Machine Learning Overview and Applications

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materials mostly taken from my "Learning from Data" book, my "Machine Learning Foundations" free online course, and works from NTU CLLab and NTU KDDCup teams

What is Machine Learning

From Learning to Machine Learning

learning: acquiring skill
with experience accumulated from observations

observations $\longrightarrow$ $\boxed{\text{learning}}$ $\longrightarrow$ skill

machine learning: acquiring skill
with experience accumulated/**computed** from data

data $\longrightarrow$ $\boxed{\text{ML}}$ $\longrightarrow$ skill

What is skill?

A More Concrete Definition

skill
$\Leftrightarrow$ improve some performance measure (e.g. prediction accuracy)

machine learning: improving some performance measure
with experience **computed** from data

data $\longrightarrow$ $\boxed{\text{ML}}$ $\longrightarrow$ improved performance measure

An Application in Computational Finance

stock data $\longrightarrow$ $\boxed{\text{ML}}$ $\longrightarrow$ more investment gain

Why use machine learning?

Yet Another Application: Tree Recognition

- ‘define’ trees and hand-program: **difficult**
- learn from data (observations) and recognize: a **3-year-old can do so**
- ‘ML-based tree recognition system’ can be **easier to build** than hand-programmed system

ML: an **alternative route** to build complicated systems

The Machine Learning Route

ML: an **alternative route** to build complicated systems

Some Use Scenarios

- when human cannot program the system manually
  —navigating on Mars
- when human cannot 'define the solution' easily
  —speech/visual recognition
- when needing rapid decisions that humans cannot do
  —high-frequency trading
- when needing to be user-oriented in a massive scale
  —consumer-targeted marketing

Give a **computer** a fish, you feed it for a day;
teach it how to fish, you feed it for a lifetime. **:-)**

Key Essence of Machine Learning

machine learning: improving some performance measure
with experience **computed** from data

data → ML → improved performance measure

1. exists some 'underlying pattern' to be learned
—so 'performance measure' can be improved
2. but no programmable (easy) definition
—so 'ML' is needed
3. somehow there is data about the pattern
—so ML has some 'inputs' to learn from

key essence: help decide whether to use ML

Snapshot Applications of Machine Learning

Daily Needs: Food, Clothing, Housing, Transportation

data → ML → skill

1. Food (Sadilek et al., 2013)
   - data: Twitter data (words + location)
   - skill: tell food poisoning likeliness of restaurant properly
2. Clothing (Abu-Mostafa, 2012)
   - data: sales figures + client surveys
   - skill: give good fashion recommendations to clients
3. Housing (Tsanas and Xifara, 2012)
   - data: characteristics of buildings and their energy load
   - skill: predict energy load of other buildings closely
4. Transportation (Stallkamp et al., 2012)
   - data: some traffic sign images and meanings
   - skill: recognize traffic signs accurately

ML is everywhere!

Education

data → ML → skill

- data: students' records on quizzes on a Math tutoring system
- skill: predict whether a student can give a correct answer to another quiz question

A Possible ML Solution

answer correctly $\approx$ ⟦recent strength of student $>$ difficulty of question⟧

- give ML 9 million records from 3000 students
- ML determines (**reverse-engineers**) strength and difficulty automatically

key part of the **world-champion** system from National Taiwan Univ. in KDDCup 2010

Entertainment: Recommender System (1/2)

data → ML → skill

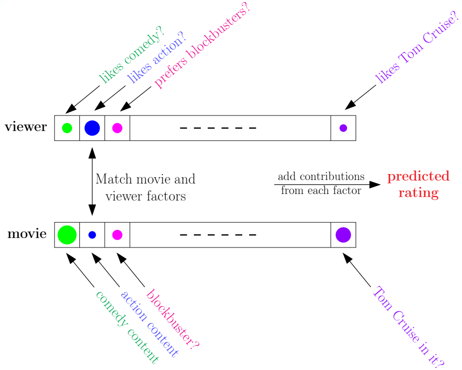
- data: how many users have rated some movies
- skill: predict how a user would rate an unrated movie

A Hot Problem

- competition held by Netflix in 2006
  - 100,480,507 ratings that 480,189 users gave to 17,770 movies
  - 10% improvement = **1 million dollar prize**
- similar competition (movies → songs) held by Yahoo! in KDDCup 2011
  - 252,800,275 ratings that 1,000,990 users gave to 624,961 songs

How can machines **learn our preferences**?

