Active Learning by Learning

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About Me
Hsuan-Tien Lin

- Associate Professor, Dept. of CSIE, National Taiwan University
- Leader of the Computational Learning Laboratory
- Co-author of the textbook “Learning from Data: A Short Course” (often ML best seller on Amazon)
- Instructor of the NTU-Coursera Mandarin-teaching ML Massive Open Online Courses
  - “Machine Learning Foundations”:
    www.coursera.org/course/ntum lone
  - “Machine Learning Techniques”:
    www.coursera.org/course/ntumltwo
Active Learning

Apple Recognition Problem

Note: Slide Taken from my “ML Techniques” MOOC

- need **apple classifier**: is this a picture of an apple?
- gather photos under CC-BY-2.0 license on Flicker (**thanks to the authors below!**) and **label them as apple/other** for learning

(APAL stands for Apple and Pear Australia Ltd)

- Dan Foy
  - https://flic.kr/p/jNQ55

- APAL
  - https://flic.kr/p/jzP1VB

- adrianbartel
  - https://flic.kr/p/bdy2hZ

- ANdrzej cH.
  - https://flic.kr/p/51DKA8

- Stuart Webster
  - https://flic.kr/p/9C3Ybd

- nachans
  - https://flic.kr/p/9XD7Ag

- APAL
  - https://flic.kr/p/jzRe4u

- Jo Jakeman
  - https://flic.kr/p/7jwtGp

- APAL
  - https://flic.kr/p/jzPYNr

- APAL
  - https://flic.kr/p/jzScif
Apple Recognition Problem

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Mr. Roboto.
https://flic.kr/p/i5BN85

Richard North
https://flic.kr/p/bHhPkB

Richard North
https://flic.kr/p/d8tGou

Emilian Vicol
https://flic.kr/p/bpmGXW

Robert McQueen
https://flic.kr/p/pZv1Mf

Crystal
https://flic.kr/p/kaPYp

jf686
https://flic.kr/p/6vjRFH

skyseeker
https://flic.kr/p/2MynV

Janet Hudson
https://flic.kr/p/7QDBbm

Rennett Stowe
https://flic.kr/p/agmnrk
unknown target function

$$f : \mathcal{X} \rightarrow \mathcal{Y}$$

training examples

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

$$\begin{align*}
(\text{apple}, +1), & (\text{banana}, +1), (\text{peach}, +1) \\
(\text{apple}, -1), & (\text{banana}, -1), (\text{peach}, -1)
\end{align*}$$

learning algorithm

$$\mathcal{A}$$

final hypothesis

$$g \approx f$$

hypothesis set

$$\mathcal{H}$$

**batch** supervised classification:

learn from **fully labeled** data
Active Learning: Learning by ‘Asking’

but labeling is **expensive**

**Protocol ⇔ Learning Philosophy**

- **batch**: ‘duck feeding’
- **active**: ‘question asking’ (iteratively)

—query $y_n$ of chosen $x_n$

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

labeled training examples

$(\text{apple}, +1), (\text{banana}, +1), (\text{apple}, +1)$

$(\text{banana}, -1), (\text{banana}, -1), (\text{apple}, -1)$

learning algorithm $\mathcal{A}$

final hypothesis $g \approx f$

hypothesis set $\mathcal{H}$

active: improve hypothesis with fewer labels (hopefully) by asking questions **strategically**
Pool-Based Active Learning Problem

Given

- labeled pool $\mathcal{D}_l = \{(\text{feature } x_n, \text{label } y_n \text{ (e.g. IsApple?)})\}_{n=1}^N$
- unlabeled pool $\mathcal{D}_u = \{\tilde{x}_s\}_{s=1}^S$

Goal

design an algorithm that iteratively

1. **strategically query** some $\tilde{x}_s$ to get associated $\tilde{y}_s$
2. move $(\tilde{x}_s, \tilde{y}_s)$ from $\mathcal{D}_u$ to $\mathcal{D}_l$
3. learn **classifier** $g^{(t)}$ from $\mathcal{D}_l$

and improve **test accuracy** of $g^{(t)}$ w.r.t #queries

how to **query strategically**?
How to Query Strategically?

Strategy 1: ask **most confused** question

Strategy 2: ask **most frequent** question

Strategy 3: ask **most helpful** question

do you use a **fixed strategy** in practice? 😊
Active Learning

Choice of Strategy

Strategy 1: uncertainty
ask most confused question

Strategy 2: representative
ask most frequent question

Strategy 3: exp.-err. reduction
ask most helpful question

• choosing one single strategy is non-trivial:

• human-designed strategy heuristic and confine machine’s ability

can we free the machine 😊 by letting it learn to choose the strategies?
Our Contributions

A philosophical and algorithmic study of active learning, which ...

