Lecture 1: The Learning Problem

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Machine Learning: a mixture of theoretical and practical tools

- theory oriented
  - derive everything **deeply** for solid understanding
  - less interesting to general audience
- techniques oriented
  - flash over the sexiest techniques **broadly** for shiny coverage
  - too many techniques, hard to choose, hard to use properly

our approach: **foundation oriented**
Foundation Oriented ML Course

- mixture of philosophical illustrations, key theory, core techniques, usage in practice, and hopefully jokes :-)
  —what every machine learning user should know
- story-like:
  - **When** Can Machines Learn? (illustrative + technical)
  - **Why** Can Machines Learn? (theoretical + illustrative)
  - **How** Can Machines Learn? (technical + practical)
  - How Can Machines Learn **Better**? (practical + theoretical)

allows students to learn ‘future/untaught’ techniques or study deeper theory easily
NTU Version

- 15-17 weeks (2+ hours)
- highly-praised with English and blackboard teaching

Coursera Version

- 8 weeks of ‘foundation’ (this course) + 7 weeks of ‘techniques’ (coming course)
- Mandarin teaching to reach more audience in need
- slides teaching improved with Coursera’s quiz and homework mechanisms

goal: try making Coursera version even better than NTU version
Which of the following description of this course is true?

1. the course will be taught in Taiwanese
2. the course will tell me the techniques that create the android Lieutenant Commander Data in Star Trek
3. the course will be 15 weeks long
4. the course will be story-like

Reference Answer: 4

1. no, my Taiwanese is unfortunately not good enough for teaching (yet)
2. no, although what we teach may serve as foundations of those (future) techniques
3. no, unless you choose to join the next course
4. yes, let’s begin the story
Roadmap

1. **When Can Machines Learn?**

   **Lecture 1: The Learning Problem**
   - Course Introduction
   - What is Machine Learning
   - Applications of Machine Learning
   - Components of Machine Learning
   - Machine Learning and Other Fields

2. Why Can Machines Learn?
3. How Can Machines Learn?
4. How Can Machines Learn Better?
The Learning Problem

From Learning to Machine Learning

**learning**: acquiring **skill**
with experience accumulated from **observations**

observations $\rightarrow$ **learning** $\rightarrow$ **skill**

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

data $\rightarrow$ **ML** $\rightarrow$ **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 $\rightarrow$ ML $\rightarrow$ improved performance measure

An Application in Computational Finance

stock data $\rightarrow$ ML $\rightarrow$ more investment gain

Why use machine learning?
The Learning Problem
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 Learning Problem
What is Machine Learning

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. :-)

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**key essence:** help decide whether to use ML
Fun Time

Which of the following is best suited for machine learning?

1. predicting whether the next cry of the baby girl happens at an even-numbered minute or not
2. determining whether a given graph contains a cycle
3. deciding whether to approve credit card to some customer
4. guessing whether the earth will be destroyed by the misuse of nuclear power in the next ten years

Reference Answer: 3

1. no pattern
2. programmable definition
3. pattern: customer behavior; definition: not easily programmable; data: history of bank operation
4. arguably no (or not enough) data yet
Daily Needs: Food, Clothing, Housing, Transportation

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!**
The Learning Problem

Applications of Machine Learning

Education

- **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 ≈ [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

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Entertainment: Recommender System (1/2)

- **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)

- **pattern:**
  - rating ← viewer/movie factors

- **learning:**
  - known rating
  - learned factors
  - unknown rating prediction

A Possible ML Solution

Key part of the world-champion (again!) system from National Taiwan Univ. in KDDCup 2011
Fun Time

Which of the following field cannot use machine learning?

1. Finance
2. Medicine
3. Law
4. none of the above

Reference Answer: 4

1. predict stock price from data
2. predict medicine effect from data
3. summarize legal documents from data
4. :-) Welcome to study this hot topic!
Components of Learning: Metaphor Using Credit Approval

Applicant Information

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
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<tbody>
<tr>
<td>age</td>
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<tr>
<td>gender</td>
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<tr>
<td>year in residence</td>
<td>1 year</td>
</tr>
<tr>
<td>year in job</td>
<td>0.5 year</td>
</tr>
<tr>
<td>current debt</td>
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</tbody>
</table>

unknown pattern to be learned:
‘approve credit card good for bank?’
Formalize the Learning Problem

