# Machine Learning for Modern Artificial Intelligence

林軒田
Hsuan-Tien Lin
htlin@csie.ntu.edu.tw

沛星互動科技
Appier

國立台灣大學
National Taiwan University

Frontiers of Sciences and Humanities Seminar Series
Academia Sinica, 2018/11/15

# Outline

ML for (Modern) AI

ML Research for Modern AI

ML for Future AI

# From Intelligence to Artificial Intelligence

intelligence: thinking and acting smartly

- humanly
- rationally

**artificial** intelligence: **computers** thinking and acting smartly

- humanly
- rationally

humanly $\approx$ **smartly** $\approx$ rationally
**—are humans rational? :-)**

# Humanly versus Rationally

*What if your self-driving car decides one death is better than two—and that one is you?* (The Washington Post `http://wpo.st/ZK-51`)

```
You're humming along in your self-driving
car, chatting on your iPhone 37 while the
machine navigates on its own.  Then a swarm
of people appears in the street, right in
the path of the oncoming vehicle.
```

**Car Acting Humanly**

to save my (and passengers') life, stay on track

**Car Acting Rationally**

avoid the crowd and crash the owner for minimum total loss

which is smarter?

**—depending on where I am, maybe? :-)**

# (Traditional) Artificial Intelligence

### Thinking Humanly

- cognitive modeling —now closer to Psychology than AI

### Thinking Rationally

- formal logic—now closer to Theoreticians than AI practitioners

### Acting Humanly

- dialog systems
- humanoid robots
- computer vision

### Acting Rationally

- recommendation systems
- cleaning robots
- cross-device ad placement

**acting** humanly or rationally:
more academia/industry attentions nowadays

# Traditional vs. Modern [My] Definition of AI

## Traditional Definition

humanly $\approx$ intelligently $\approx$ rationally

## My Definition

intelligently $\approx$ easily

**is your smart phone 'smart'? :-)**

**user-needs-driven** AI is important

# Examples of User-Needs-Driven AI

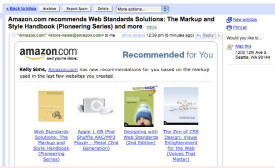
## Siri

By Bernard Goldbach [CC BY 2.0]

## iRobot

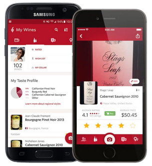

By Yuan-Chou Lo [CC BY-NC-ND 2.0]

## Amazon Recommendations



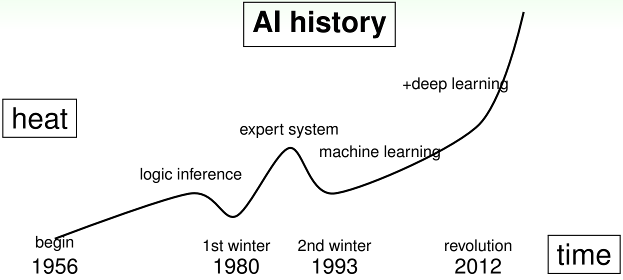

By Kelly Sims [CC BY 2.0]

## Vivino




from `nordic.businessinsider.com`

# AI Milestones




- first AI winter: AI cannot solve 'combinatorial explosion' problems
- second AI winter: expert system failed to scale

