6.891: Lecture 20 (November 19th, 2003)

Information Extraction, and Partially Supervised Approaches

Overview

- Information extraction
- A partially supervised method: cotraining and coboosting (applied to named entity classification)

Information Extraction

Named Entity Recognition

INPUT: Profits soared at Boeing Co., easily topping forecasts on Wall Street, as their CEO Alan Mulally announced first quarter results.

OUTPUT: Profits soared at [Company Boeing Co.], easily topping forecasts on [Location Wall Street], as their CEO [Person Alan Mulally] announced first quarter results.

Relationships between Entities

INPUT: Boeing is located in Seattle. Alan Mulally is the CEO.

OUTPUT:

{Relationship = Company-Location
Company = Boeing
Location = Seattle}

{Relationship = Employer-Employee
Employer = Boeing Co.
Employee = Alan Mulally}

Extraction From Entire Documents

Hi [PERSON Ted] and [PERSON Hill],
Just a reminder that the game move will need to be entered [TIME tonight]. We will need data on operations, rawmaterials ordering, and details of the bond to be sold.
[PERSON Hill]: I will be in the [LOCATION lobby] after the class at [TIME 9 pm]. how about we meet in the [LOCATION lobby] around that time (i.e when both our classes are over).
[PERSON Ted]: Let me know how you are going to provide the bond related input information. We can either meet in the [LOCATION lobby] around [TIME 5.30 pm] or you can e-mail me the info.
Thanks, [PERSON Ajay]

$\Downarrow$

TIME	9 pm, 18th September
LOCATION	Lobby, Building NE43
PERSON	David Hill, Ajay Sinclair
TOPIC	data on operations. . .

TIME	5.30 pm, 18th September
LOCATION	Lobby, Building NE43
PERSON	Ted Jones, Ajay Sinclair
TOPIC	bond related input information

10TH DEGREE is a full service advertising agency specializing in direct and interactive marketing. Located in Irvine CA, 10TH DEGREE is looking for an Assistant Interactive Account Manager to help manage and coordinate interactive marketing initiatives for a marquee automotive account. Experience in online marketing, automotive and/or the advertising agency field is a plus.

Assistant Account Manager Responsibilities

Ensures smooth implementation of programs and initiatives Helps manage the delivery of projects and key client deliverables ...

Compensation: $50,000 – $80,000 Hiring Organization: 10TH DEGREE

Principals only. Recruiters, please don't contact this job poster. Please, no phone calls about this job! Please do not contact job poster about other services, products or commercial interests. Reposting this message elsewhere is NOT OK. this is in or around Orange County - Irvine

$\Downarrow$

INDUSTRY	Advertising
POSITION	Assistant Account Manager
LOCATION	Irvine, CA
COMPANY	10th Degree
SALARY	$50,000 – $80,000

A Second Theme: Partially Supervised Approaches

- Last lecture (Yarowsky' work) we studied approaches that used a small set of "seed" rules, and a large amount of unlabeled data

- Motivation: reduce need for (expensive) "labeled" data

- Today: more work on partially supervised approaches

A Key Property: Redundancy

The ocean reflects the color of the sky, but even on cloudless days the color of the ocean is not a consistent blue. Phytoplankton, microscopic plant life that floats freely in the lighted surface waters, may alter the color of the water. When a great number of organisms are concentrated in an area, the plankton changes the color of the ocean surface. This is called a 'bloom.'

$$\Downarrow$$

w_{-1} = Phytoplankton	word-within-k = ocean
w_{+1} = life	word-within-k = reflects
w_{-2}, w_{-1} = (Phytoplankton,microscopic)	word-within-k = bloom
w_{-1}, w_{+1} = (microscopic,life)	word-within-k = color
w_{+1}, w_{+2} = (life,that)	...

There are often many features which indicate the sense of the word

Another Useful Property: "One Sense per Discourse"

- Yarowsky observes that if the same word appears more than once in a document, then it is very likely to have the same sense every time

Yarowsky's Algorithm

1. Label the data with a small set of "seed" rules

   An example: for the "plant" sense distinction, initial seeds are `word-within-k=life` and `word-within-k=manufacturing`

2. From the seed data, learn a decision list of all rules with weight above some threshold (e.g., all rules with weight > 0.97)

3. Using the new rules, relabel the data
   (usually we will now end up with more data being labeled)

4. Induce a new set of rules with weight above the threshold from the labeled data

5. If some examples are still not labeled, return to step 2

Supervised Learning

- We have domains $\mathcal{X}$, $\mathcal{Y}$
- We have **labeled** examples (x_i, y_i) for $i = 1 \ldots n$
- Task is to learn a function $F : \mathcal{X} \rightarrow \mathcal{Y}$

