Machine Learning
(機器學習)

Lecture 2: The Learning Problems

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Roadmap

1. **When** Can Machines Learn?

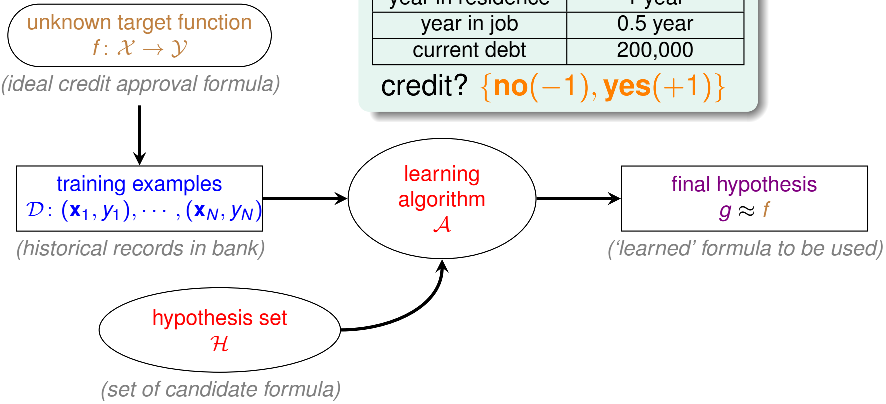
Lecture 2: The Learning Problems

- 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 $\mathcal{X}$

Credit Approval Problem Revisited

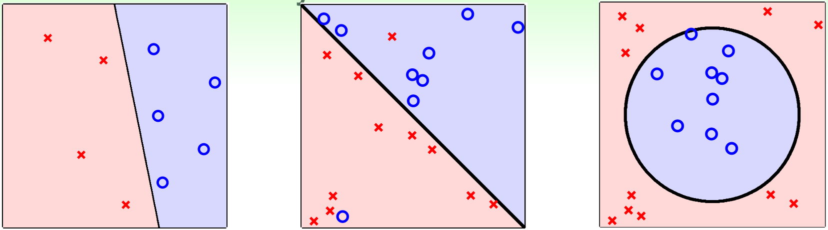
age	23 years
gender	female
annual salary	NTD 1,000,000
year in residence	1 year
year in job	0.5 year
current debt	200,000

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



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

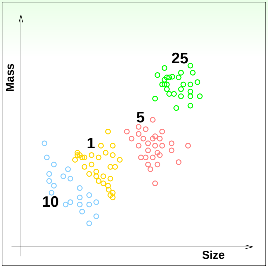
More Binary Classification Problems



- 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 $\Rightarrow 0, 1, \cdots, 9$
- emails $\Rightarrow$ spam, primary, social, promotion, update (Google)

many applications in practice

Multiclass Classification for Object Recognition: Which Fruit?

?

(image by Robert-Owen-Wahl from Pixabay)

apple

orange

strawberry

kiwi

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

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

Which Fruit**s**?

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

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**

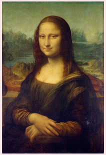
Other Regression Problems

- 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

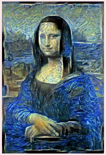


(Leonardo da Vinci, in Public Domain)

$+$

(Van Gogh, in Public Domain)

$\Rightarrow$



(Pjfinlay, with CC0)

all images are downloaded from Wikipedia

Other Image Generation Problems

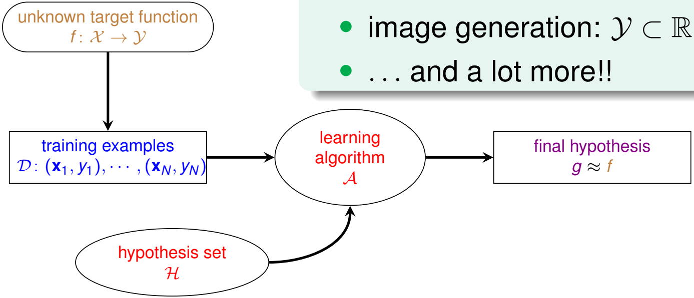
- noisy image $\Rightarrow$ clean image
- low-resolution image $\Rightarrow$ high-resolution image

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

Mini Summary

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

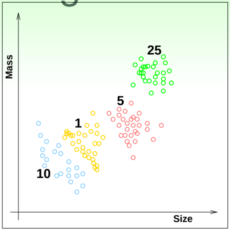
- **binary classification**: $\mathcal{Y} = \{-1, +1\}$
- multiclass classification: $\mathcal{Y} = \{1, 2, \cdots, K\}$
- multilabel classification: $\mathcal{Y} = 2^{\{1,2,\cdots,K\}}$
- **regression**: $\mathcal{Y} = \mathbb{R}$
- image generation: $\mathcal{Y} \subset \mathbb{R}^{w \times h \times c}$
- ... and a lot more!!



core tools: binary classification and regression

Questions?