Entertainment: Recommender System (2/2)



A Possible ML Solution

- pattern:
  rating ← viewer/movie factors
- learning:
  known rating
  → learned factors
  → unknown rating prediction

key part of the **world-champion** (again!)
system from National Taiwan Univ.
in KDDCup 2011

Components of Machine Learning

Components of Learning: Metaphor Using Credit Approval

Applicant Information

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 pattern to be learned:

'approve credit card good for bank?'

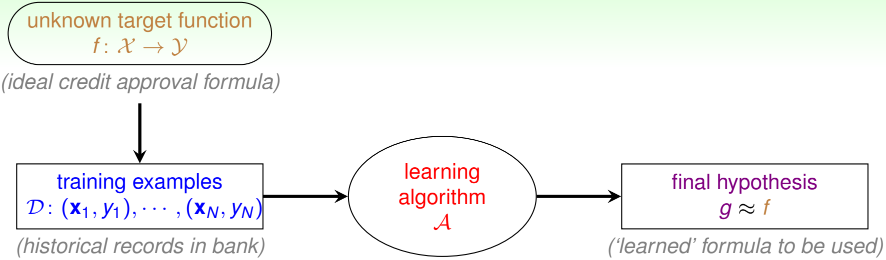
Formalize the Learning Problem

Basic Notations

- input: $\mathbf{x} \in \mathcal{X}$ (customer application)
- output: $y \in \mathcal{Y}$ (good/bad after approving credit card)
- unknown pattern to be learned $\Leftrightarrow$ target function: $f\colon \mathcal{X} \to \mathcal{Y}$ (ideal credit approval formula)
- data $\Leftrightarrow$ training examples: $\mathcal{D} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \cdots, (\mathbf{x}_N, y_N)\}$ (historical records in bank)
- hypothesis $\Leftrightarrow$ skill with hopefully good performance: $g\colon \mathcal{X} \to \mathcal{Y}$ ('learned' formula to be used)

$$\{(\mathbf{x}_n, y_n)\} \text{ from } f \longrightarrow \boxed{\text{ML}} \longrightarrow g$$

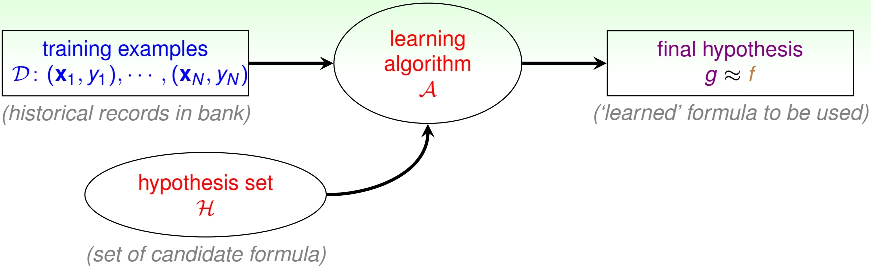
Learning Flow for Credit Approval



- target f **unknown**
  (i.e. no programmable definition)
- hypothesis g hopefully $\approx f$
  but possibly **different** from f
  (perfection 'impossible' when f unknown)

What does g look like?

