Active Learning by Learning

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

National Taiwan University

Institute of Information Systems and Applications,
National Tsing Hua University,
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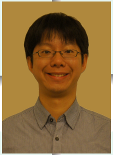
joint work with Wei-Ning Hsu (AAAI 2015)

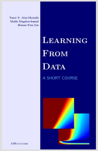
About Me

Professor
National Taiwan University

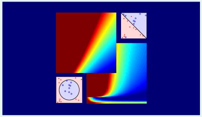
Chief Data Science Consultant
(former Chief Data Scientist)
Appier Inc.

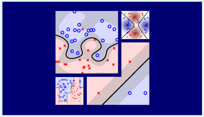


Co-author
Learning from Data



Instructor
NTU-Coursera Mandarin MOOCs
ML Foundations/Techniques





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

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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 Robert Vicol

https://flic.kr/p/bpmGXW

Nathaniel McQueen

https://flic.kr/p/pZv1Mf

Crystal

https://flic.kr/p/kaPYp

jfh686

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

skyseeker

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

Janet Hudson

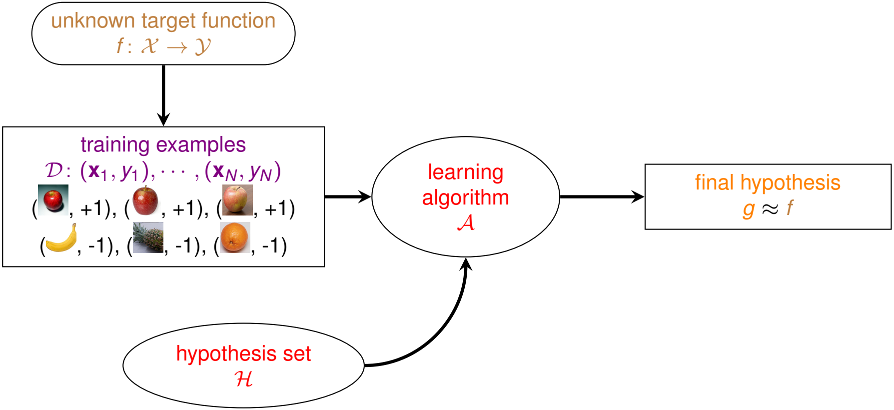
https://flic.kr/p/7QDBbm

Rennett Stowe

https://flic.kr/p/agmnrk

Batch (Traditional) Machine Learning

Note: Flow Taken from my “ML Foundations” MOOC



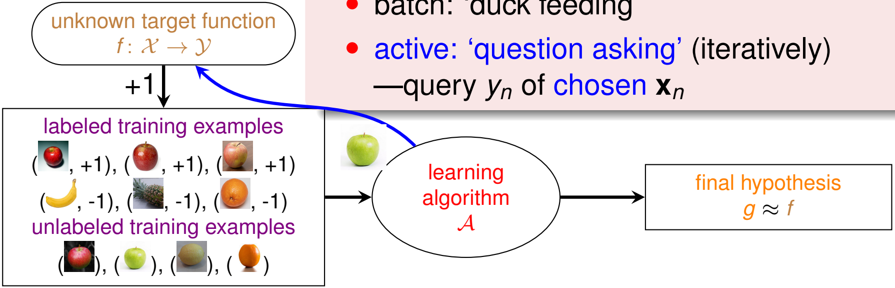
batch supervised classification:
learn from fully labeled data

Active Learning: Learning by 'Asking'

but labeling is expensive

Protocol ⇔ Learning Philosophy

- batch: 'duck feeding'
- active: 'question asking' (iteratively)
  —query y_n of chosen $\mathbf{x}_n$



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

Pool-Based Active Learning Problem

Given

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

Goal

design an algorithm that iteratively

1. strategically query some $\tilde{\mathbf{x}}_s$  to get associated $\tilde{y}_s$
2. move $(\tilde{\mathbf{x}}_s, \tilde{y}_s)$ 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?

by DFID - UK Department for International Development;

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? ☺

Choice of Strategy

Strategy 1: uncertainty

ask most confused question

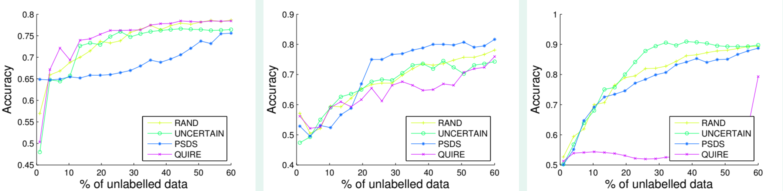
Strategy 2: representative

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 kids
- 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 kids ☺

will describe key philosophical ideas behind our proposed approach

Idea: Trial-and-Reward Like Human

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K strategies:

$\mathcal{A}_1, \mathcal{A}_2, \cdots, \mathcal{A}_K$

try one strategy

"goodness" of strategy as reward

two issues: try and reward

Reduction to Bandit

when do humans trial-and-reward?
gambling ☺

K strategies: $\mathcal{A}_1, \mathcal{A}_2, \cdots, \mathcal{A}_K$

try one strategy

"goodness" of strategy as reward

K bandit machines: $\mathcal{B}_1, \mathcal{B}_2, \cdots, \mathcal{B}_K$

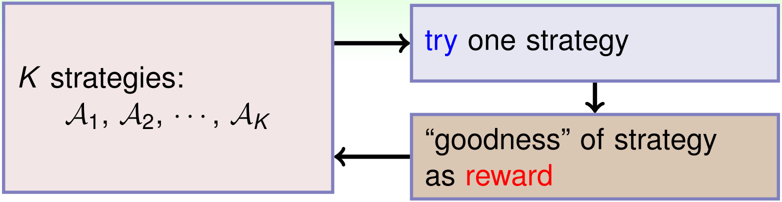
try one bandit machine

"luckiness" of machine as reward

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

intelligent choice of strategy
$\Longrightarrow$ intelligent choice of bandit machine

Active Learning by Learning



Given: K existing active learning strategies

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

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

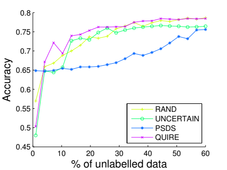
only remaining problem: what reward?

Ideal Reward

ideal reward after updating classifier $g^{(t)}$ by the query $(\mathbf{x}_{n_t}, y_{n_t})$:

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

- 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

Training Accuracy as Reward

test accuracy $\cancel{\frac{1}{M}\sum_{m=1}^{M} [\![y_m = g^{(t)}(\mathbf{x}_m)]\!]}$ infeasible, naïve replacement:

accuracy $\frac{1}{t}\sum_{\tau=1}^{t} [\![y_{n_\tau} = g^{(t)}(\mathbf{x}_{n_\tau})]\!]$ on labeled pool $\{(\mathbf{x}_{n_\tau}, y_{n_\tau})\}_{\tau=1}^{t}$

- training accuracy as reward:
  training accuracy $\approx$ test accuracy?
- not necessarily!!
  —for active learning strategy that asks easiest questions:
  - training accuracy high: $\mathbf{x}_{n_\tau}$ 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 $\cancel{\frac{1}{t}\sum_{\tau=1}^{t} [\![y_{n_\tau} = g^{(t)}(\mathbf{x}_{n_\tau})]\!]}$ biased,
want less-biased estimator

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

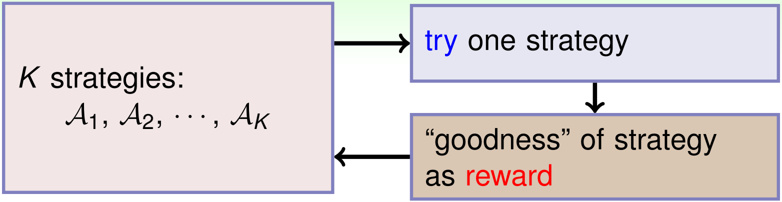
$$\text{weighted training accuracy } \frac{1}{t}\sum_{\tau=1}^{t} \frac{1}{p_\tau} [\![y_{n_\tau} = g(\mathbf{x}_{n_\tau})]\!]$$

$$\approx \quad \frac{1}{N}\sum_{n=1}^{N} [\![y_n = g(\mathbf{x}_n)]\!] \text{ in expectation}$$

- with probabilistic query like EXP4.P:
  weighted training accuracy $\approx$ test accuracy

weighted training accuracy:
less biased approx. of test accuracy on the fly

Active Learning by Learning (Hsu and Lin, 2015)



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2. query the $\tilde{x}_s$ suggested by $\mathcal{A}_k$, and compute $g^{(t)}$
3. evaluate weighted training accuracy of $g^{(t)}$ as reward of trial to update EXP4.P

other possible rewards?

