Machine Learning 10-701

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Today:

- Semi-supervised learning
- Co-Training
- Never ending learning

Recommended reading:
(see class website)

- Carlson et al., 2010
- Blum & Mitchell 1998

When can Unlabeled Data Help Learn f: X→Y ?

Consider problem setting:

- Set *X* of instances drawn from unknown distribution *P(X)*
- Wish to learn target function *f: X→ Y* (or, P(Y|X))
- Given a set *H* of possible hypotheses for *f*

Given:

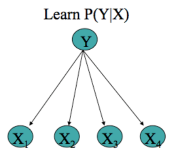
- i.i.d. labeled examples $L = \{\langle x_1, y_1 \rangle \dots \langle x_m, y_m \rangle\}$
- i.i.d. unlabeled examples $U = \{x_{m+1}, \dots x_{m+n}\}$

Wish to find hypothesis with lowest true error:

$$\hat{f} \leftarrow \arg\min_{h \in H} \Pr_{x \in P(X)} [h(x) \neq f(x)]$$

When can Unlabeled Data Help Learn f: X→Y ?

- EM



Y	X1	X2	X3	X4
1	0	0	1	1
0	0	1	0	0
0	0	0	1	0
?	0	1	1	0
?	0	1	0	1

- Metric regularization
  - [Schuurmans & Southey, MLJ 2002]
  - use unlabeled data to detect (and avoid) overfitting

- CoTraining, Multiview learning, CoRegularization

CoTraining

- In some settings, available data features are redundant and we can train two classifiers based on disjoint features

- In this case, the two classifiers should agree on the classification for each unlabeled example

- Therefore, we can use the unlabeled data to constrain joint training of both classifiers

Redundantly Sufficient Features

Professor Faloutsos

my advisor

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Christos Faloutsos

Current Position: Assoc. Professor of Computer Science. (97-98: on leave at CMU)
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Research Interests:

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- Fractals for clustering and spatial access methods;
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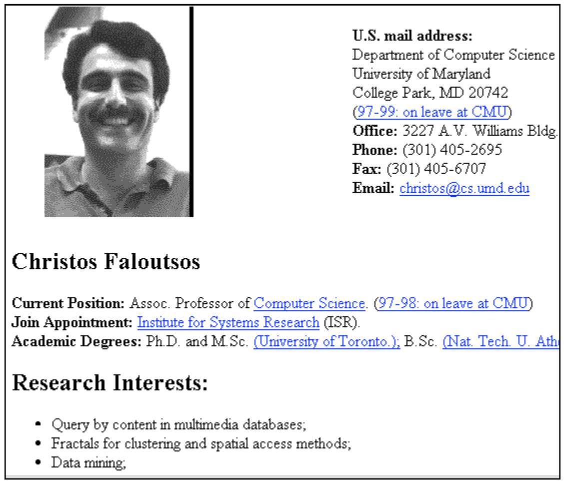

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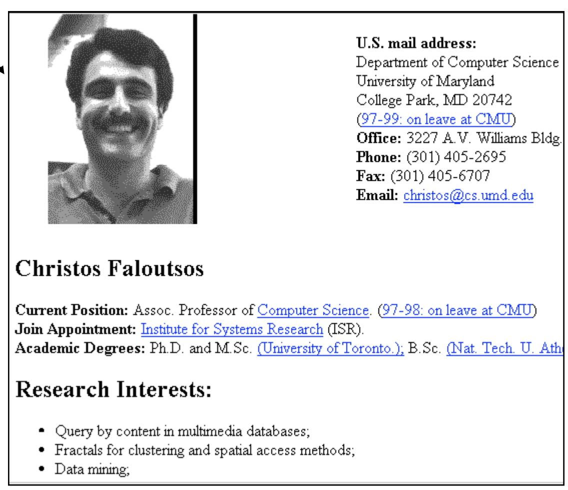

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CoTraining Algorithm #1
[Blum&Mitchell, 1998]

Given: labeled data L,

unlabeled data U

Loop:

Train g1 (hyperlink classifier) using L

Train g2 (page classifier) using L

Allow g1 to label *p* positive, *n* negative examps from U

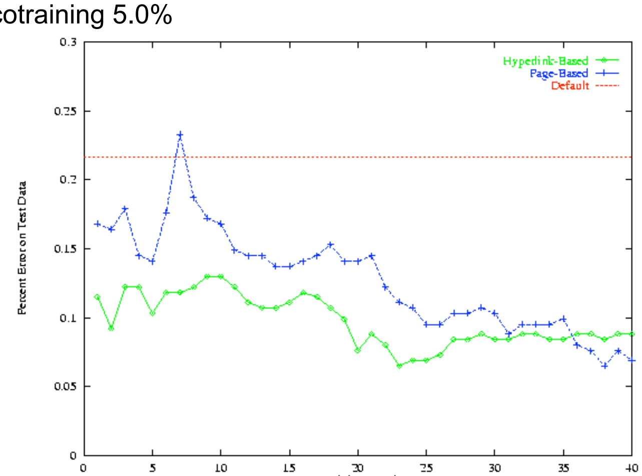
Allow g2 to label *p* positive, *n* negative examps from U