reason of winters: **expectation mismatch**

# What's Different Now?

### More Data
- cheaper storage
- Internet companies

### Better Algorithms
- decades of research
- e.g. deep learning

### Faster Computation
- cloud computing
- GPU computing

### Healthier Mindset
- reasonable wishes
- key breakthroughs

**data-enabled** AI: mainstream nowadays

# Machine Learning and AI

**Easy-to-Use**

**Acting Humanly**

**Acting Rationally**

## Machine Learning

**machine learning**: core behind modern (data-enabled) AI

# ML Connects Big Data and AI

## From Big Data to Artificial Intelligence

big data → **ML** → artificial intelligence

ingredient

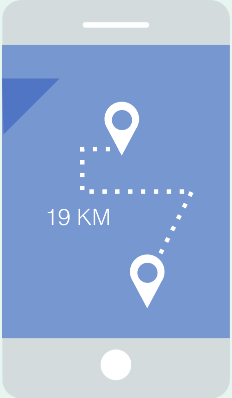
→ tools/steps

→ dish

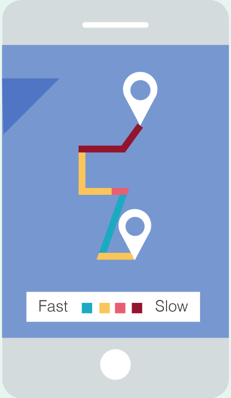


Appier **Chief Data Scientist**
$\equiv$ restaurant **Head Chef**

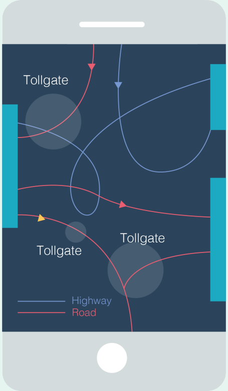
# Bigger Data Towards Better AI




best route by shortest path



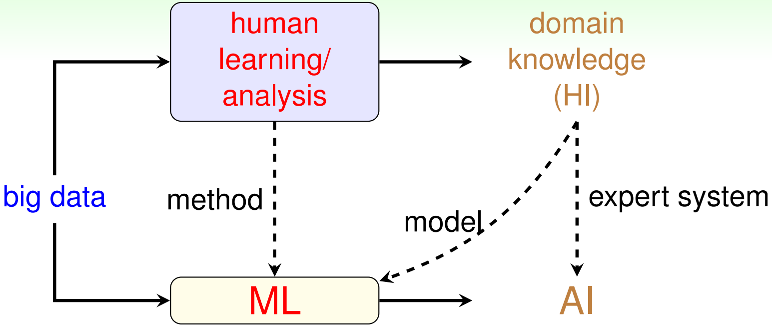

best route by current traffic




best route by predicted travel time

big data **can** make machine look smarter

# ML for Modern AI




- human sometimes **faster learner** on **initial (smaller) data**
- industry: **black plum is as sweet as white**

often important to leverage human learning, especially **in the beginning**

# Outline

ML for (Modern) AI

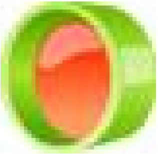
ML Research for Modern AI

ML for Future AI

# Cost-Sensitive Multiclass Classification

# What is the Status of the Patient?


?



H7N9-infected

cold-infected

healthy

- a **classification** problem
  —grouping ‘patients’ into different ‘status’

**are all mis-prediction costs equal?**

# Patient Status Prediction

error measure = society cost

| actual \ predicted | H7N9 | cold | healthy |
|---|---|---|---|
| H7N9 | 0 | 1000 | **100000** |
| cold | 100 | 0 | 3000 |
| healthy | 100 | 30 | 0 |

- H7N9 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;
**how about computer-aided diagnosis**?

# Our Works

| | binary | multiclass |
|---|---|---|
| regular | well-studied | well-studied |
| cost-sensitive | known (Zadrozny et al., 2003) | ongoing (our works, among others) |

**selected works of ours**

- cost-sensitive SVM (Tu and Lin, ICML 2010)
- cost-sensitive one-versus-one (Lin, ACML 2014)
- cost-sensitive deep learning (Chung et al., IJCAI 2016)

why are people **not**
using those **cool ML works for their AI? :-)**

# Issue 1: Where Do Costs Come From?

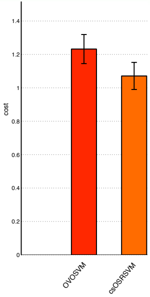
## A Real Medical Application: Classifying Bacteria

- by human doctors: **different treatments** $\Longleftrightarrow$ serious costs
- cost matrix averaged from two doctors:

| | Ab | Ecoli | HI | KP | LM | Nm | Psa | Spn | Sa | GBS |
|---|---|---|---|---|---|---|---|---|---|---|
| Ab | 0 | 1 | 10 | 7 | 9 | 9 | 5 | 8 | 9 | 1 |
| Ecoli | 3 | 0 | 10 | 8 | 10 | 10 | 5 | 10 | 10 | 2 |
| HI | 10 | 10 | 0 | 3 | 2 | 2 | 10 | 1 | 2 | 10 |
| KP | 7 | 7 | 3 | 0 | 4 | 4 | 6 | 3 | 3 | 8 |
| LM | 8 | 8 | 2 | 4 | 0 | 5 | 8 | 2 | 1 | 8 |
| Nm | 3 | 10 | 9 | 8 | 6 | 0 | 8 | 3 | 6 | 7 |
| Psa | 7 | 8 | 10 | 9 | 9 | 7 | 0 | 8 | 9 | 5 |
| Spn | 6 | 10 | 7 | 7 | 4 | 4 | 9 | 0 | 4 | 7 |
| Sa | 7 | 10 | 6 | 5 | 1 | 3 | 9 | 2 | 0 | 7 |
| GBS | 2 | 5 | 10 | 9 | 8 | 6 | 5 | 6 | 8 | 0 |

issue 2: is cost-sensitive classification **really useful**?