Human-Designed Criterion as Reward

(Baram et al., 2004) COMB approach:

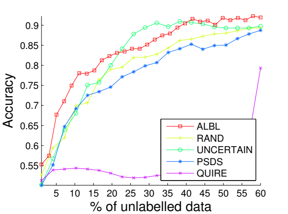
bandit + balancedness of $g^{(t)}$ on unlabeled data as reward

- 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

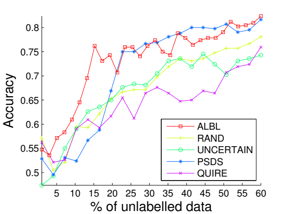
Comparison with Single Strategies

UNCERTAIN Best



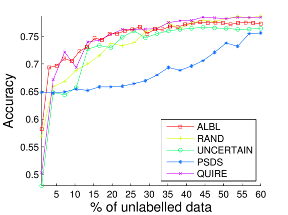
vehicle

PSDS Best



sonar

QUIRE Best



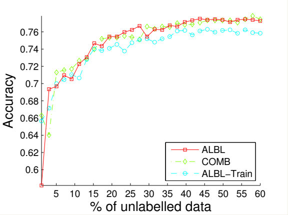
diabetes

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

ALBL: effective in making intelligent choices

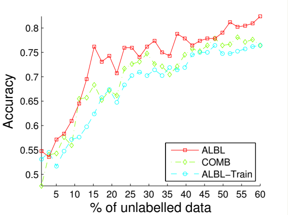
Comparison with Other Bandit-Driven Algorithms

ALBL ≈ COMB



diabetes

ALBL > COMB



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

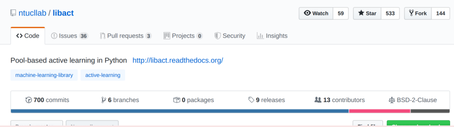
Summary

Active Learning by Learning

- based on bandit learning + less biased 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 approach

open-source tool developed

https://github.com/ntucllab/libact



Wait! Discussion and more!

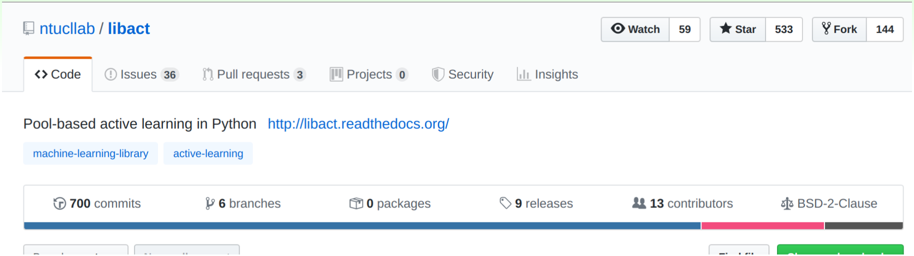
Discussion for Theoreticians

weighted training accuracy $\frac{1}{t}\sum_{\tau=1}^{t}\frac{1}{p_\tau}[\![y_{n_\tau} = g^{(t)}(\mathbf{x}_{n_\tau})]\!]$ as reward

- is reward unbiased estimator of test performance?
  no for learned $g^{(t)}$ (yes for fixed g)
- is reward fixed before playing?
  no because $g^{(t)}$ learned from $(\mathbf{x}_{n_t}, y_{n_t})$
- is reward independent of each other?
  no because past history all in reward

ALBL: tools from theoreticians
\+ wild/unintended usage

Have We Made Active Learning More Realistic? (1/2)



Yes!

open-source tool `libact` developed (Yang, 2017)

`https://github.com/ntucllab/libact`

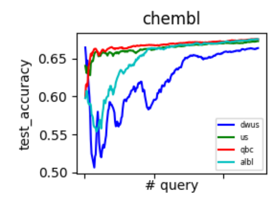
- including uncertainty, QUIRE, PSDS, . . ., and ALBL
- received $>$ 500 stars and continuous issues

"`libact` is a Python package designed to make active learning easier for real-world users"

Have We Made Active Learning More Realistic? (2/2)

No!

- single-most raised issue: hard to install on Windows/Mac —because several strategies requires some C packages
- performance in a recent industry project:



- uncertainty sampling often suffices
- ALBL dragged down by bad strategy

"`libact` is a Python package designed to make active learning easier for real-world users"

Other Attempts for Realistic Active Learning

"learn" a strategy beforehand rather than on-the-fly?

- transfer active learning experience (Chu and Lin, 2016)

—not easy to realize in open-source package

other active learning tasks?

- NLP (Yuan et al., 2020)
- reinforcement learning (Chen et al., 2020)
- annotation cost-sensitive (Tsou and Lin, 2019)
- classification cost-sensitive (Huang and Lin, 2016)

many more needs to be satisfied: mini-batch, multi-label query, weak-label query, etc.

Lessons Learned from Research on Active Learning by Learning

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1. scalability bottleneck of artificial intelligence: choice of methods/models/parameter/...
2. think outside of the math box: 'non-rigorous' usage may be good enough
3. important to be brave yet patient
   - idea: 2012
   - paper: (Hsu and Lin, AAAI 2015); software: (Yang et al., 2017)
4. easy-to-use in design $\neq$ easy-to-use in reality

Thank you! Questions?