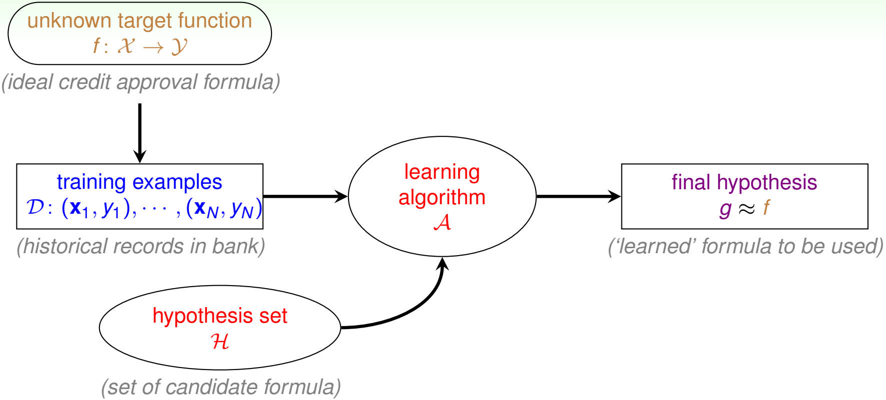
The Learning Model



- assume $g \in \mathcal{H} = \{h_k\}$, i.e. approving if
  - h_1: annual salary > NTD 800,000
  - h_2: debt > NTD 100,000 (really?)
  - h_3: year in job ≤ 2 (really?)
- hypothesis set $\mathcal{H}$:
  - can contain **good or bad hypotheses**
  - up to $\mathcal{A}$ to pick the 'best' one as g

learning model = $\mathcal{A}$ and $\mathcal{H}$

Practical Definition of Machine Learning



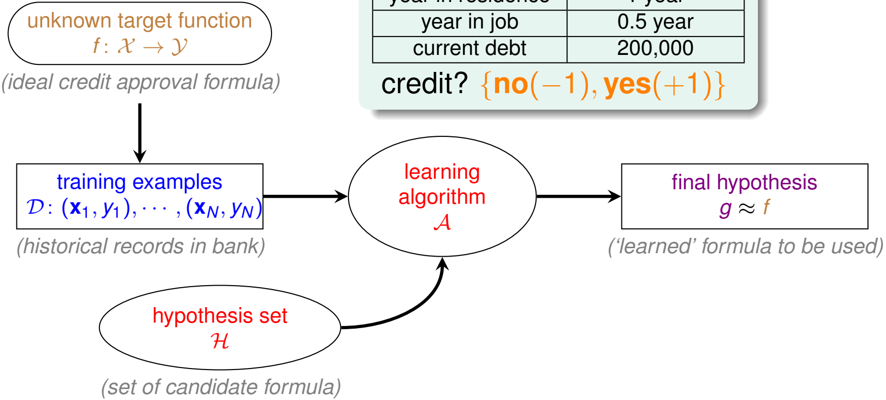
machine learning:
use data to compute hypothesis g
that approximates target f

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

Credit Approval Problem Revisited

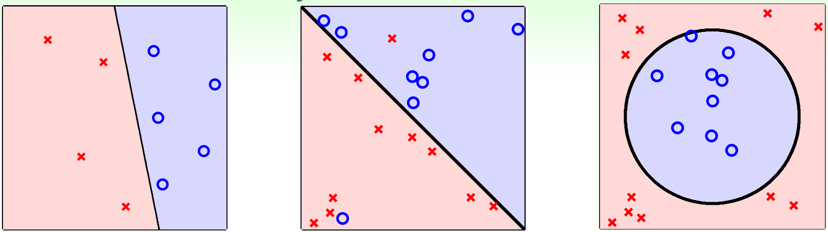
age	23 years
gender	female
annual salary	NTD 1,000,000
year in residence	1 year
year in job	0.5 year
current debt	200,000

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



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

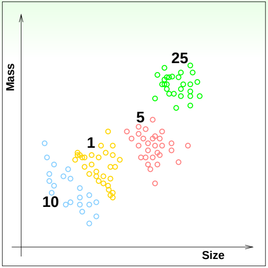
More Binary Classification Problems



- 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)
- $\mathcal{Y} = \{1\text{c}, 5\text{c}, 10\text{c}, 25\text{c}\}$, 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**

Mini Summary

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

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

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
$\mathcal{A}$

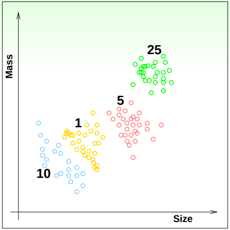
final hypothesis
$g \approx f$

hypothesis set
$\mathcal{H}$

core tools: binary classification and regression

Learning with Different Data Label y_n

Supervised: Coin Recognition Revisited



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

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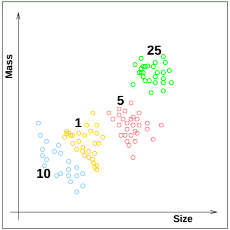
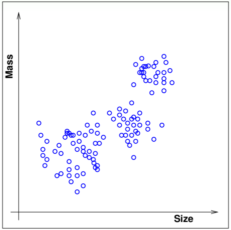
supervised learning:
every $\mathbf{x}_n$ **comes with corresponding** y_n

