

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

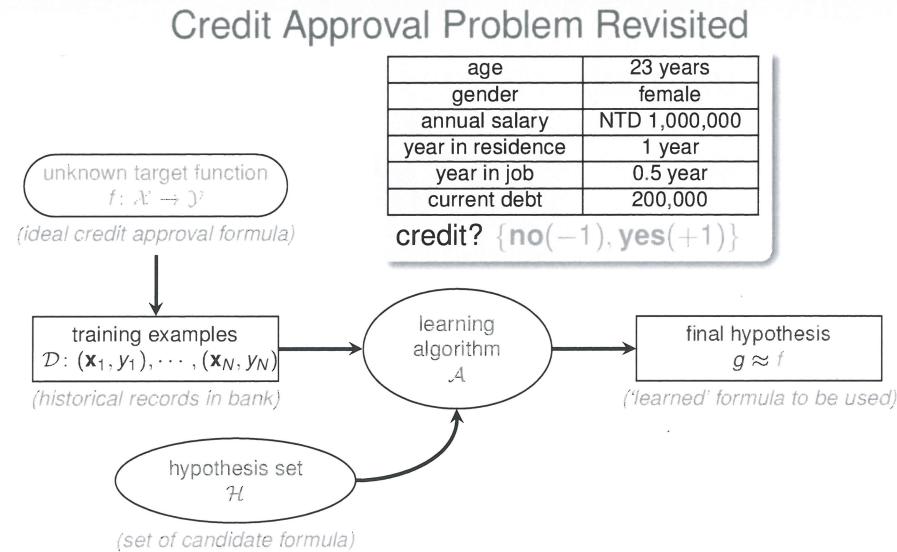
Lecture 3: Types of Learning

- 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?

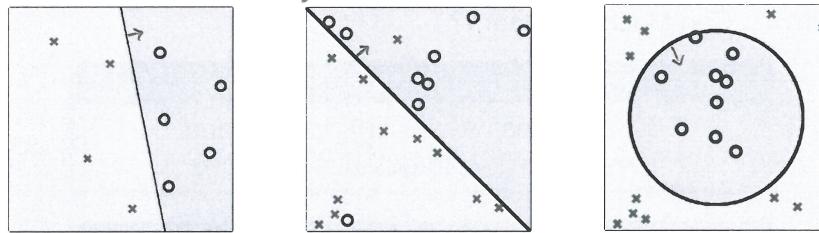
③ How Can Machines Learn?

④ How Can Machines Learn Better?



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

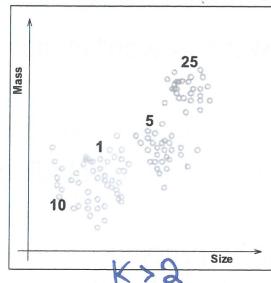
More Binary Classification Problems



- credit approve/disapprove
- email spam/non-spam
- patient sick/not sick
- ad profitable/not profitable 有利可圖
- 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 $\mathcal{Y} = \{1, 2, \dots, K\}$ (abstractly)
- binary classification: special case with $K = 2$

Other Multiclass Classification Problems

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

many applications in practice,
especially for 'recognition'

視覺 聰敏 計算

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

回歸分析

Other Regression Problems

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

大氣

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

序列標注問題

Structured Learning: Sequence Tagging Problem

I *love* *ML*
 pronoun verb noun

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

Other Structured Learning Problems

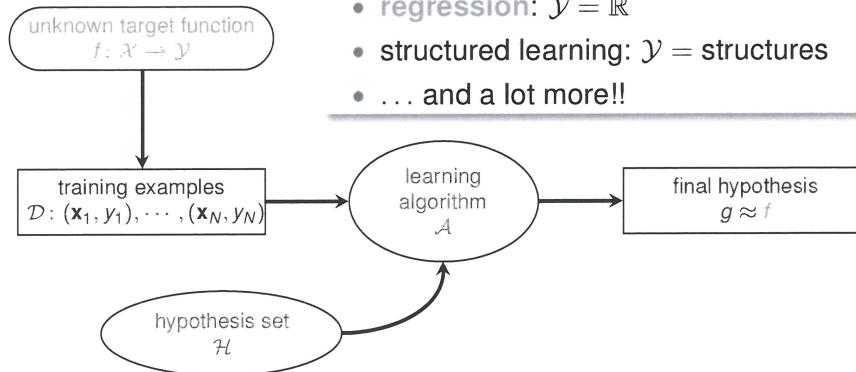
- protein data \Rightarrow protein folding
- speech data \Rightarrow speech parse tree