**Basic Notations**

- **input**: \( x \in \mathcal{X} \) (customer application)
- **output**: \( y \in \mathcal{Y} \) (good/bad after approving credit card)
- **unknown pattern to be learned** ⇔ **target function**: \( f: \mathcal{X} \rightarrow \mathcal{Y} \) (ideal credit approval formula)
- **data** ⇔ **training examples**: \( \mathcal{D} = \{ (x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N) \} \) (historical records in bank)
- **hypothesis** ⇔ **skill** with hopefully **good performance**: \( g: \mathcal{X} \rightarrow \mathcal{Y} \) (‘learned’ formula to be used)

\[ \{(x_n, y_n)\} \text{ from } f \xrightarrow{\text{ML}} g \]
The Learning Problem

Components of Machine Learning

Learning Flow for Credit Approval

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

(ideal credit approval formula)

training examples
\( \mathcal{D} : (x_1, y_1), \cdots, (x_N, y_N) \)

(historical records in bank)

learning algorithm
\( \mathcal{A} \)

final hypothesis
\( g \approx f \)

(‘learned’ formula to be used)

- 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 Problem

The Learning Model

- **training examples** \( \mathcal{D}: (x_1, y_1), \ldots, (x_N, y_N) \)

(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)

- **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 \( \leq 2 \) (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

unknown target function

\( f : \mathcal{X} \rightarrow \mathcal{Y} \)

(ideal credit approval formula)

training examples

\( \mathcal{D} : (x_1, y_1), \ldots, (x_N, y_N) \)

(historical records in bank)

learning algorithm \( A \)

learning algorithm \( A \)

final hypothesis

\( g \approx f \)

('learned' formula to be used)

hypothesis set \( \mathcal{H} \)

(set of candidate formula)

machine learning:

use data to compute hypothesis \( g \) that approximates target \( f \)
How to use the four sets below to form a learning problem for song recommendation?

\[ S_1 = [0, 100] \]
\[ S_2 = \text{all possible (userid, songid) pairs} \]
\[ S_3 = \text{all formula that ‘multiplies’ user factors & song factors, indexed by all possible combinations of such factors} \]
\[ S_4 = 1,000,000 \text{ pairs of ((userid, songid), rating)} \]

1. \[ S_1 = X, S_2 = Y, S_3 = H, S_4 = D \]
2. \[ S_1 = Y, S_2 = X, S_3 = H, S_4 = D \]
3. \[ S_1 = D, S_2 = H, S_3 = Y, S_4 = X \]
4. \[ S_1 = X, S_2 = D, S_3 = Y, S_4 = H \]

Reference Answer: 2

\[ S_4 \xrightarrow{A \text{ on } S_3} (g: S_2 \rightarrow S_1) \]
### Machine Learning and Data Mining

#### Machine Learning
- Use data to compute hypothesis $g$ that approximates target $f$

#### Data Mining
- Use (huge) data to find property that is interesting

- **if ‘interesting property’ same as ‘hypothesis that approximate target’**
  - $\text{ML} = \text{DM}$ (usually what KDDCup does)

- **if ‘interesting property’ related to ‘hypothesis that approximate target’**
  - $\text{DM can help ML, and vice versa}$ (often, but not always)

- Traditional DM also focuses on efficient computation in large database

**difficult to distinguish ML and DM in reality**
Machine Learning and Artificial Intelligence

**Machine Learning**

- use data to compute hypothesis \( g \) that approximates target \( f \)

**Artificial Intelligence**

- compute *something* that shows intelligent behavior

- \( g \approx f \) is something that shows intelligent behavior
  - **ML can realize AI**, among other routes
- e.g. chess playing
  - traditional AI: game tree
  - ML for AI: ‘learning from board data’

**ML is one possible route to realize AI**
Machine Learning and Statistics

Machine Learning
use data to compute hypothesis $g$
that approximates target $f$

Statistics
use data to make inference
about an unknown process

- $g$ is an inference outcome; $f$ is something unknown
  —statistics can be used to achieve ML
- traditional statistics also focus on provable results with math
  assumptions, and care less about computation

statistics: many useful tools for ML
Which of the following claim is not totally true?

1. machine learning is a route to realize artificial intelligence
2. machine learning, data mining and statistics all need data
3. data mining is just another name for machine learning
4. statistics can be used for data mining

Reference Answer: 3

While data mining and machine learning do share a huge overlap, they are arguably not equivalent because of the difference of focus.
When Can Machines Learn?

Lecture 1: The Learning Problem

- Course Introduction
  foundation oriented and story-like
- What is Machine Learning
  use data to approximate target
- Applications of Machine Learning
  almost everywhere
- Components of Machine Learning
  $A$ takes $D$ and $H$ to get $g$
- Machine Learning and Other Fields
  related to DM, AI and Stats

• next: a simple and yet useful learning model ($H$ and $A$)

Why Can Machines Learn?

How Can Machines Learn?

How Can Machines Learn Better?