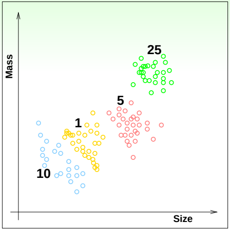
Reference Answer: 3

The $1,000$ records are the labeled $(\mathbf{x}_n, y_n)$; the other $999,000$ pictures are the unlabeled $\mathbf{x}_n$.

Batch Learning: Coin Recognition Revisited



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

learning algorithm
$\mathcal{A}$

final hypothesis
$g \approx f$

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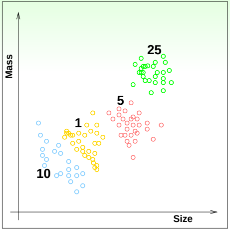
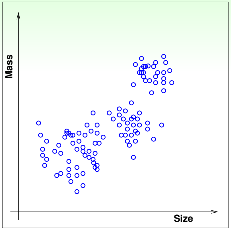
batch supervised multiclass classification:
learn from **all known** data

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

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Connection to What We Have Learned

- PLA can be easily adapted to online protocol (how?)

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Connection to What We Have Learned

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

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  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

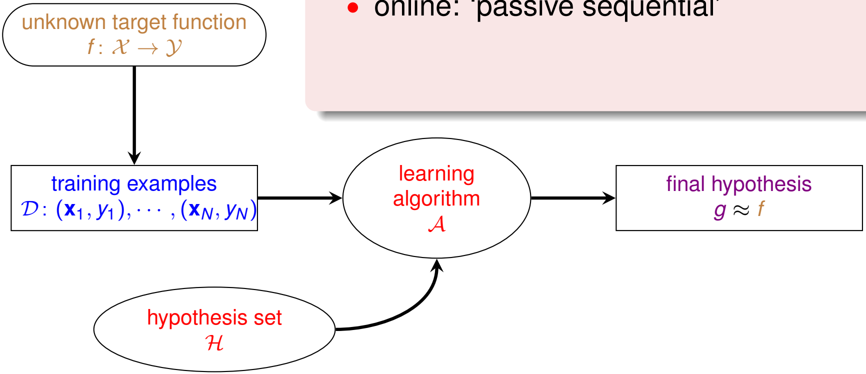
- PLA can be easily adapted to online protocol (how?)
- reinforcement learning is often done online (why?)

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

Active Learning: Learning by 'Asking'

Protocol $\Leftrightarrow$ Learning Philosophy

- batch: 'duck feeding'
- online: 'passive sequential'



Active Learning: Learning by 'Asking'

Protocol ⇔ Learning Philosophy

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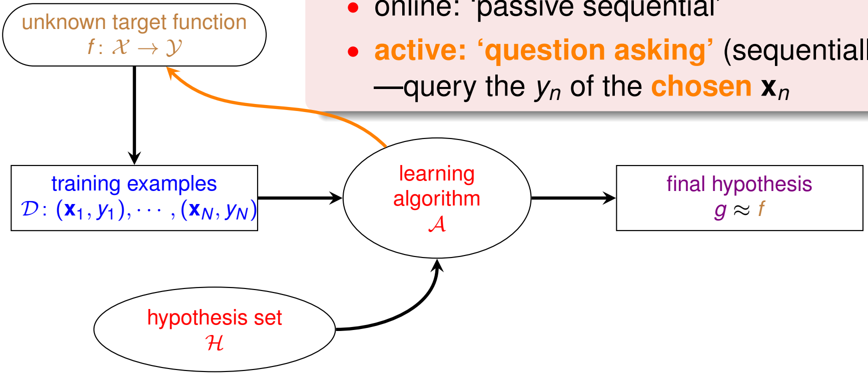