a fancy but complicated learning problem

Mini Summary

Learning with Different Output Space \mathcal{Y}

- binary classification: $\mathcal{Y} = \{-1, +1\}$
- multiclass classification: $\mathcal{Y} = \{1, 2, \dots, K\}$
- regression: $\mathcal{Y} = \mathbb{R}$
- structured learning: $\mathcal{Y} = \text{structures}$
- ... 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?

- ① binary classification
- ② multiclass classification
- ③ regression
- ④ structured learning

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- ③ regression
- ④ structured learning

Reference Answer: ②

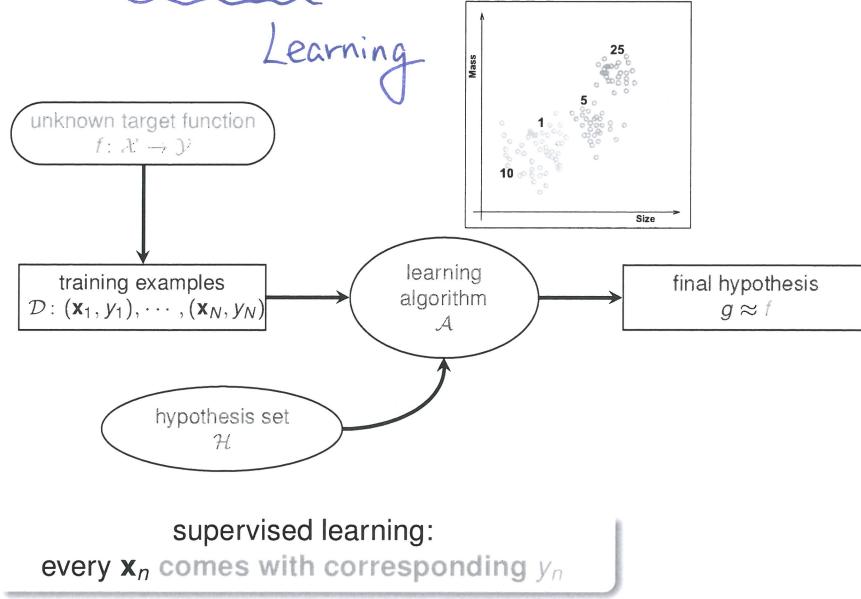
There is an 'explicit' \mathcal{Y} that contains four classes.

監督式學習

Types of Learning

Learning with Different Data Label y_n

Supervised: Coin Recognition Revisited



Hsuan-Tien Lin (NTU CSIE)

Machine Learning Foundations

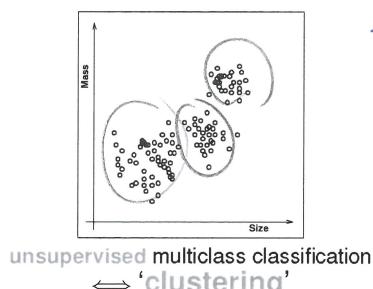
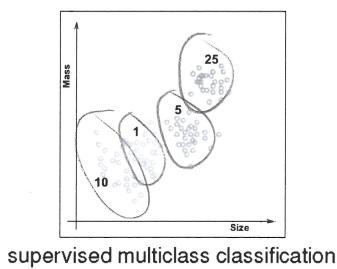
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非監督式學習

Types of Learning

Learning with Different Data Label y_n

Unsupervised: Coin Recognition without y_n



分群
很難去
分辨

Other Clustering Problems

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

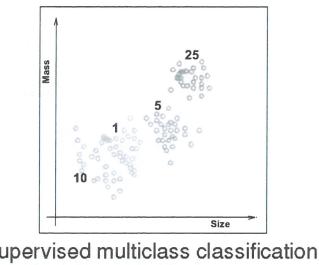
clustering: a challenging but useful problem

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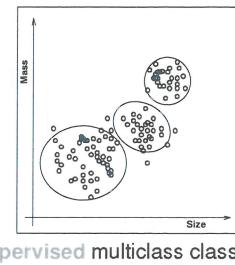
Machine Learning Foundations

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Unsupervised: Coin Recognition without y_n



supervised multiclass classification

unsupervised multiclass classification
↔ '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!!

