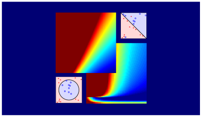
Machine Learning Foundations
(機器學習基石)



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

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

(ideal credit approval formula)

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

(historical records in bank)

learning algorithm
$\mathcal{A}$

final hypothesis
$g \approx f$

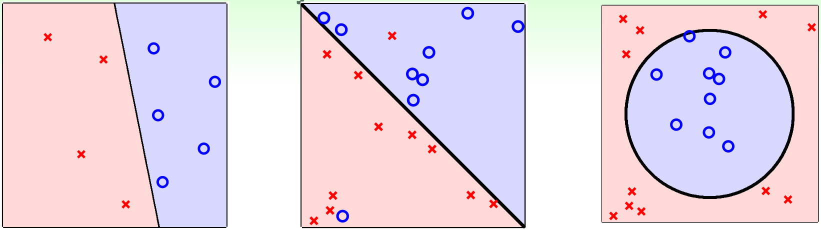
('learned' formula to be used)

hypothesis set
$\mathcal{H}$

(set of candidate formula)

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

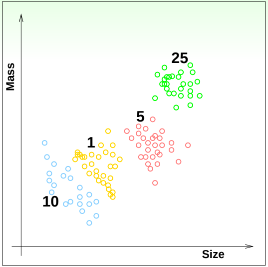
More Binary Classification Problems



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

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'

Multiclass Classification: Which Fruit?

?

(image by Robert-Owen-Wahl from Pixabay)

apple

orange

strawberry

kiwi

(images by Pexels, PublicDomainPictures, 192635, Rob van der Meijden from Pixabay)

$$\mathcal{Y} = \{\text{apple}, \text{orange}, \text{strawberry}, \text{kiwi}\}$$

Multilabel Classification: Which Fruits?

?: {apple, orange, kiwi}

(image by Michal Jarmoluk from Pixabay)

apple

orange

strawberry

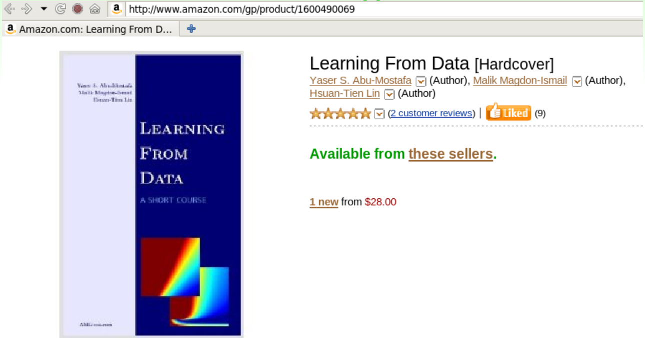
kiwi

(images by Pexels, PublicDomainPictures, 192635, Rob van der Meijden from Pixabay)

multilabel classification:
classify input to multiple (or no) categories

$$\mathcal{Y} = 2^{\{\text{apple},\text{orange},\text{strawberry},\text{kiwi}\}}$$

What Tags?



?: {machine learning, ~~data structure~~, data mining, ~~object oriented programming~~, artificial intelligence, ~~compiler~~, ~~architecture~~, ~~chemistry~~, textbook, ~~children book~~, ~~... etc.~~ }

another multilabel classification problem:
tagging input to multiple categories

Binary Relevance: Multilabel Classification via Yes/No

binary classification

$\{$yes, no$\}$

multilabel w/ L classes: L yes/no questions

machine learning (Y), data structure (N), data mining (Y), OOP (N), AI (Y), compiler (N), architecture (N), chemistry (N), textbook (Y), children book (N), etc.

- Binary Relevance (BR): reduction (transformation) to multiple isolated binary classification
- disadvantages (addressed by more sophisticated models):
  - isolation—hidden relations not exploited
    (e.g. ML and DM highly correlated, ML subset of AI, textbook & children book disjoint)
  - imbalanced—few yes, many no

BR for multilabel classification:
uses binary classification as a core tool

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

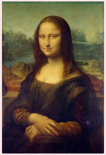
Other Regression Problems

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

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

Sophisticated Output: Image Generation Problems

Style Transfer

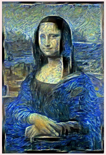


(Leonardo da Vinci, in Public Domain)

$+$

(Van Gogh, in Public Domain)