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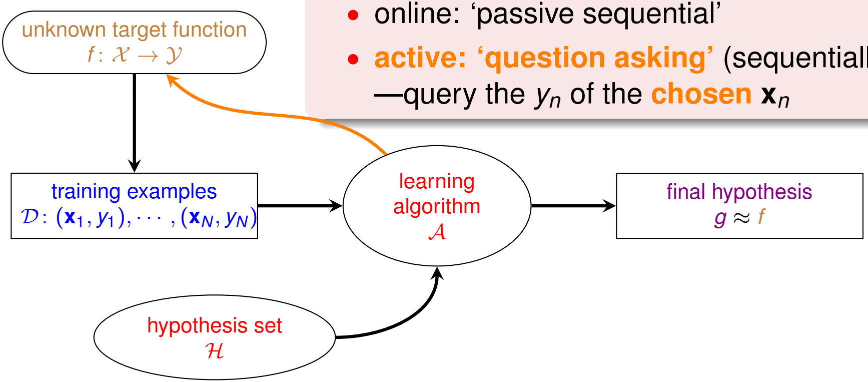
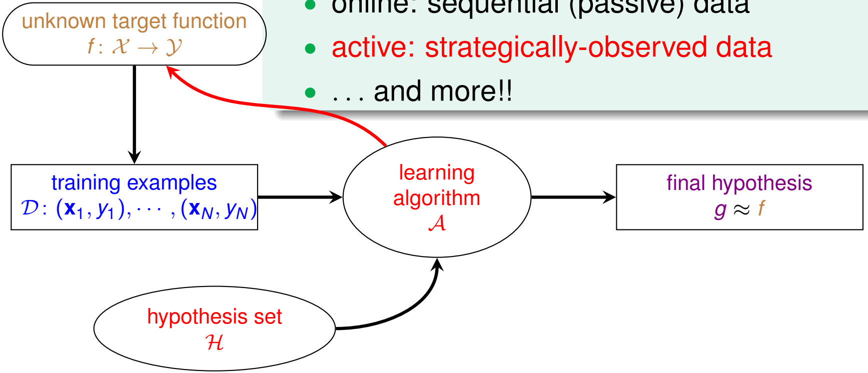


active: improve hypothesis with fewer labels (hopefully) by asking questions **strategically**

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

Fun Time

What is this learning problem?

A photographer has $100,000$ pictures, each containing one baseball player. He wants to automatically categorize the pictures by its player inside. He starts by categorizing $1,000$ pictures by himself, and then writes an algorithm that tries to categorize the other pictures if it is 'confident' on the category while pausing for (& learning from) human input if not. What protocol best describes the nature of the algorithm?

1. batch
2. online
3. active
4. random

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3. active
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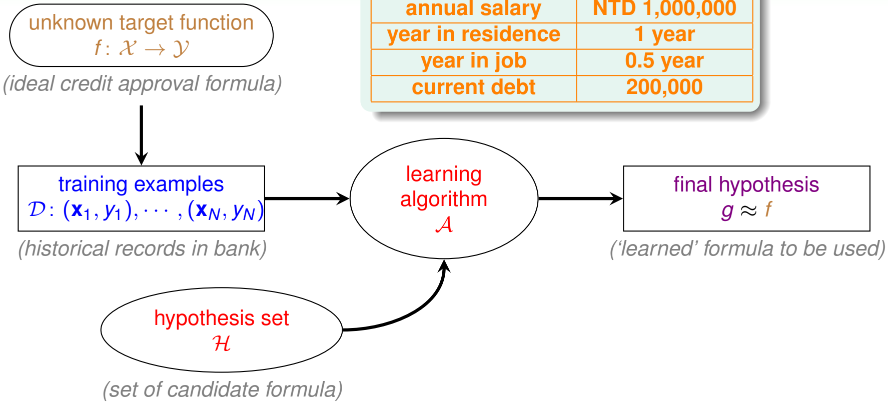
Reference Answer: 3

The algorithm takes a active but naïve strategy: ask when 'confused'. **You should probably do the same when taking a class. :-)**

Credit Approval Problem Revisited

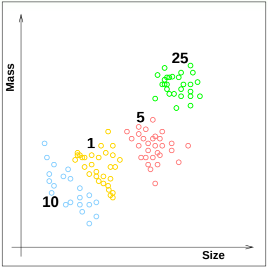
age	23 years
gender	female
annual salary	NTD 1,000,000
year in residence	1 year
year in job	0.5 year
current debt	200,000