Supervised: Coin Recognition Revisited



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

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

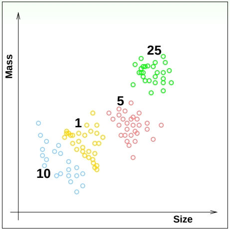
learning algorithm
$\mathcal{A}$

final hypothesis
$g \approx f$

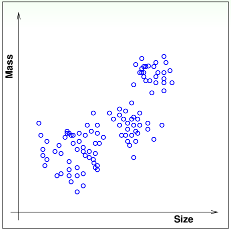
hypothesis set
$\mathcal{H}$

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

Unsupervised: Coin Recognition without y_n



supervised multiclass classification



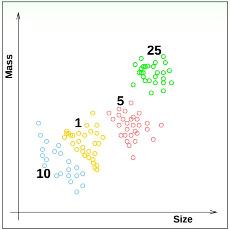
unsupervised multiclass classification
$\Longleftrightarrow$ '**clustering**'

Other Clustering Problems

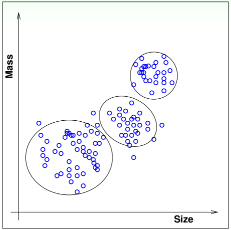
- articles $\Rightarrow$ topics
- consumer profiles $\Rightarrow$ consumer groups

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
- consumer profiles $\Rightarrow$ consumer groups

clustering: a challenging but useful problem

Unsupervised: Learning without y_n

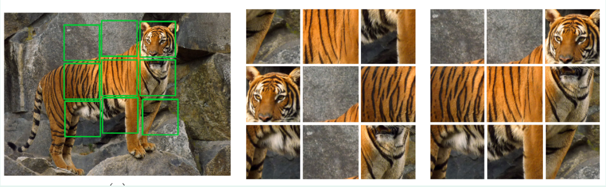
Other Unsupervised Learning Problems

- 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: diverse, with possibly very different performance goals

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

jigsaw puzzle: pieces $\rightarrow$ full picture



(Figure 1 of Noroozi and Favaro,

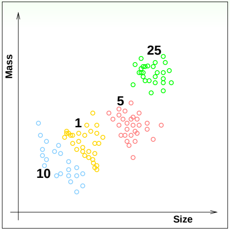
Unsupervised Learning of Visual Representations by Solving Jigsaw Puzzles. ECCV 2016)

Other Popular Goals

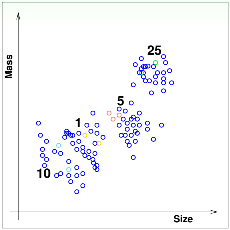
- colorization: grayscale image $\rightarrow$ colored image
- center word prediction: chunk of text $\rightarrow$ center word
- next sentence prediction: sentence A $\rightarrow$ is sentence B next?

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

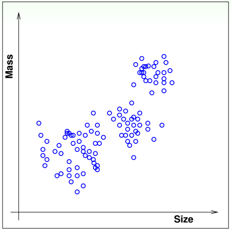
Semi-supervised: Coin Recognition with Some y_n



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

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

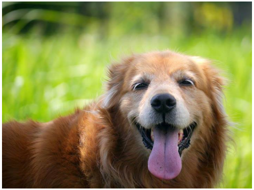
a 'very different' but natural way of learning

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

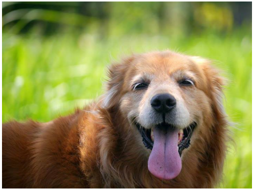
a ‘very different’ but natural way of learning

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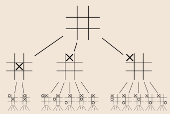
reinforcement: learn with **‘partial/implicit information’** (often sequentially)

THE Most Well-known Reinforcement Learning Agent

AlphaGo

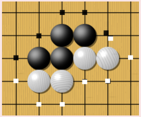
Non-ML Techniques

Monte C. Tree Search
≈ **move simulation** in brain



ML Techniques

Deep Learning
≈ **board analysis** in human brain



Reinforcement Learn.
≈ **(self)-practice** in human training

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)