$\Rightarrow$



(Pjfinlay, with CC0)

all images are downloaded from Wikipedia

Other Image Generation Problems

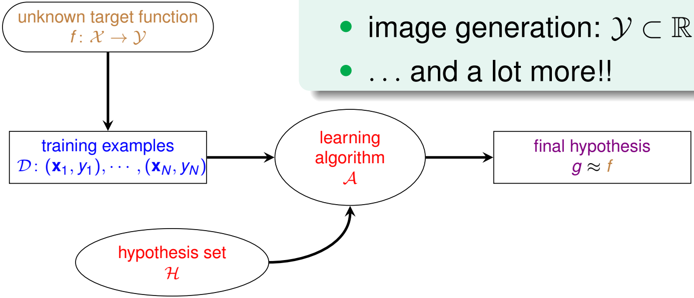
- noisy image $\Rightarrow$ clean image
- low-resolution image $\Rightarrow$ high-resolution image

$\mathcal{Y}$: a 'manifold' $\subset \mathbb{R}^{w \times h \times c}$,
arguably not just multi-pixel regression

Mini Summary

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

- binary classification: $\mathcal{Y} = \{-1, +1\}$
- multiclass classification: $\mathcal{Y} = \{1, 2, \cdots, K\}$
- multilabel classification: $\mathcal{Y} = 2^{\{1,2,\cdots,K\}}$
- regression: $\mathcal{Y} = \mathbb{R}$
- image generation: $\mathcal{Y} \subset \mathbb{R}^{w \times h \times c}$
- ... 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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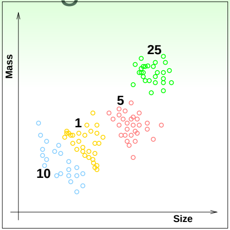
1. binary classification
2. multiclass classification
3. regression
4. structured learning

Reference Answer: 2

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

Supervised: Coin Recognition Revisited



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

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

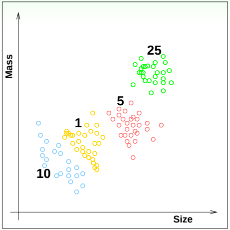
learning algorithm
$\mathcal{A}$

final hypothesis
$g \approx f$

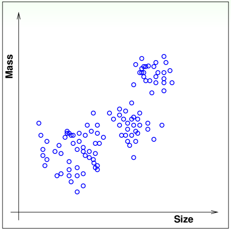
hypothesis set
$\mathcal{H}$

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

Unsupervised: Coin Recognition without y_n



supervised multiclass classification



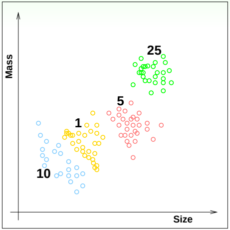
unsupervised multiclass classification
$\Longleftrightarrow$ 'clustering'

Other Clustering Problems

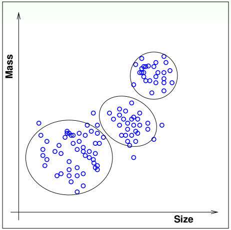
- articles $\Rightarrow$ topics
- consumer profiles $\Rightarrow$ consumer groups

clustering: a challenging but useful problem

Unsupervised: Coin Recognition without y_n



supervised multiclass classification



unsupervised multiclass classification
$\Longleftrightarrow$ 'clustering'

Other Clustering Problems

- articles $\Rightarrow$ topics
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clustering: a challenging but useful problem

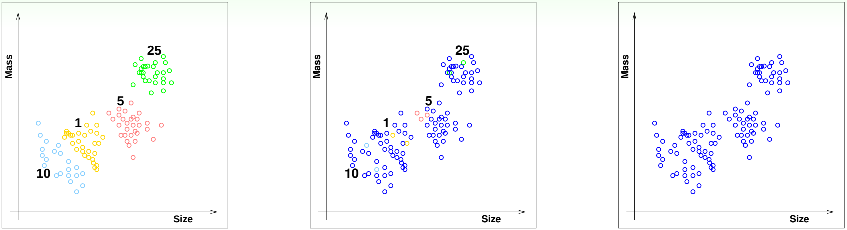
Unsupervised: Learning without y_n

Other Unsupervised Learning Problems

- clustering: $\{\mathbf{x}_n\} \Rightarrow \text{cluster}(\mathbf{x})$
  ($\approx$ '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: diverse, with possibly very different performance goals

Semi-supervised: Coin Recognition with Some y_n



supervised semi-supervised unsupervised (clustering)