Statistical Assumptions

- We have domains $\mathcal{X}$, $\mathcal{Y}$
- We have **labeled** examples (x_i, y_i) for $i = 1 \ldots n$
- Task is to learn a function $F : \mathcal{X} \rightarrow \mathcal{Y}$
- Typical assumption is that there is some distribution $D(x, y)$ from which examples are drawn
- Aim is to find a function F with a low value for

$$Er(F) = \sum_{x,y} D(x, y)[[F(x) \neq y]]$$

i.e., minimize probability of error on new examples

Partially Supervised Learning

- We have domains $\mathcal{X}$, $\mathcal{Y}$
- We have **labeled** examples (x_i, y_i) for $i = 1 \ldots n$
  (n is typically small)
- We have **unlabeled** examples (x_i) for $i = (n+1) \ldots (n+m)$
- Task is to learn a function $F : \mathcal{X} \rightarrow \mathcal{Y}$
- New questions:
  - Under what assumptions is unlabeled data "useful"?
  - Can we find NLP problems where these assumptions hold?
  - Which algorithms are suggested by the theory?

Named Entity Classification

- Classify entities as organizations, people or locations

Steptoe & Johnson	=	Organization
Mrs. Frank	=	Person
Honduras	=	Location

- Need to learn (weighted) rules such as

contains(Mrs.)	$\Rightarrow$	Person
full-string=Honduras	$\Rightarrow$	Location
context=company	$\Rightarrow$	Organization

An Approach Using Minimal Supervision

- Assume a small set of "seed" rules

contains(Incorporated)	$\Rightarrow$	Organization
full-string=Microsoft	$\Rightarrow$	Organization
full-string=I.B.M.	$\Rightarrow$	Organization
contains(Mr.)	$\Rightarrow$	Person
full-string=New_York	$\Rightarrow$	Location
full-string=California	$\Rightarrow$	Location
full-string=U.S.	$\Rightarrow$	Location

- Assume a large amount of unlabeled data

  .., says Mr. Cooper, a vice president of ...

- Methods gain leverage from redundancy:

  Either Spelling or Context alone is often sufficient to determine an entity's type

Cotraining

- We have domains $\mathcal{X}$, $\mathcal{Y}$
- We have **labeled** examples (x_i, y_i) for $i = 1 \ldots n$
- We have **unlabeled** examples (x_i) for $i = (n+1) \ldots (n+m)$
- We assume each example x_i splits into two views, x_{1i} and x_{2i}
- e.g., if x_i is a feature vector in $\mathbb{R}^{2d}$, then x_{1i} and x_{2i} are representations in $\mathbb{R}^d$.

The Data

- Approx 90,000 spelling/context pairs collected
- Two types of contexts identified by a parser

1. Appositives

   .., says Mr. Cooper, a vice president of ...

2. Prepositional Phrases

   Robert Haft , president of the Dart Group Corporation ...

Features: Two Views of Each Example

.., says Mr. Cooper, a vice president of ...

$\Downarrow$

Spelling Features	Contextual Features
Full-String = Mr. Cooper	appositive = president
Contains(Mr.)	
Contains(Cooper)	

Two Assumptions Behind Cotraining

Assumption 1: Either view is sufficient for learning

There are functions F_1 and F_2 such that

$$F(x) = F_1(x_1) = F_2(x_2) = y$$

for all (x, y) pairs

Examples of Problems with Two Natural Views

- Named entity classification (spelling vs. context)

- Web page classification [Blum and Mitchell, 1998]
  One view = words on the page, other view is pages linking to a page

- Word sense disambiguation: a random split of the text?

A Key Property: Redundancy

The ocean reflects the color of the sky, but even on cloudless days the color of the ocean is not a consistent blue. Phytoplankton, microscopic plant life that floats freely in the lighted surface waters, may alter the color of the water. When a great number of organisms are concentrated in an area, the plankton changes the color of the ocean surface. This is called a 'bloom.'

$$\Downarrow$$

w_{-1} = Phytoplankton	word-within-k = ocean
w_{+1} = life	word-within-k = reflects
w_{-2}, w_{-1} = (Phytoplankton,microscopic)	word-within-k = bloom
w_{-1}, w_{+1} = (microscopic,life)	word-within-k = color
w_{+1}, w_{+2} = (life,that)	$\ldots$

There are often many features which indicate the sense of the word

Two Assumptions Behind Cotraining

Assumption 2:

Some notion of independence between the two views

e.g., The **Conditional-independence-given-label** assumption:
If $D(x_1, x_2, y)$ is the distribution over examples, then

$$D(x_1, x_2, y) = D_0(y)D_1(x_1 \mid y)D_2(x_2 \mid y)$$

for some distributions D_0, D_1 and D_2

Why are these Assumptions Useful?