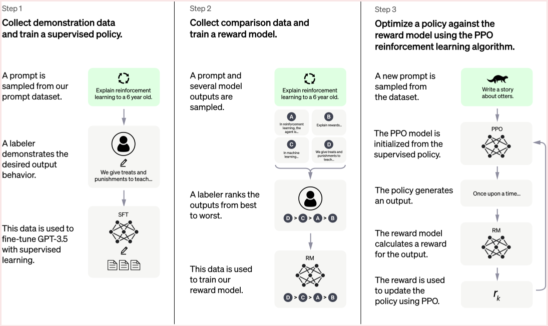
GPT-3

Self-Supervised

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

chatGPT

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

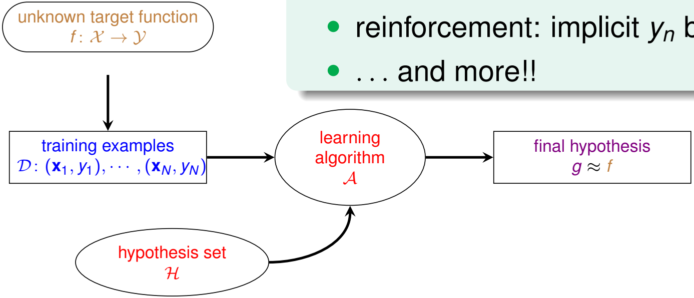


staged-ML important for building huge ML systems

Mini Summary

Learning with Different Data Label y_n

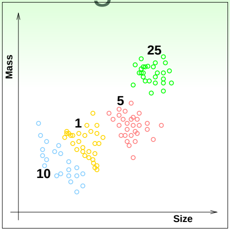
- **supervised**: all y_n
- unsupervised: no y_n
- self-supervised: self-defined y'_n from $\mathbf{x}_n$
- semi-supervised: some y_n
- weakly-supervised: no true y_n
- reinforcement: implicit y_n by goodness$(\tilde{y}_n)$
- . . . and more!!



core tool: supervised learning

Questions?

Batch Learning: Coin Recognition Revisited



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

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

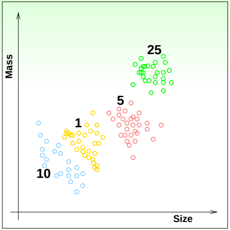
learning algorithm
$\mathcal{A}$

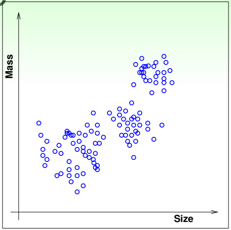
final hypothesis
$g \approx f$

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**

Online + Batch for Real-World Applications

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

online prediction for each request

batch labelled data collected daily

purely online

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

purely batch

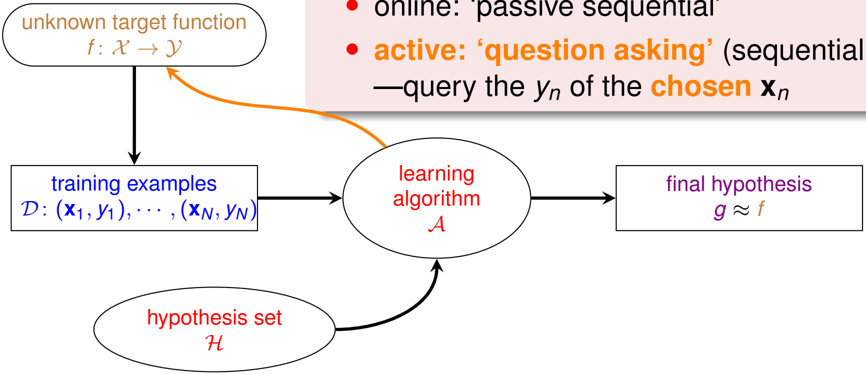
- cannot capture drifts/trends well
- complete re-training possibly costly

real-world ML system
different from **textbook settings**

Active Learning: Learning by 'Asking'

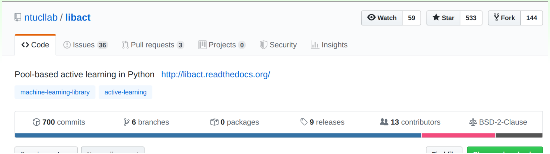
Protocol $\Leftrightarrow$ Learning Philosophy

- 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`

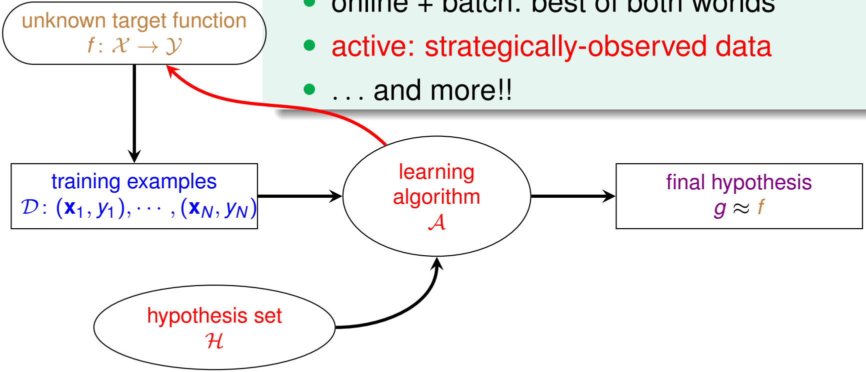
- including many popular strategies
- received $>$ 500 **stars** and continuous **issues**

"`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

Questions?