Unsupervised: Coin Recognition without y_n



supervised multiclass classification



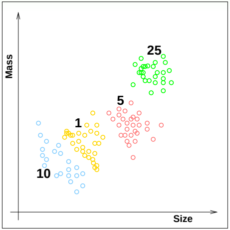
unsupervised multiclass classification $\Longleftrightarrow$ '**clustering**'

Other Clustering Problems

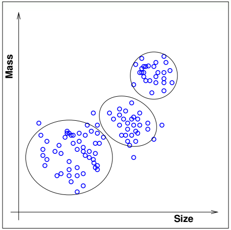
- articles $\Rightarrow$ topics
- consumer profiles $\Rightarrow$ consumer groups

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

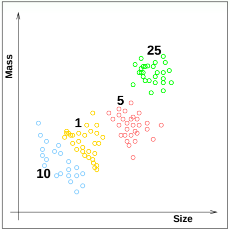
Unsupervised: Learning without y_n

Other Unsupervised Learning Problems

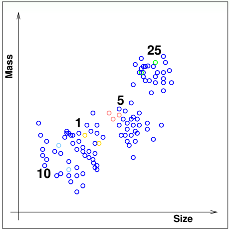
- clustering: $\{\mathbf{x}_n\} \Rightarrow \text{cluster}(\mathbf{x})$
  (≈ 'unsupervised multiclass classification')
  —i.e. articles ⇒ topics
- **density estimation**: $\{\mathbf{x}_n\} \Rightarrow \text{density}(\mathbf{x})$
  (≈ 'unsupervised bounded regression')
  —i.e. traffic reports with location ⇒ 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

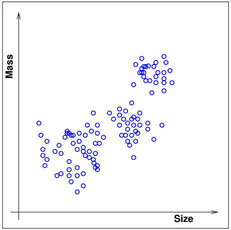
Semi-supervised: Coin Recognition with Some y_n



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

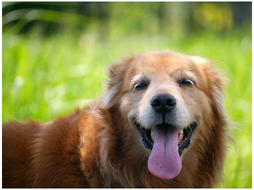
a 'very different' but natural way of learning

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

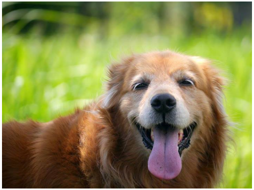
a 'very different' but natural way of learning

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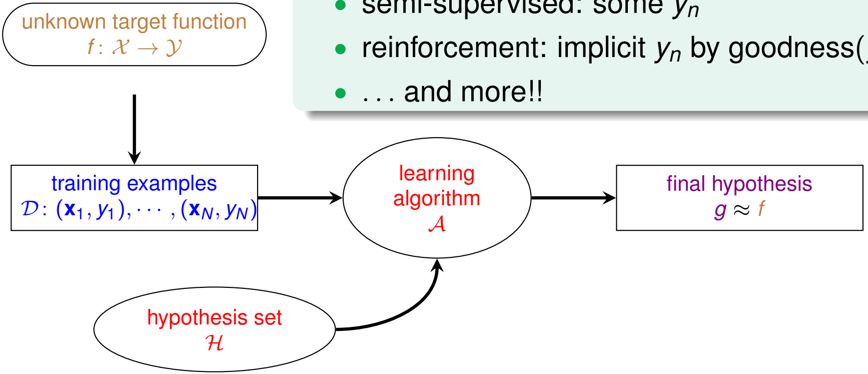
reinforcement: learn with **'partial/implicit information'** (often sequentially)

Mini Summary

Learning with Different Data Label y_n

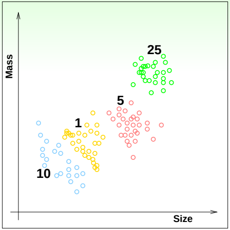
- **supervised**: all y_n
- unsupervised: no y_n
- semi-supervised: some y_n
- reinforcement: implicit y_n by goodness($\tilde{y}_n$)
- . . . and more!!