密度
估計

異常檢測

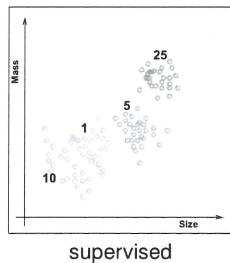
unsupervised learning: diverse, with possibly
very different performance goals

半監督式學習

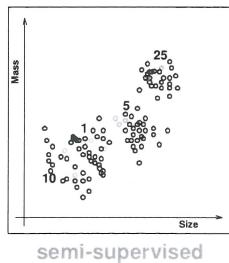
Types of Learning

Learning with Different Data Label y_n

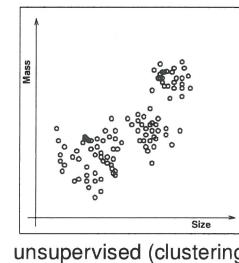
Semi-supervised: Coin Recognition with Some y_n



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

Types of Learning

Learning with Different Data Label y_n

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 $y_n = \text{sit}$ when $x_n = \text{'sit down'}$
- but can 'punish' to say $\tilde{y}_n = \text{pee}$ is wrong



Other Reinforcement Learning Problems Using (x, \tilde{y} , 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)

增強性學習

Types of Learning

Learning with Different Data Label y_n

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 $y_n = \text{sit}$ when $x_n = \text{'sit down'}$
- but can 'reward' to say $\tilde{y}_n = \text{sit is good}$



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

- (customer, ad choice, ad click earning) \Rightarrow ad system
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reinforcement: learn with 'partial/implicit information' (often sequentially)

Types of Learning

Learning with Different Data Label y_n

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!!

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

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

learning algorithm
 \mathcal{A}

final hypothesis
 $g \approx f$

hypothesis set
 \mathcal{H}

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?

- ① supervised
- ② unsupervised
- ③ semi-supervised
- ④ reinforcement

部分有 $y \Rightarrow$ Semi-supervised.
 ↑

1000000 中 1000 張有 y

Fun Time

What is this learning problem?

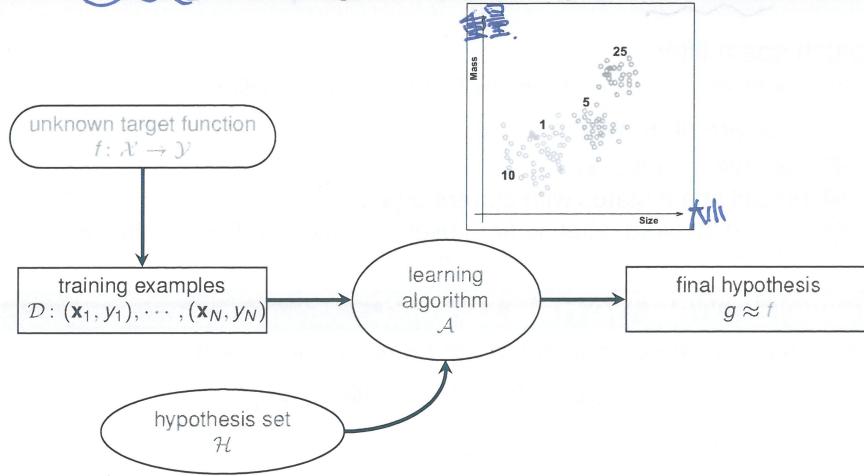
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- ① supervised
- ② unsupervised
- ③ semi-supervised
- ④ reinforcement

Reference Answer: ③

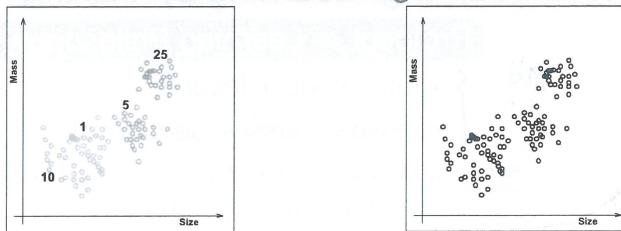
The 1,000 records are the labeled (\mathbf{x}_n, y_n) ; the other 999,000 pictures are the unlabeled \mathbf{x}_n .