# Cost-Sensitive vs. Traditional on Bacteria Data

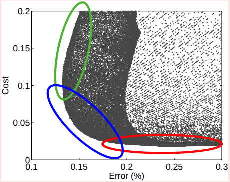



(Jan et al., BIBM 2011)

**cost-sensitive** better than **traditional**;
but why are people **still not**
using those cool ML works for their AI? :-)

# Issue 3: Error Rate of Cost-Sensitive Classifiers

## The Problem




- cost-sensitive classifier: low cost but high error rate
- traditional classifier: low error rate but high cost
- how can we get the blue classifiers?: low error rate and low cost

cost-and-error-sensitive:
more suitable for **real-world medical needs**

# Improved Classifier for Both Cost and Error

(Jan et al., KDD 2012)

## Cost

| | |
|---|---|
| iris | ≈ |
| wine | ≈ |
| glass | ≈ |
| vehicle | ≈ |
| vowel | ◯ |
| segment | ◯ |
| dna | ◯ |
| satimage | ≈ |
| usps | ◯ |
| zoo | ◯ |
| splice | ≈ |
| ecoli | ≈ |
| soybean | ≈ |

## Error

| | |
|---|---|
| iris | ◯ |
| wine | ◯ |
| glass | ◯ |
| vehicle | ◯ |
| vowel | ◯ |
| segment | ◯ |
| dna | ◯ |
| satimage | ◯ |
| usps | ◯ |
| zoo | ◯ |
| splice | ◯ |
| ecoli | ◯ |
| soybean | ◯ |

now, **are people using those cool ML works for their AI? :-)**

# Lessons Learned from Research on Cost-Sensitive Multiclass Classification


?


H7N9-infected

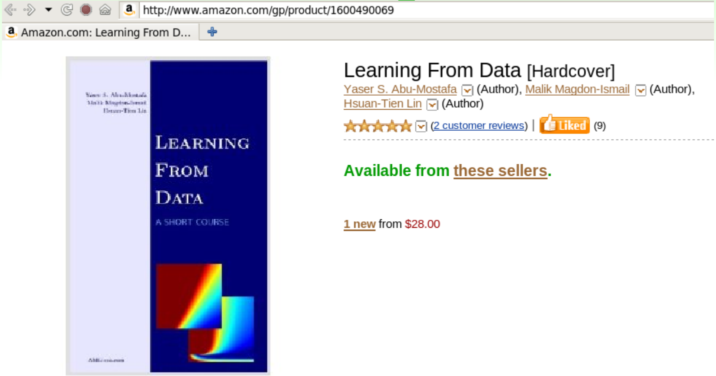

cold-infected


healthy

1. more realistic (generic) in academia
   $\neq$ **more realistic (feasible) in application**
   e.g. the ‘cost’ of **inputting a cost matrix? :-)**
2. **cross-domain collaboration** important
   e.g. getting the ‘cost matrix’ from **domain experts**
3. not easy to win **human trust**
   —humans are somewhat **multi-objective**

# Label Space Coding for Multilabel Classification

# What **Tags**?




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

a **multilabel** classification problem:
**tagging** input to multiple categories

# Binary Relevance: Multilabel Classification via Yes/No

**Binary Classification**

{yes, no}

**multilabel w/ $L$ classes: $L$ Y/N 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** approach: transformation to **multiple isolated binary classification**
- disadvantages:
  - **isolation**—hidden relations not exploited (e.g. ML and DM highly correlated, ML subset of AI, textbook & children book disjoint)
  - **unbalanced**—few yes, many no

**Binary Relevance**: simple (& good) benchmark with known disadvantages

# From Label-set to Coding View

| | label set | apple | orange | strawberry | **binary code** |
|---|---|---|---|---|---|
|  | {o} | 0 (N) | 1 (Y) | 0 (N) | $[0, 1, 0]$ |
|  | {a, o} | 1 (Y) | 1 (Y) | 0 (N) | $[1, 1, 0]$ |
|  | {a, s} | 1 (Y) | 0 (N) | 1 (Y) | $[1, 0, 1]$ |
|  | {o} | 0 (N) | 1 (Y) | 0 (N) | $[0, 1, 0]$ |
|  | {} | 0 (N) | 0 (N) | 0 (N) | $[0, 0, 0]$ |

subset of $2^{\{1,2,\cdots,L\}}$ $\Leftrightarrow$ **length-$L$ binary code**

# A NIPS 2009 Approach: Compressive Sensing

## General Compressive Sensing

sparse (many 0) binary vectors $\mathbf{y} \in \{0, 1\}^L$ can be **robustly compressed** by projecting to $M \ll L$ basis vectors $\{\mathbf{p}_1, \mathbf{p}_2, \cdots, \mathbf{p}_M\}$