core tool: supervised learning

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

Batch Learning: Coin Recognition Revisited



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

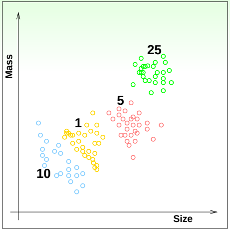
learning algorithm
$\mathcal{A}$

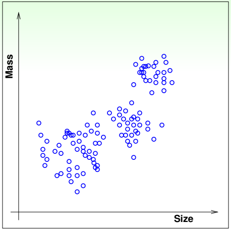
final hypothesis
$g \approx f$

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

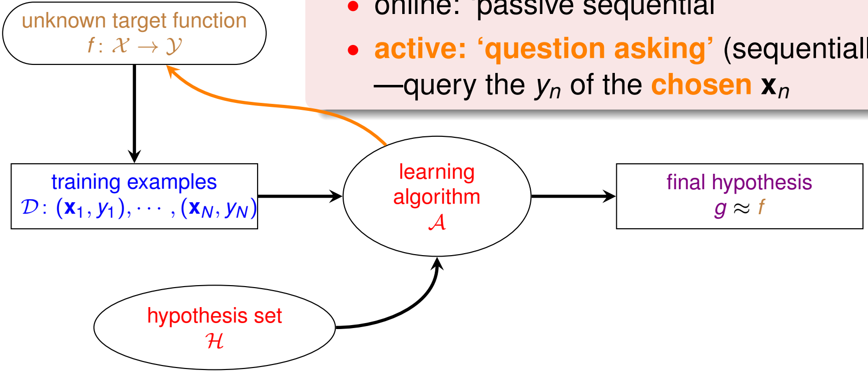
- PLA can be easily adapted to online protocol (how?)
- reinforcement learning is often done online (why?)

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** $\mathbf{x}_n$

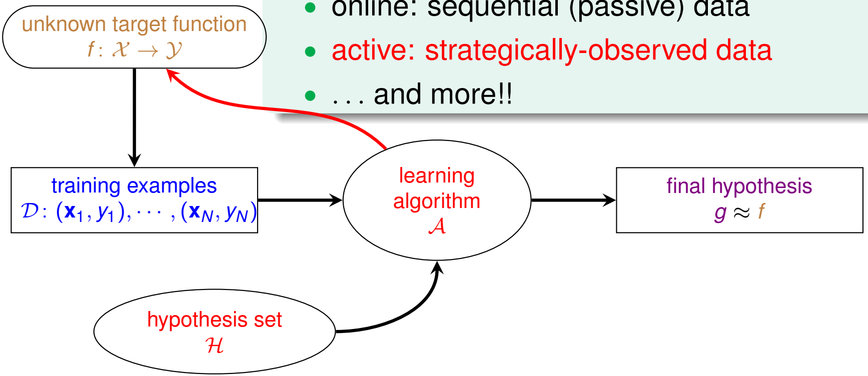


active: improve hypothesis with fewer labels (hopefully) by asking questions **strategically**

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

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**

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)

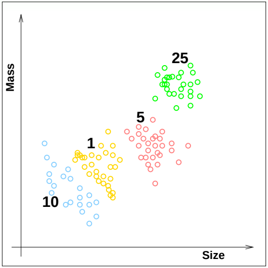
hypothesis set
$\mathcal{H}$

(set of candidate formula)

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

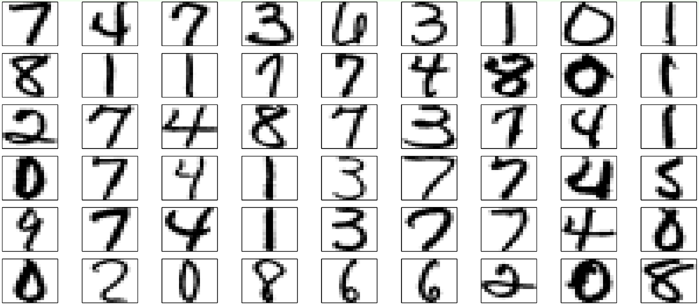
More on Concrete Features

- **(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

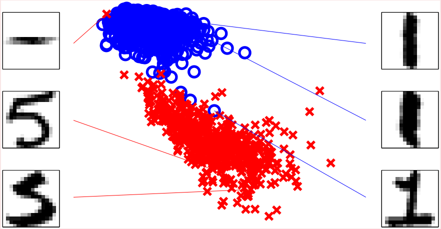
Raw Features: Digit Recognition Problem (1/2)