Batch Learning: Coin Recognition Revisited



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)

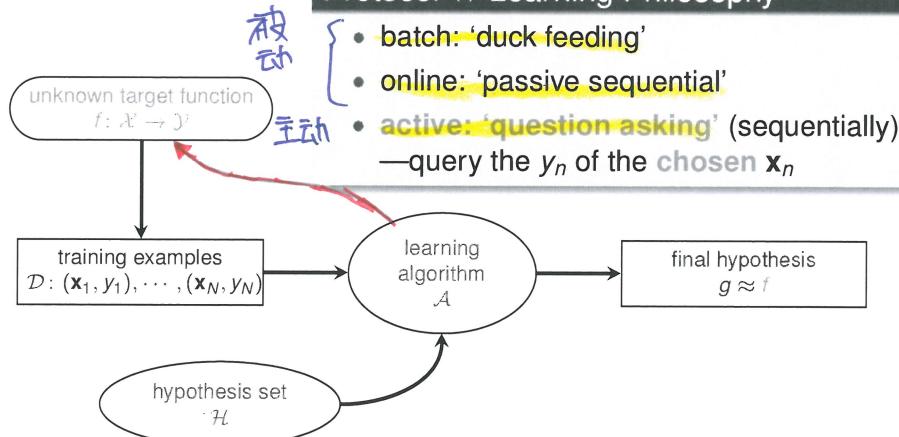
Connection to What We Have Learned

- 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 \Leftrightarrow Learning Philosophy

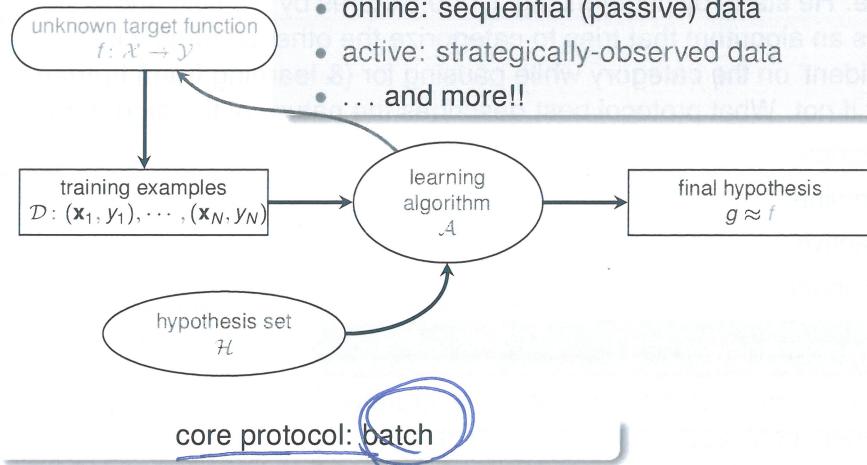


active: improve hypothesis with fewer labels
(hopefully) by asking questions strategically

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!!



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

机器問 ⇒ active

Fun Time

What is this learning problem?

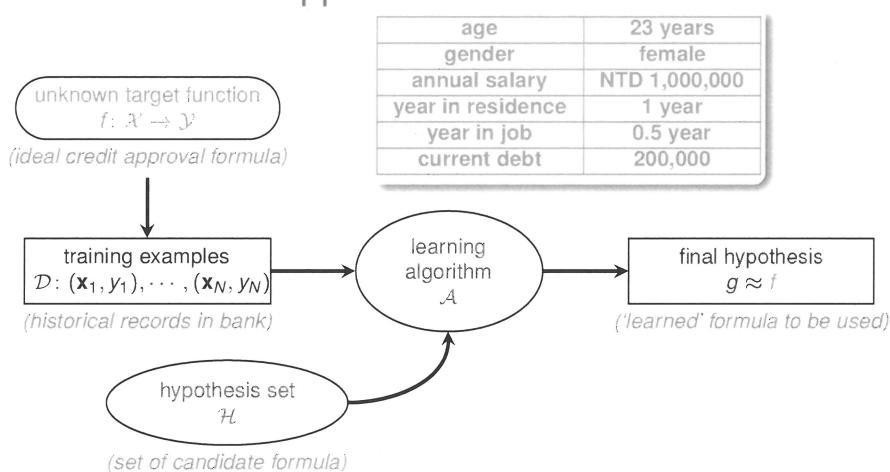
A photographer has 100,000 pictures, each containing one baseball player. He wants to automatically categorize the pictures by its player inside. He starts by categorizing 1,000 pictures by himself, and then writes an algorithm that tries to categorize the other pictures if it is ‘confident’ on the category 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