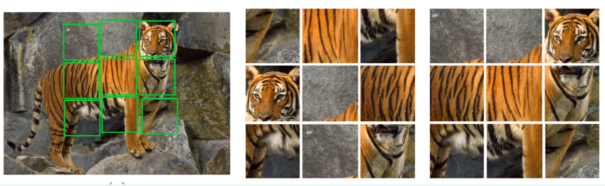
Other Semi-supervised Learning Problems

- 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

Self-supervised: Unsupervised + Self-defined Goal(s)

jigsaw puzzle: pieces $\rightarrow$ full picture



(Figure 1 of Noroozi and Favaro,

Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles. ECCV 2016)

Other Popular Goals

- colorization: grayscale image $\rightarrow$ colored image
- center word prediction: chunk of text $\rightarrow$ center word
- next sentence prediction: sentence A $\rightarrow$ is sentence B next?

self-supervised learning: recipe to learn 'physical knowledge' before actual task

Weakly-supervised: Learning without True y_n

complementary label: $\bar{y}_n$ ('not' label) instead of y_n

(Figure 1 of Yu et al., Learning with Biased Complementary Labels, ECCV 2018)

Other Weak Supervisions

- partial label: a set Y_n that contains true y_n
- noisy label: y'_n, a noisy version of true y_n
- proportion label: aggregated statistics of a set of y_n

weakly-supervised learning: another realistic (?) family to reduce labeling burden

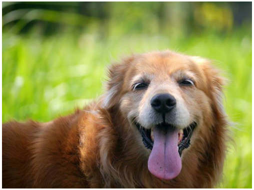
Reinforcement Learning

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

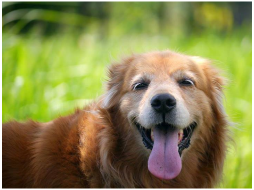
a 'very different' but natural way of learning

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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THE Most Well-known Reinforcement Learning Agent

AlphaGo

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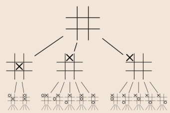
Non-ML Techniques

Monte C. Tree Search $\approx$ move simulation in brain



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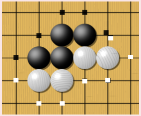
ML Techniques

Deep Learning $\approx$ board analysis in human brain



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Reinforcement Learn. $\approx$ (self)-practice in human training

(Public Domain, from Wikipedia)

good AI: important to use the right techniques—ML & others, including human

The LATEST Well-known RL Agent

(Public Domain, from Wikipedia; used here for education purpose; all other rights still belong to OpenAI)

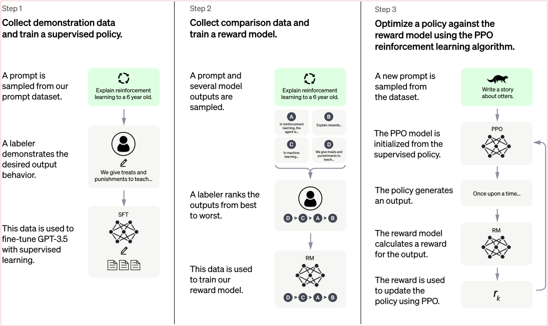
GPT-3

Self-Supervised

- mainly next-token prediction from 2048 tokens
- 175 billion parameters trained with 500 billion tokens

chatGPT

Supervised (Few-Shot) + Supervised (Ranking) + Reinforcement

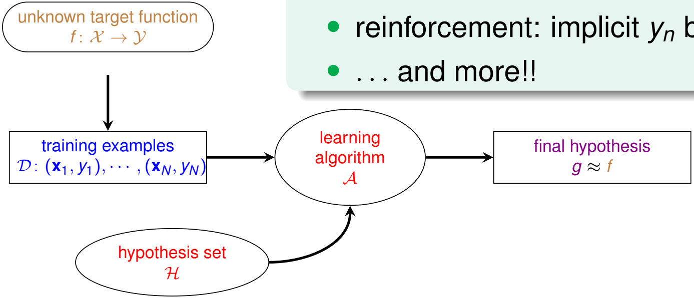


staged-ML important for building huge ML systems

Mini Summary

Learning with Different Data Label y_n

- supervised: all y_n
- unsupervised: no y_n
- self-supervised: self-defined y_n' from $\mathbf{x}_n$
- semi-supervised: some y_n
- weakly-supervised: no true 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?