- 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 or machines to **convert to concrete ones**

Time Features: Stock Prediction Problem

Stock Prediction Problem

- given previous (time, price) pairs, predict whether the price would go up or down tomorrow?
- a 'binary classification' problem (or a regression one if predicting the price itself)
- $\mathcal{X} \subseteq \mathbb{R}$ representing time, $\mathcal{Y} = \mathbb{R}^+$ representing price

Other Problems with Time Features

- timestamp when student performance in online tutoring system (KDDCup 2010)
- rating time given by user in recommender system (KDDCup 2011)

time features: can carry trend

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

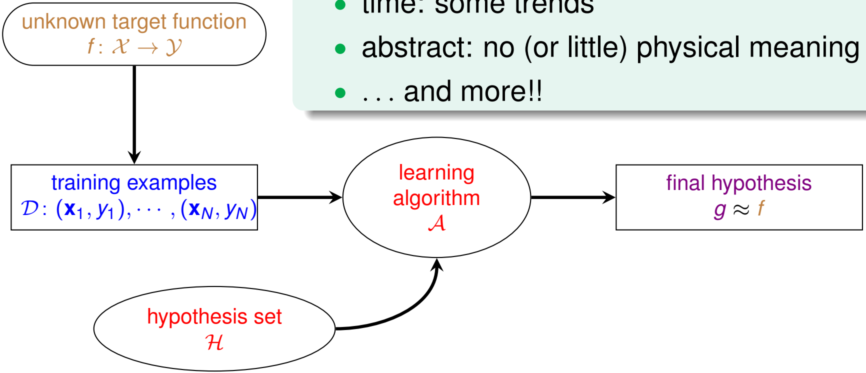
- student ID in online tutoring system (KDDCup 2010)
- advertisement ID in online ad system

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

Mini Summary

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

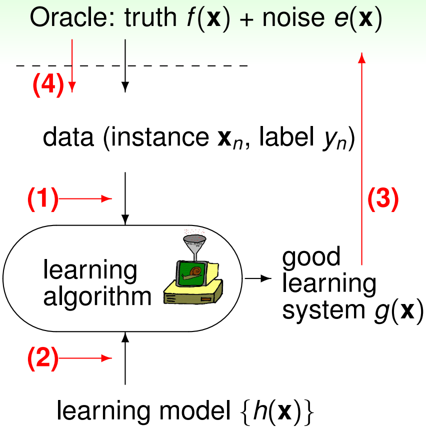
- **concrete**: sophisticated (and related) physical meaning
- raw: simple physical meaning
- time: some trends
- abstract: no (or little) physical meaning
- … and more!!



'easy' input: concrete

Machine Learning Research in CLLab

Making Machine Learning **Realistic**: Now



CLLab Works: **Loosen the Limits of ML**

1. cost-sensitive classification: limited protocol (classification) + **auxiliary info. (cost)**
2. multi-label classification: limited protocol (classification) + **structure info. (label relation)**
3. active learning: limited protocol (unlabeled data) + **requested info. (query)**
4. online learning: limited protocol (streaming data) + **feedback info. (loss)**

next: (1) cost-sensitive classification

Which Digit Did You Write?

?

one (1)

two (2)

three (3)

a **classification** problem
—grouping "pictures" into different "categories"

Traditional Classification Problem

Oracle: truth $f(\mathbf{x})$ + noise $e(\mathbf{x})$

data (instance $\mathbf{x}_n$, label y_n)

learning algorithm  → good learning system $g(\mathbf{x})$

learning model $\{g_\alpha(\mathbf{x})\}$

1. input: a batch of examples (digit $\mathbf{x}_n$, intended label y_n)
2. desired output: some $g(\mathbf{x})$ such that $g(\mathbf{x}) \neq y$ **seldom** for future examples $(\mathbf{x}, y)$
3. evaluation for some digit

($\mathbf{x} =$ , $y = 2$)

$$—g(\mathbf{x}) = \begin{cases} 1 : \textit{wrong}; \\ 2 : \textit{right}; \\ 3 : \textit{wrong} \end{cases}$$

Are all the **wrong**s equally bad?

