Active Learning by Learning

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2015 IR Workshop, IIS Sinica, Taiwan
joint work with Wei-Ning Hsu, presented in AAAI 2015
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/ntumalone
  - “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](https://flic.kr/p/jNQ55)
- APAL: [https://flic.kr/p/jzP1VB](https://flic.kr/p/jzP1VB)
- adrianbartel: [https://flic.kr/p/bdy2hZ](https://flic.kr/p/bdy2hZ)
- ANdrzej cH.: [https://flic.kr/p/51DKA8](https://flic.kr/p/51DKA8)
- Stuart Webster: [https://flic.kr/p/9C3Ybd](https://flic.kr/p/9C3Ybd)
- nachans: [https://flic.kr/p/9XD7Ag](https://flic.kr/p/9XD7Ag)
- APAL: [https://flic.kr/p/jzRe4u](https://flic.kr/p/jzRe4u)
- Jo Jakeman: [https://flic.kr/p/7jwtGp](https://flic.kr/p/7jwtGp)
- APAL: [https://flic.kr/p/jzPYNr](https://flic.kr/p/jzPYNr)
- APAL: [https://flic.kr/p/jzScif](https://flic.kr/p/jzScif)

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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 Vicol

https://flic.kr/p/pZv1Mf

Nathaniel McQueen

https://flic.kr/p/vlMf

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

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Active Learning by Learning
unknown target function
\[ f : \mathcal{X} \rightarrow \mathcal{Y} \]

training examples
\[ \mathcal{D} : (x_1, y_1), \cdots, (x_N, y_N) \]
(\text{apple, +1}), (\text{cherry, +1}), (\text{banana, +1})
(\text{apple, -1}), (\text{cherry, -1}), (\text{banana, -1})

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

labeled training examples
(\(\text{apple}, +1\)), (\(\text{orange}, +1\)), (\(\text{apple}, +1\))
(\(\text{banana}, -1\)), (\(\text{orange}, -1\)), (\(\text{apple}, -1\))

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**?
Active Learning

How to Query Strategically?

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<table>
<thead>
<tr>
<th>Strategy 1</th>
<th>Strategy 2</th>
<th>Strategy 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>ask <strong>most confused</strong> question</td>
<td>ask <strong>most frequent</strong> question</td>
<td>ask <strong>most helpful</strong> question</td>
</tr>
</tbody>
</table>

**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
Online Choice of Strategy

Idea: Trial-and-Reward Like Human

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\( K \) strategies:
\( A_1, A_2, \ldots, A_K \)

\text{try} one strategy

“goodness” of strategy as \text{reward}

two issues: \text{try} and \text{reward}
when do humans **trial-and-reward?**

**gambling 😊**

---

**K** strategies:

$A_1, A_2, \ldots, A_K$

- **try** one strategy
- "goodness" of strategy as **reward**

**K** bandit machines:

$B_1, B_2, \ldots, B_K$

- **try** one bandit machine
- "luckiness" of machine as **reward**

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

intelligent choice of strategy  
$\Rightarrow$  
intelligent choice of **bandit machine**
Online Choice of Strategy

Active Learning by Learning

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

Ideal reward after updating classifier $g^{(t)}$ by the query $(x_{nt}, y_{nt})$:

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

- **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

\[
\frac{1}{M} \sum_{m=1}^{M} \left[ y_m = g^{(t)}(x_m) \right]
\]

infeasible, naïve replacement:

\[
\frac{1}{t} \sum_{\tau=1}^{t} \left[ y_{n_{\tau}} = g^{(t)}(x_{n_{\tau}}) \right]
\]
on \text{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 \( \frac{1}{t} \sum_{\tau=1}^{t} \left[ y_{n_{\tau}} = g^{(t)}(x_{n_{\tau}}) \right] \) is 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 \(\tau\),

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

  \( \approx \frac{1}{N} \sum_{n=1}^{N} \left[ y_{n} = g(x_{n}) \right] \) 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
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
Experiments

Comparison with Single Strategies

**UNCERTAIN** Best

**PSDS** Best

**QUIRE** Best

- **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

\[ ALBL \approx COMB \]

\[ ALBL > COMB \]

- **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
## Conclusion

### 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**

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Thank you! Questions?