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

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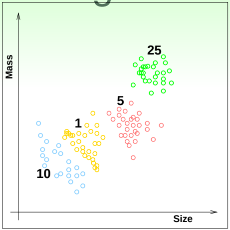
1. supervised
2. unsupervised
3. semi-supervised
4. reinforcement

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



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

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

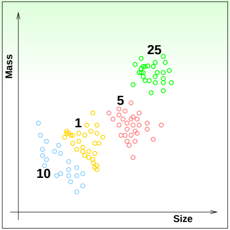
learning algorithm
$\mathcal{A}$

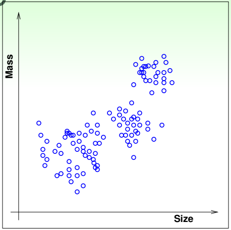
final hypothesis
$g \approx f$

hypothesis set
$\mathcal{H}$

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

Online + Batch for Real-World Applications

model re-trained with historical daily batch data, incrementally or completely → online prediction for each request

online prediction for each request ↓ batch labelled data collected daily

batch labelled data collected daily → model re-trained with historical daily batch data, incrementally or completely

purely online

- incremental update costly online
- delayed labels hard to handle properly

purely batch

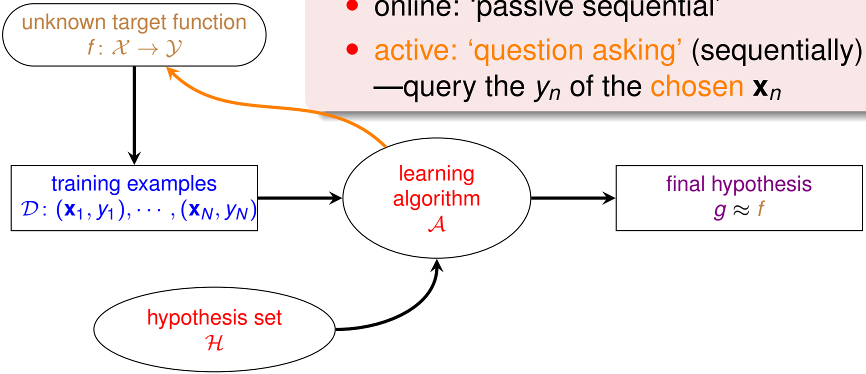
- cannot capture drifts/trends well
- complete re-training possibly costly

real-world ML system
different from textbook settings

Active Learning: Learning by 'Asking'

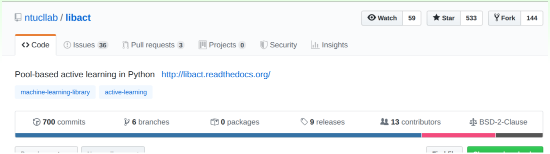
Protocol ⇔ Learning Philosophy

- 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

Making Active Learning More Realistic



open-source tool `libact` developed by NTU CLLab (Yang, 2017)

`https://github.com/ntucllab/libact`

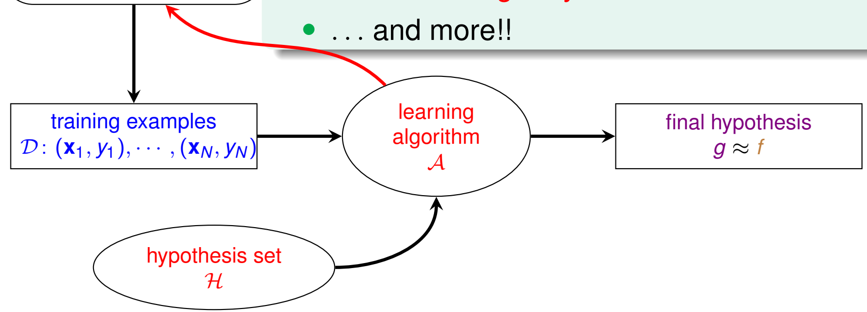
- including many popular strategies
- received $>$ 500 stars and continuous issues

"`libact` is a Python package designed to make active learning easier for real-world users"

Mini Summary

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

- batch: all known data
- online: sequential (passive) data
- online + batch: best of both worlds
- 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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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?