What is the Status of the Patient?

?

H1N1-infected

cold-infected

healthy

another **classification** problem
—grouping “patients” into different “status”

Patient Status Prediction

error measure = society cost

actual \ predicted	H1N1	cold	healthy
H1N1	0	1000	**100000**
cold	100	0	3000
healthy	100	30	0

- H1N1 mis-predicted as healthy: **very high cost**
- cold mis-predicted as healthy: high cost
- cold correctly predicted as cold: no cost

human doctors consider costs of decision; **can computer-aided diagnosis do the same**?

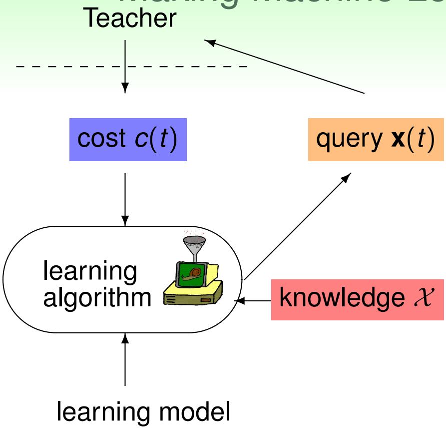
Our Contributions

	binary	multiclass
regular	well-studied	well-studied
cost-sensitive	known (Zadrozny, 2003)	ongoing (our works)

theoretic, algorithmic and empirical studies of cost-sensitive classification

- ICML 2010: a theoretically-supported algorithm with **superior experimental results**
- BIBM 2011: application to real-world **bacteria classification** with promising experimental results
- KDD 2012: a cost-sensitive **and error-sensitive** methodology (achieving both low cost and **few wrongs**)

Making Machine Learning Realistic: **Next**



Interactive Machine Learning

1. environment
2. exploration
3. dynamic
4. partial feedback

let us teach machines as “easily” as teaching students

Case: Interactive Learning for Online Advertisement

Traditional Machine Learning for Online Advertisement

- data gathering: system **randomly shows ads** to **some previous users**
- expert building: system **analyzes data gathered** to **determine best (fixed) strategy**

Interactive Machine Learning for Online Advertisement

- environment : system serves **online users with profile**
- exploration : system **decides to show an ad** to the user
- dynamic : system receives data from **real-time user click**
- partial feedback : system receives **reward only if clicking**

Preliminary Success: ICML 2012 Exploration & Exploitation Challenge

Interactive Machine Learning for Online Advertisement

- environment : system serves **online users with profile**
- exploration : system **decides to show an ad** to the user
- dynamic : system receives data from **real-time user click**
- partial feedback : system receives **reward only if clicking**

NTU beats two MIT teams to be the phase 1 winner!

NAME	AFFILIATION	LAST SCORE (CTR * 10 000)	BEST SCORE (CTR * 10 000)	RANK
Ku-Chun	NTU	882.9	**905.9**	1
tvirot	MIT	903.9	**903.9**	2
edjoesu	MIT	889.9	**903.4**	3

interactive: more challenging than traditional machine learning, but **realistic**

More on KDDCup

What is KDDCup?

Background

- an annual competition on KDD (knowledge discovery and data mining)
- organized by ACM SIGKDD, starting from 1997, now **the most prestigious data mining competition**
- usually lasts 3-4 months
- participants include famous research labs (IBM, AT&T) and top universities (Stanford, Berkeley)

Aim of KDDCup

Aim

- bridge the gap between theory and **practice**, such as
  - scalability and efficiency
  - missing data and noise
  - heterogeneous data
  - unbalanced data
  - combination of different models
- define the **state-of-the-art**

KDDCups: 2008 to 2013 I

2008

- organizer: Siemens
- topic: breast cancer prediction (medical)
- data size: 0.2M
- teams: > 200
- NTU: **co-champion** with IBM (led by Prof. Shou-de Lin)

2009

- organizer: Orange
- topic: customer behavior prediction (business)
- data size: 0.1M
- teams: > 400
- NTU: **3rd place** of slow track

KDDCups: 2008 to 2013 II

2010

- organizer: PSLC Data Shop
- topic: student performance prediction (education)
- data size: 30M
- teams: > 100
- NTU: **champion** and **student-team champion**