## Comp. Sensing for Multilabel Classification (Hsu et al., NIPS 2009)

1. **compress**: encode original data by **compressive sensing**
2. **learn**: get regression function from compressed data
3. **decode**: decode regression predictions to sparse vector by **compressive sensing**

**Compressive Sensing**: seemly strong competitor **from related theoretical analysis**

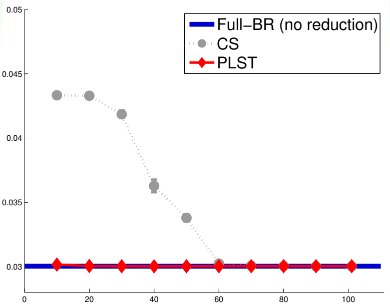
# Our Proposed Approach: Compressive Sensing ⇒ PCA

**Principal Label Space Transformation (PLST), i.e. PCA for Multilabel Classification** (Tai and Lin, NC Journal 2012)

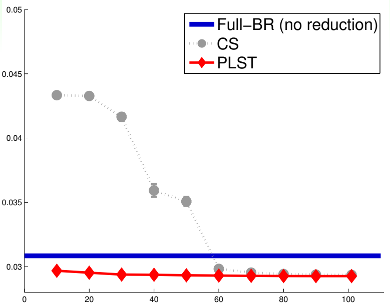
1. **compress**: encode original data by **PCA**
2. **learn**: get regression function from compressed data
3. **decode**: decode regression predictions to label vector by **reverse PCA + quantization**

**does PLST perform better than CS?**

# Hamming Loss Comparison: PLST vs. CS




mediamill (Linear Regression)




mediamill (Decision Tree)

- **PLST** better than CS: faster, **better** performance
- similar findings across **data sets** and **regression algorithms**

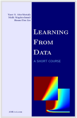
Why? CS creates
**harder-to-learn** regression tasks

# Our Works Continued from PLST

1. **Compression** Coding (Tai & Lin, NC Journal 2012 with 186 citations)
   —**condense** for efficiency: better (than CS) approach PLST
   — key tool: PCA from Statistics/Signal Processing
2. **Learnable-Compression** Coding (Chen & Lin, NIPS 2012 with 124 citations)
   —**condense learnably** for **better** efficiency: better (than PLST) approach CPLST
   — key tool: Ridge Regression from Statistics (+ PCA)
3. **Cost-Sensitive** Coding (Huang & Lin, ECML Journal Track 2017)
   —**condense cost-sensitively** towards application needs: better (than CPLST) approach CLEMS
   — key tool: Multidimensional Scaling from Statistics

cannot thank **statisticans**
enough for those tools!

# Lessons Learned from Label Space Coding for Multilabel Classification

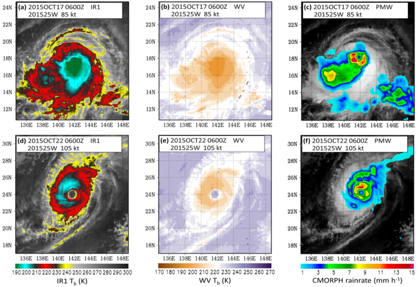



**?**: {machine learning, ~~data structure~~, data mining, ~~object oriented programming~~, artificial intelligence, ~~compiler~~, ~~architecture~~, ~~chemistry~~, textbook, ~~children book~~, ~~… etc.~~ }

1. Is Statistics the same as ML? Is Statistics the same as AI?
   - **does it really matter?**
   - Modern AI should embrace **every useful tool from other fields**.
2. good tools **not necessarily most sophisticated tools**
   e.g. PCA possibly more useful than CS
3. more-cited paper $\neq$ more-useful AI solution
   —citation count **not the only impact measure**