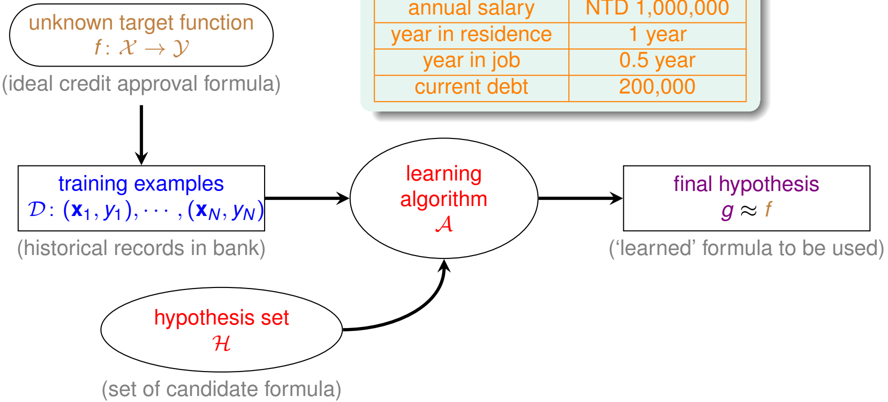
1. batch
2. online
3. active
4. random

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

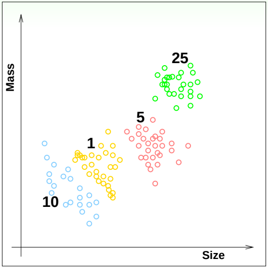
age	23 years
gender	female
annual salary	NTD 1,000,000
year in residence	1 year
year in job	0.5 year
current debt	200,000



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

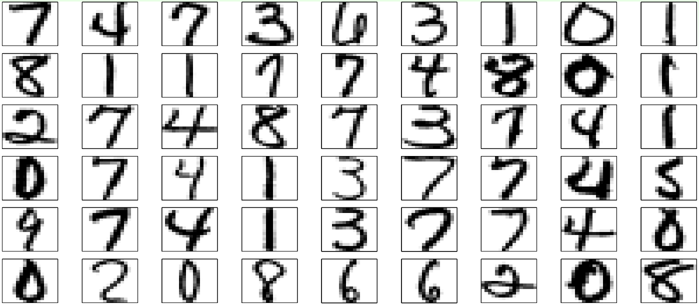
More on Concrete Features

- (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

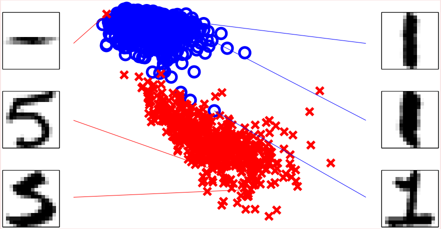
Raw Features: Digit Recognition Problem (1/2)



- 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)

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)

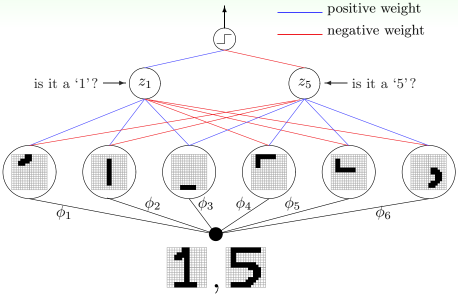
- given previous (userid, itemid, rating) tuples, predict the rating that some userid would give to itemid?
- a regression problem with $\mathcal{Y} \subseteq \mathbb{R}$ as rating and $\mathcal{X} \subseteq \mathbb{N} \times \mathbb{N}$ as (userid, itemid)
- 'no physical meaning'; thus even more difficult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

Deep Learning: 'Automatic' Conversion from Raw (or Abstract) to Concrete



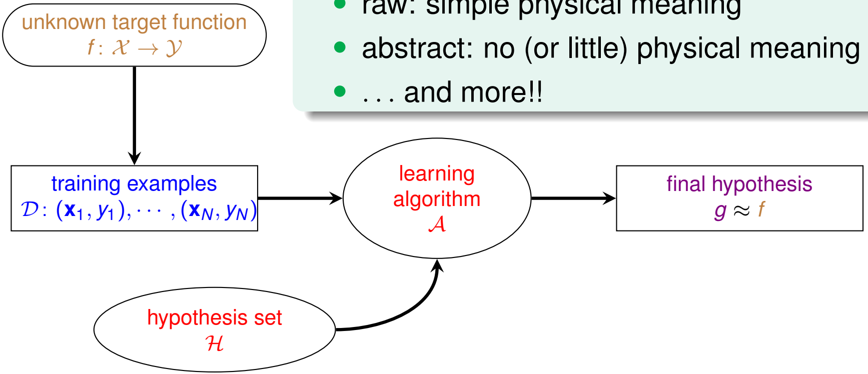
- layered extraction: simple to complex features
- natural for difficult learning task with raw features, like vision

deep learning: currently popular in vision/speech/...

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

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
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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], sophisticated
- Learning with Different Data Label y_n
  [supervised], un/semi/self-s., 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?