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 $f \colon \mathcal{X} \to \mathcal{Y}$

(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)

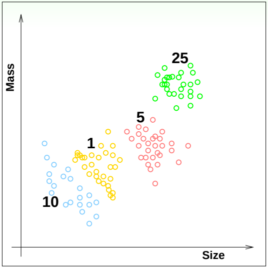
hypothesis set $\mathcal{H}$

(set of candidate formula)

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

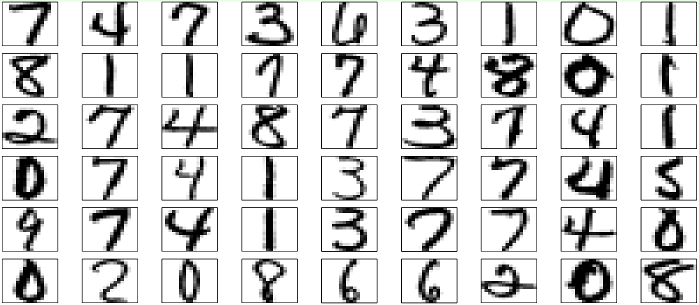
More on Concrete Features

- **(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

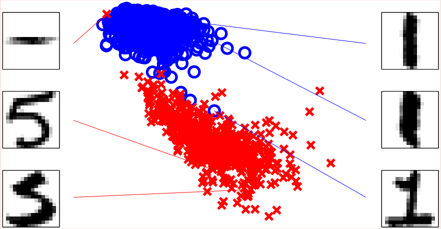
Raw Features: Digit Recognition Problem (1/2)



- 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

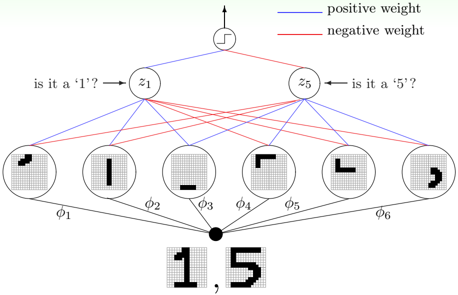
- 16 by 16 gray image $\mathbf{x} \equiv (0, 0, 0.9, 0.6, \cdots) \in \mathbb{R}^{256}$
- '**simple** physical meaning'; thus more difficult for ML than concrete features

Other Problems with Raw Features

- image pixels, speech signal, etc.

raw features: often need human ('feature engineering') or machines to **convert to concrete ones**

Deep Learning: 'Automatic' Conversion from Raw 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**/...

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

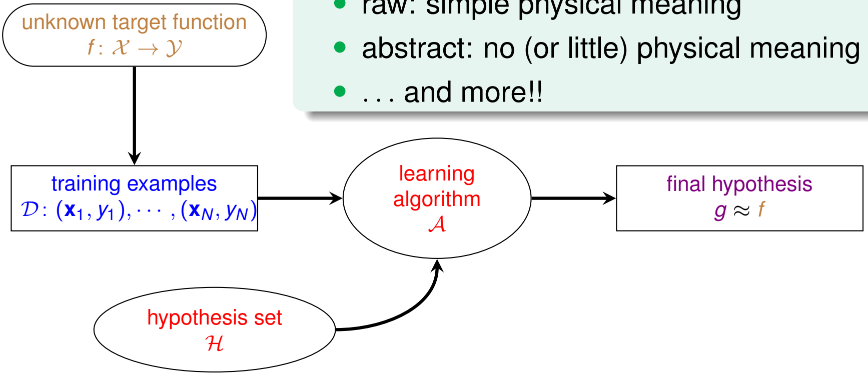
- student ID in online tutoring system (KDDCup 2010)
- advertisement ID in online ad system

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

Questions?

Summary

1. **When** Can Machines Learn?

Lecture 1: Basics of Machine Learning

Lecture 2: The Learning Problems

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

  [classification], [regression], others
- Learning with Different Data Label y_n

  [supervised], un/semi/weakly-sup., 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?!**