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

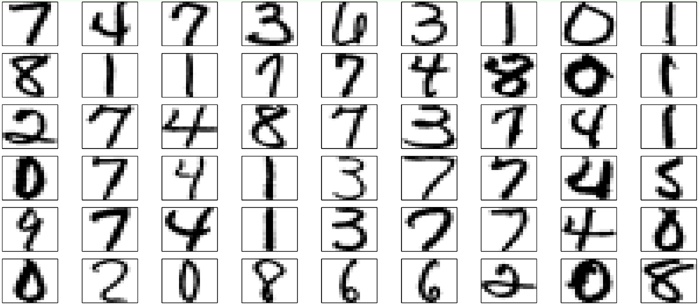
More on Concrete Features

- **(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

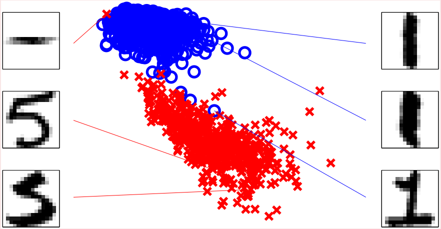
Raw Features: Digit Recognition Problem (1/2)



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

Raw Features: Digit Recognition Problem (2/2)

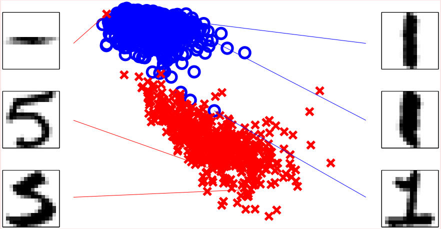
by Concrete Features



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

Raw Features: Digit Recognition Problem (2/2)

by Concrete Features



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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

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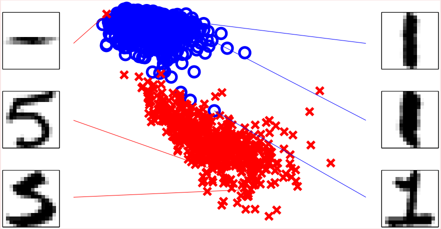

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Other Problems with Raw Features

- image pixels, speech signal, etc.

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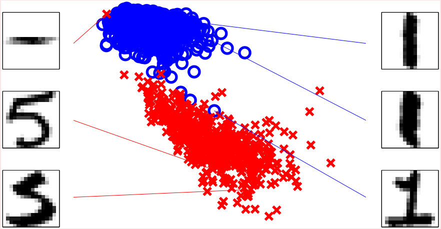

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Other Problems with Raw Features

- 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)**

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Other Problems with Abstract Features

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

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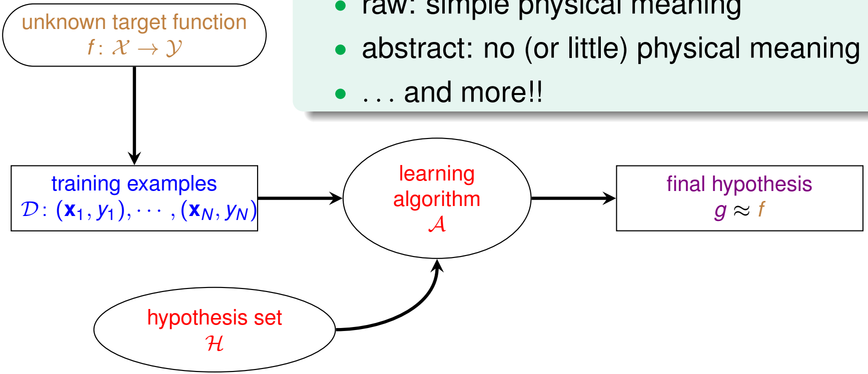
abstract: again need '**feature conversion**/extraction/construction'

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

Fun Time

What features can be used?

Consider a problem of building an online image advertisement system that shows the users the most relevant images. What features can you choose to use?

1. concrete
2. concrete, raw
3. concrete, abstract
4. concrete, raw, abstract

Fun Time

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Reference Answer: 4

concrete user features, raw image features, and maybe abstract user/image IDs

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?