2011

- organizer: Yahoo!
- topic: music preference prediction (recommendation)
- data size: 300M
- teams: > 1000
- NTU: **double champions**

KDDCups: 2008 to 2013 III

2012

- organizer: Tencent
- topic: webuser behavior prediction (Internet)
- data size: 150M
- teams: > 800
- NTU: **champion of track 2**

2013

- organizer: Microsoft Research
- topic: paper-author relationship prediction (academia)
- data size: 600M
- teams: > 500
- NTU: **double champions**

KDDCup 2011

from

YAHOO! LABS

Music Recommendation Systems

- host: Yahoo!
- **11 years** of Yahoo! music data
- **2 tracks** of competition
- official dates: **March 15 to June 30**
- 1878 teams submitted to track 1;
  1854 teams submitted to track 2

NTU Team for KDDCup 2011

- 3 faculties:
  Profs. Chih-Jen Lin, Hsuan-Tien Lin and Shou-De Lin
- 1 course (starting in 2010)
  Data Mining and Machine Learning: Theory and Practice
- 3 TAs and 19 students:
  most were **inexperienced in music recommendation in the beginning**
- official classes: April to June;
  actual classes: December to June

our motto: study state-of-the-art approaches
and then **creatively improve them**

Previously: How Much Did You Like These Movies?

`http://www.netflix.com`

(1M dollar competition between 2007-2009)

goal: use "movies you've rated" to automatically
predict your **preferences** on future movies

The Track 1 Problem (1/2)

Given Data

$263M$ examples (user u, item i, rating r_{ui}, date t_{ui}, time τ_{ui})

user	item	rating	date	time
1	21	10	102	23:52
1	213	90	1032	21:01
4	45	95	768	09:15
...				

- u, i: abstract IDs
- r_{ui}: integer between 0 and 100, **mostly multiples of** 10

Additional Information: Item Hierarchy

- track (46.85%)
- album (19.01%)
- artist (28.84%)
- genre (5.30%)

The Track 1 Problem (2/2)

Data Partitioned by Organizers

- training: 253M; validation: 4M; test (w/o rating): 6M
- per user, **training < validation < test in time**
  - $\geq$ 20 examples total
  - 4 examples in validation; 6 in test
- **fixed random half of test: leaderboard**; **another half: award decision**

Goal

predictions $\hat{r}_{ui} \approx r_{ui}$ on the test set, measured by

$$RMSE = \sqrt{\text{average}(\hat{r}_{ui} - r_{ui})^2}$$

— one submission allowed **every eight hours**

Three Properties of Track 1 Data

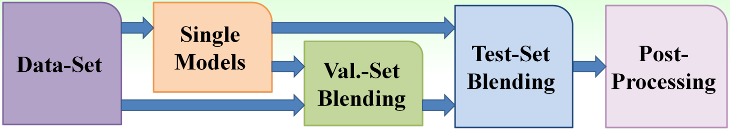
$\mathbf{R} =$

	track$_1$	track$_2$	album$_3$	author$_4$	$\cdots$	genre$_I$
user$_1$	100	80	70	**?**	$\cdots$	–
user$_2$	–	0	**?**	80	$\cdots$	–
$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$	$\cdots$
user$_U$	**?**	–	20	–	$\cdots$	0

similar to Netflix data, but with the following differences......

- scale: larger data
  —study mature models that are **computationally feasible**
- taxonomy: relation graph of tracks, albums, authors and genres
  —**include as features** for combining models nonlinearly
- time: detailed; training earlier than test
  —**include as features** for combining models nonlinearly;
  respect time-closeness during training

Framework of Our Solution



System Architecture

- **improve standard models**: design **variants within 6 families of state-of-the-art models** (reaches RMSE 22.7915)
- **blend the models**: improve prediction power by **blending the variants carefully** (reaches RMSE 21.3598)
- **aggregate the blended predictors**: construct a linear ensemble with **test performance estimators** (reaches RMSE 21.0253)
- **post-process the ensemble**: add a final touch based on **observations from data analysis** (reaches RMSE 21.0147)

not only **hard work** (200+ models included),
but also **key techniques**

That's about all. Thank you!