# Tropical Cyclone Intensity Estimation

# Experienced Meteorologists Can 'Feel' and Estimate Tropical Cyclone Intensity from Image

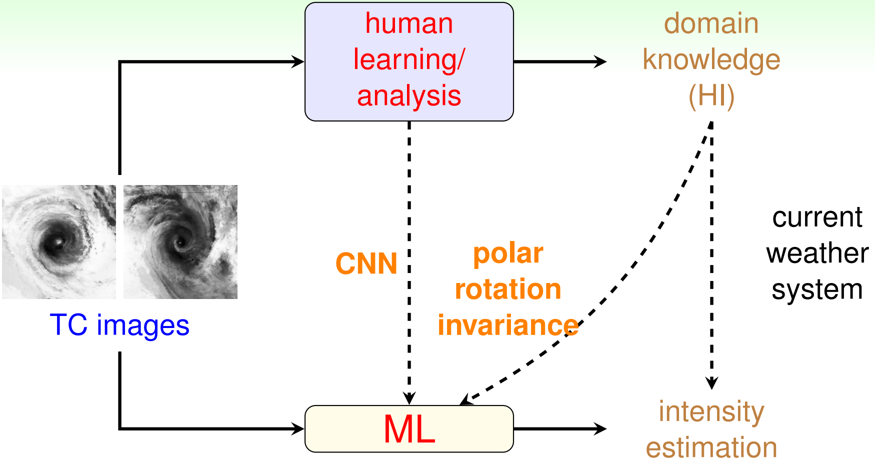



## Can ML do the same/better?

- lack of **ML-ready datasets**
- lack of **model that properly utilizes domain knowledge**

issues addressed in
our latest work (Chen et al., KDD 2018)

# Flow behind Our Proposed Model




is proposed **CNN-TC** better than current weather system?

# Results

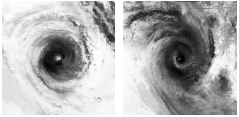
## RMS Error

| | |
|---|---|
| ADT | 11.75 |
| AMSU | 14.40 |
| SATCON | 9.66 |
| **CNN-TC** | **9.03** |

**CNN-TC much better** than current weather system (SATCON)

why are people **not**
using this **cool ML model? :-)**

# Lessons Learned from Research on Tropical Cyclone Intensity Estimation



1. again, **cross-domain collaboration** important
   e.g. even from 'organizing data' to be ML-ready
2. not easy to claim **production ready**
   —can ML be used for '**unseenly-strong** TC'?
3. good AI system requires **both human and machine learning**
   —still an 'art' to blend the two

# Outline

ML for (Modern) AI

ML Research for Modern AI

ML for Future AI

# AI: Now and Next

### 2010–2015

AI becomes **promising**, e.g.

- initial success of **deep learning** on ImageNet
- mature tools for SVM (**LIBSVM**) and others

### 2016–2020

AI becomes **competitive**, e.g.

- super-human performance of **alphaGo** and others
- all big technology companies become **AI-first**

### 2021–

AI becomes **necessary**

- “You’ll not be replaced by AI, but **by humans who know how to use AI**”

  (Sun, Chief AI Scientist of Appier, 2018)

# Building AI as a Service

Appier

CrossX AIXON AIQUA

**(yes, we are hiring!!)**

**Human Knowledge**

**kickstart** your AI faster **with little data and little ML**

**System Engineering**

data pipeline, ML **exception handling**, ML **QA testing**, etc.

**Data Technology**

ML **and any other tools that can be helpful**

# Modern AI Trends

CrossX AIXON AIQUA

**as User Interface**

e.g. Appier AIQUA platform

- reach users better via **friendly push notification**

**as Core Components**

e.g. Appier CrossX for EC marketing

- personalized **recommendation**
- user **segmentation**

**as Business Consultant**

e.g. Appier Aixon platform

- **valuable user** prediction
- user **interest visualization**

# Needs of ML for Future AI

| more creative | more explainable | more interactive |
|---|---|---|
| win human **respect** | win human **trust** | win human **heart** |
| e.g. Appier's 2018 work on **design matching clothes** | e.g. my students' work on **automatic bridge bidding** | e.g. my student's work (w/ DeepQ) on **efficient disease diagonsis** |
| (Shih et al., AAAI 2018) | (Yeh et al., IEE ToG 2018) | (Peng et al., NIPS 2018) |

# Summary

- ML for (Modern) AI:
  tools + human knowledge $\Rightarrow$ **easy-to-use application**
- ML Research for Modern AI:
  need to be **more open-minded**
  —in methodology, in collaboration, in KPI
- ML for Future AI:
  crucial to be '**human-centric**'

**Thank you! Questions?**