- allows machine to make **intelligent choice of strategies**, just like my cute daughter
- studies **sound feedback scheme** to tell machine about goodness of choice, just like what I do
- results in **promising active learning performance**, just like (hopefully) bright future of my daughter 😊

will describe **key philosophical ideas** behind our proposed approach
Idea: Trial-and-Reward Like Human

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K strategies:
A_1, A_2, \cdots, A_K

try one strategy

“goodness” of strategy as reward

two issues: try and reward
Online Choice of Strategy

Reduction to Bandit

when do humans trial-and-reward?  

gambling 😊

- $K$ strategies: $\mathcal{A}_1, \mathcal{A}_2, \ldots, \mathcal{A}_K$
  - try one strategy
  - "goodness" of strategy as reward

- $K$ bandit machines: $\mathcal{B}_1, \mathcal{B}_2, \ldots, \mathcal{B}_K$
  - try one bandit machine
  - "luckiness" of machine as reward

—will take one well-known probabilistic bandit learner (EXP4.P)

intelligent choice of strategy $\implies$ intelligent choice of bandit machine
Given: $K$ existing active learning strategies

for $t = 1, 2, \ldots, T$

1. let EXP4.P decide strategy $A_k$ to try
2. query the $\tilde{x}_s$ suggested by $A_k$, and compute $g^{(t)}$
3. evaluate goodness of $g^{(t)}$ as reward of trial to update EXP4.P

only remaining problem: what reward?
ideal reward after updating classifier $g(t)$ by the query $(x_{nt}, y_{nt})$:

$$\text{accuracy } \frac{1}{M} \sum_{m=1}^{M} \left[ y_m = g(t)(x_m) \right] \text{ on test set } \{(x_m, y_m)\}_{m=1}^{M}$$

- **test accuracy** as reward:
  area under query-accuracy curve $\equiv$ cumulative reward

- **test accuracy infeasible** in practice
  —labeling **expensive**, remember? 😊

difficulty: approximate test accuracy on the fly
Design of Reward

Training Accuracy as Reward

test accuracy \[ \frac{1}{M} \sum_{m=1}^{M} I[y_m = g(t(x_m))] \] infeasible, naïve replacement:

accuracy \[ \frac{1}{t} \sum_{\tau=1}^{t} I[y_{n\tau} = g(t(x_{n\tau}))] \] on labeled pool \( \{(x_{n\tau}, y_{n\tau})\}_{\tau=1}^{t} \)

- **training accuracy** as reward: training accuracy \( \approx \) test accuracy?

- not necessarily!!
  —for active learning strategy that asks **easiest** questions:
    - training accuracy **high**: \( x_{n\tau} \) easy to label
    - test accuracy **low**: not enough information about **harder instances**

training accuracy: too **biased** to approximate test accuracy
Weighted Training Accuracy as Reward

- **Training accuracy**
  \[ \frac{1}{t} \sum_{\tau=1}^{t} \left[ y_{n_\tau} \cdot g^{(t)}(x_{n_\tau}) \right] \]
  biased, want **unbiased estimator**

- **non-uniform sampling** theorem: if \((x_{n_\tau}, y_{n_\tau})\) sampled with probability \(p_\tau > 0\) from data set \(\{(x_n, y_n)\}_{n=1}^{N}\) in iteration \(\tau\),

  \[
  \text{weighted training accuracy} \quad \frac{1}{t} \sum_{\tau=1}^{t} \frac{1}{p_\tau} \left[ y_{n_\tau} = g(x_{n_\tau}) \right]
  \]

  \[\approx \frac{1}{N} \sum_{n=1}^{N} \left[ y_n = g(x_n) \right] \text{ in expectation} \]

- with **probabilistic query** like EXP4.P:
  weighted training accuracy \(\approx\) test accuracy

**weighted** training accuracy: **unbiased** approx. of test accuracy on the fly
Design of Reward

Human-Designed Criterion as Reward

(Baram et al., 2004) COMB approach:

bandit + **balancedness** of $g^{(t)}$ on unlabeled data as reward

- why? human criterion that matches classifier to **domain assumption**
- but many active learning applications are on **unbalanced data**! —assumption may be **unrealistic**

existing strategies: active learning by acting;
COMB: active learning by acting;
ours: active learning by learning

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Active Learning by Learning
Experiments

Comparison with Single Strategies

- **no single best strategy** for every data set
  —choosing/blending needed
- **ALBL** consistently **matches the best**
  —similar findings across other data sets

**ALBL**: effective in **making intelligent choices**
Experiments

Comparison with Other Adaptive Blending Algorithms

- **ALBL \approx COMB**
- **ALBL > COMB**

**diabetes**

**sonar**

- **ALBL > ALBL-Train** generally
  - *importance-weighted* mechanism needed for correcting biased training accuracy

- **ALBL** consistently comparable to or better than **COMB**
  - *learning performance* more useful than human-criterion

**ALBL**: effective in utilizing performance
Active Learning by Learning

- based on **bandit learning** + **unbiased performance estimator** as reward
- effective in **making intelligent choices** —comparable or superior to the best of existing strategies
- effective in **utilizing learning performance** —superior to human-criterion-based blending

New Directions

- **open-source tool** being developed
- extending to **more sophisticated active learning problems**

Thank you! Questions?