Reference Answer: ③

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

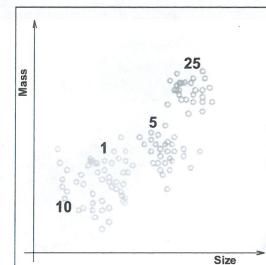
Credit Approval Problem Revisited



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

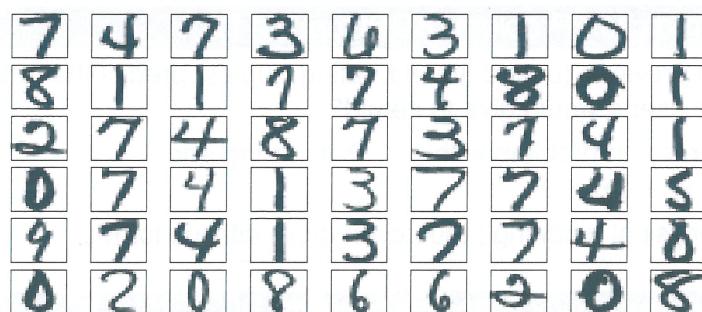
More on Concrete Features

- **(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

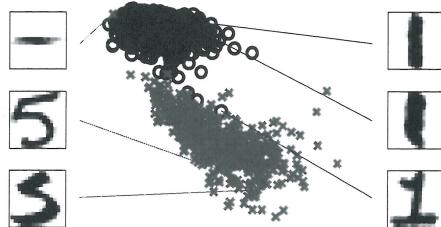
Raw Features: Digit Recognition Problem (1/2)



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

Raw Features: Digit Recognition Problem (2/2)

by Concrete Features



by Raw Features

- 16 by 16 gray image $\mathbf{x} \equiv (0, 0, 0.9, 0.6, \dots) \in \mathbb{R}^{256}$
- ‘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)

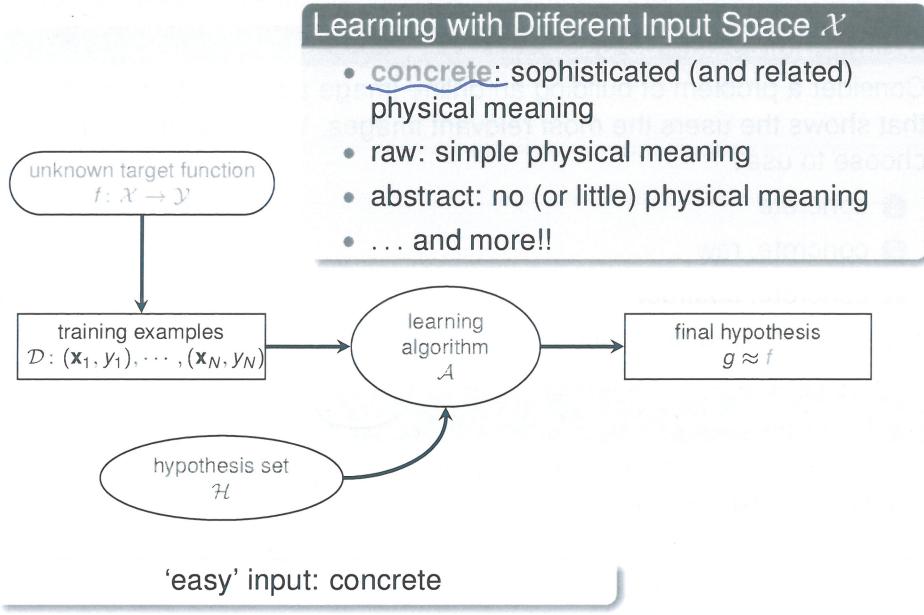
- given previous (userid, itemid, rating) tuples, predict the rating that some userid would give to itemid?
- a regression problem with $\mathcal{Y} \subseteq \mathbb{R}$ as rating and $\mathcal{X} \subseteq \mathbb{N} \times \mathbb{N}$ as (userid, itemid)
- ‘no physical meaning’; thus even more difficult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



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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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

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?