Add these self-labeled examples to L

CoTraining: Experimental Results

- begin with 12 labeled web pages (academic course)
- provide 1,000 additional unlabeled web pages
- average error: learning from labeled data 11.1%;
- average error: cotraining 5.0%

Typical run:



CoTraining setting:

- wish to learn f: X → Y, given L and U drawn from P(X)
- features describing X can be partitioned (X = X1 x X2)

  such that f can be computed from either X1 or X2

$$(\exists g_1, g_2)(\forall x \in X) \quad g_1(x_1) = f(x) = g_2(x_2)$$

One result [Blum&Mitchell 1998]:

- If
  - X1 and X2 are conditionally independent given Y
  - f is PAC learnable from noisy *labeled* data
- Then
  - f is PAC learnable from weak initial classifier plus polynomial number of *unlabeled* examples

Classifier with accuracy > 0.5

Can Unlabeled Data Help Estimate True Error?

Consider two functions making *independent errors*

P(disagree)=P(g1 right, g2 wrong) + P(g2 right, g1 wrong)

e.g., If true error of g1 is 0.1, true error of g2 is 0.1, what is P(disagree?)

PAC Generalization Bounds on CoTraining

[Dasgupta et al., NIPS 2001]

This theorem assumes X1 and X2 are conditionally independent given Y

Theorem 1 *With probability at least* $1-\delta$ *over the choice of the sample* S, *we have that for all* h_1 *and* h_2, *if* $\gamma_i(h_1,h_2,\delta) > 0$ *for* $1 \le i \le k$ *then (a)* f *is a permutation and (b) for all* $1 \le i \le k$,

$$P(h_1 \neq i \mid f(y) = i, h_1 \neq \perp) \quad \le \quad \frac{\widehat{P}(h_1 \neq i \mid h_2 = i, h_1 \neq \perp) + \epsilon_i(h_1,h_2,\delta)}{\gamma_i(h_1,h_2,\delta)}.$$

The theorem states, in essence, that if the sample size is large, and h_1 and h_2 largely agree on the unlabeled data, then $\widehat{P}(h_1 \neq i \mid h_2 = i, h_1 \neq \perp)$ is a good estimate of the error rate $P(h_1 \neq i \mid f(y) = i, h_1 \neq \perp)$.

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$$\gamma_i(h_1,h_2,\delta) \quad = \quad \widehat{P}(h_1 = i \mid h_2 = i, h_1 \neq \perp) - \widehat{P}(h_1 \neq i \mid h_2 = i, h_1 \neq \perp) - 2\epsilon_i(h_1,h_2,\delta)$$

$$\epsilon_i(h_1,h_2,\delta) \quad = \quad \sqrt{\frac{(\ln 2)(|h_1| + |h_2|) + \ln \frac{2k}{\delta}}{2|S(h_2 = i,\ h_1 \neq \perp)|}}$$

Co Regularization

- Let's build our assumption that g1 and g2 must agree directly into the objective we're optimizing

- e.g.,

$$\langle\theta_1,\theta_2\rangle \leftarrow \arg\min_{\langle\theta_1,\theta_2\rangle} \sum_{x^l\in L}(y^l - g_1(x^l;\theta_1))^2$$
$$+ \sum_{x^l\in L}(y^l - g_2(x^l;\theta_2))^2$$
$$+ \sum_{x^u\in U}(g_1(x^u;\theta_1) - g2(x^u;\theta_2))^2$$

CoTraining Summary

- Unlabeled data improves supervised learning when example features are redundantly sufficient
  - Family of algorithms that train multiple classifiers

- Theoretical results
  - If X1,X2 conditionally independent given Y, Then
    - PAC learnable from weak initial classifier plus unlabeled data
    - disagreement between g1(x1) and g2(x2) bounds final classifier error

- Many real-world problems of this type
  - Semantic lexicon generation [Riloff, Jones 99], [Collins, Singer 99]
  - Web page classification [Blum, Mitchell 98]
  - Word sense disambiguation [Yarowsky 95]
  - Speech recognition [de Sa, Ballard 98]
  - Visual classification of cars [Levin, Viola, Freund 03]

Further Reading

- Semi-Supervised Learning, O. Chapelle, B. Sholkopf, and A. Zien (eds.), MIT Press, 2006. (excellent book)
- EM for Naïve Bayes classifiers: K.Nigam, et al., 2000. "Text Classification from Labeled and Unlabeled Documents using EM", *Machine Learning,* 39, pp.103—134.
- CoTraining: A. Blum and T. Mitchell, 1998. “Combining Labeled and Unlabeled Data with Co-Training,” *Proceedings of the 11th Annual Conference on Computational Learning Theory (COLT-98).*
- S. Dasgupta, et al., “PAC Generalization Bounds for Co-training”, *NIPS 2001*
- Model selection: D. Schuurmans and F. Southey, 2002. “Metric-Based methods for Adaptive Model Selection and Regularization,” Machine Learning, 48, 51—84.