Active Learning via Reduction To Supervised Classification

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Active Learning

Can a learning algorithm effectively interactively choose which examples to label?

The Active Learning Setting

Repeatedly:

1. Observe unlabeled example x.
2. Make prediction $\hat{y}$.
3. Asking for label? Yes/no
4. If yes, observe label y.

Goal: Simultaneously minimize the number of mistakes and the number of labels requested.

Good solutions imply more efficient learning *and* a better understanding of how to deal with other forms of interactive learning.

Typical heuristics for active learning

Start with a pool of unlabeled data

Pick a few points at random and get their labels

Repeat

- Fit a classifier to the labels seen so far
- Query the unlabeled point that is closest to the boundary (or most uncertain, or most likely to decrease overall uncertainty,...)

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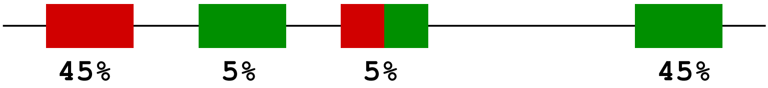

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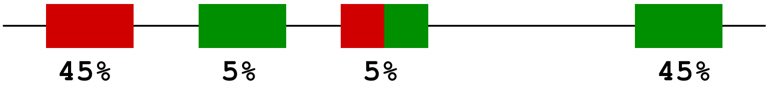

Even with infinitely many labels, converges to a classifier with 5% error instead of the best achievable, 2.5%. *Not consistent!*

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4. BHLZ 2010: Yes, given an efficient loss optimization algorithm. This talk.

Importance Weighted Active Learning via Reduction

$S = \emptyset$
While (unlabeled examples remain)

1. Receive unlabeled example x.
2. Set $p = \text{Rejection-Threshold}(x, S)$.
3. If $U(0,1) \leq p$, get label y, and add $(x, y, \frac{1}{p})$ to S.
4. Let $h = \text{Learn}(S)$.

Consistency: (BDL2009) For all reasonable choices of Rejection-Threshold, the algorithm is consistent.

What should Rejection-Threshold be?

On the kth unlabeled point, let:
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Success: (BHLZ2010) If there is a small disagreement coefficient θ, the algorithm requires only $O\left(\theta\sqrt{k \log k}\right)$ + a minimum due to noise (K2006).

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Characterizes known examples where active learning can help.
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Disagreement coefficient is $\theta = \max_\epsilon \frac{\Pr(\text{interesting}_\epsilon\ x)}{\epsilon}$
(See ICML 2009 tutorial for examples)

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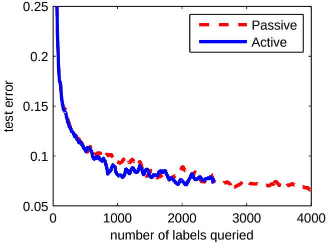
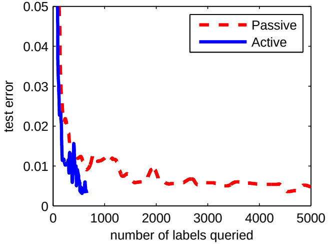
p too small, implies that condition (1) is violated with a reasonable probability.

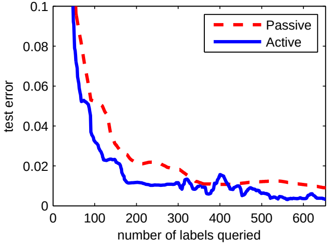
Decision Tree Experiments



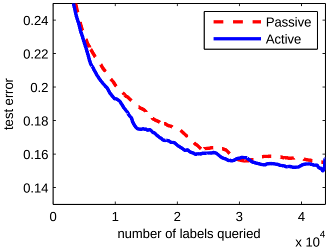
MNIST 3s vs 5s



KDDCUP99

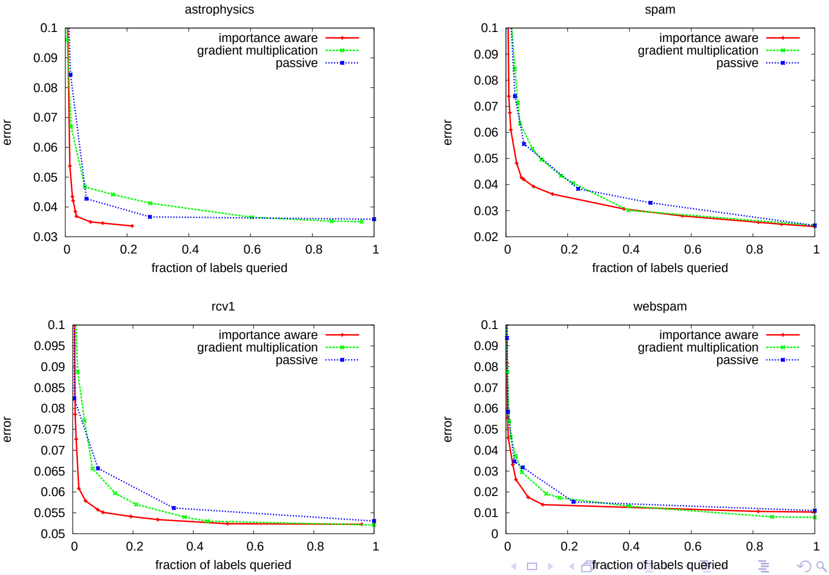


KDDCUP99 (close-up)



MNIST multi-class (close-up)

Online Linear Learning results (with Nikos)



Demonstration

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9. Allows you to switch learning algorithms later (!)
10. Empirically, yields substantial label savings.

The Future

Active Learning is only one kind of interactive learning. Does a similar strategy work with other forms of interactive learning?

Bibliography

1. Nina Balcan, Alina Beygelzimer, John Langford, Agnostic Active Learning. ICML 2006.
2. Alina Beygelzimer, Sanjoy Dasgupta, and John Langford, Importance Weighted Active Learning, ICML 2009.
3. Alina Beygelzimer, Daniel Hsu, John Langford, Tong Zhang, Agnostic Active Learning Without Constraints, NIPS 2010.
4. Sanjoy Dasgupta, Daniel J. Hsu, and Claire Monteleoni. A general agnostic active learning algorithm. NIPS 2007.
5. Hanneke, S. A Bound on the Label Complexity of Agnostic Active Learning. ICML 2007.
6. Matti Kaariainen, Active Learning in the Non-realizable Case, ALT 2006.
7. Nikos Karampatziakis and John Langford, Importance Weight Aware Gradient Updates, http://arxiv.org/abs/1011.1576