- Two examples/scenarios:
  - Rote learning, and a graph interpretation
  - Constraints on hypothesis spaces

Rote Learning, and a Graph Interpretation

- In a rote learner, functions F_1 and F_2 are look-up tables

Spelling	Category
Robert-Jordan	PERSON
Washington	LOCATION
Washington	LOCATION
Jamie-Gorelick	PERSON
Jerry-Jasinowski	PERSON
PacifiCorp	COMPANY
...	...

Context	Category
partner	PERSON
partner-at	COMPANY
law-in	LOCATION
firm-in	LOCATION
partner	PERSON
partner-of	COMPANY
...	...

- Note: this can be a very inefficient learning method
  (no chance to learn generalizations such as "any name containing *Mr.* is a person")

Rote Learning, and a Graph Interpretation

- Each node in the graph is a spelling or context
  A node for *Robert Jordan*, *Washington*, *law-in*, *partner* etc.

- Each (x_{1i}, x_{2i}) pair is an edge in the graph
  e.g., (Robert Jordan, partner)

- An edge between two nodes mean they have **the same label**
  (relies on assumption 1: each view is sufficient for classification)

- As quantity of unlabeled data increases, graph becomes more connected
  (relies on assumption 2: some independence between the two views)

Constraints on Hypothesis Spaces

- Usual case: n training examples (x_i, y_i) for $i = 1 \ldots n$
- We assume a distribution $D(x, y)$ over training/test examples
- From lecture 17:

Theorem: For any finite hypothesis class $\mathcal{H}$, distribution $D(x, y)$, and $\delta > 0$, with probability at least $1 - \delta$ over the choice of training sample, for all $F \in \mathcal{H}$,

$$Er(F) \leq \hat{Er}(F) + \sqrt{\frac{\log |\mathcal{H}| + \log \frac{1}{\delta}}{2n}}$$

where n is the number of training examples

This implies that $\frac{\log |\mathcal{H}|}{2n}$ has to be small for $Er(F)$ to be small

Constraints on Hypothesis Spaces

- New case: n training examples (x_{1i}, x_{2i}, y_i) for $i = 1 \ldots n$, m unlabeled examples (x_{1i}, x_{2i}) for $i = (n+1) \ldots (n+m)$

- We assume a distribution $D(x_1, x_2, y)$ over training/test examples

- We have hypothesis spaces $\mathcal{H}_1$ and $\mathcal{H}_2$

- With labeled data alone, if n is number of training examples, then $\frac{\log |\mathcal{H}_1|}{2n}$ must be small

- With additional unlabeled data, we can consider the restricted hypothesis space

$$\mathcal{H}_1' = \{F_1 \ : \quad F_1 \in \mathcal{H}_1, \exists F_2 \in \mathcal{H}_2 \text{ s.t. } F_1(x_{1i}) = F_2(x_{2i}) \text{ for } i = (n+1)\ldots(n+m)\}$$

i.e., we only consider functions F_1 which agree with at least one F_2 on all unlabeled examples

- Basic idea: we don't know the label for an unlabeled example, **but we do know that the two functions must agree on it**

- Now, we need $\frac{\log |\mathcal{H}_1'|}{2n}$ to be small
if $|\mathcal{H}_1'| << |\mathcal{H}_1|$ then we need fewer training examples

Cotraining Summary

- $n + m$ training examples $x_i = (x_{1i}, x_{2i})$
- First n examples have labels y_i
- Learn functions F_1 and F_2 such that

$$F_1(x_{1i}) = F_2(x_{2i}) = y_i \qquad i = 1 \ldots n$$

$$F_1(x_{1i}) = F_2(x_{2i}) \qquad i = n+1 \ldots n+m$$

A Linear Model

- How to build a classifier from spelling features alone?
  A linear model:

  - $\mathbf{GEN}(x_1)$ is possible labels $\{person, location, organization\}$
  - $\mathbf{\Phi}(x_1, y)$ is a set of features on spelling/label pairs, e.g.,

$$\mathbf{\Phi}_{100}(x_1, y) = \begin{cases} 1 & \text{if } x_1 \text{ contains } \textit{Mr.}\text{, and } y = \textit{person} \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbf{\Phi}_{101}(x_1, y) = \begin{cases} 1 & \text{if } x_1 \text{ is } \textit{IBM}\text{, and } y = \textit{person} \\ 0 & \text{otherwise} \end{cases}$$

  - $\mathbf{W}$ is parameter vector, as usual choose

$$F_1(x_1, \mathbf{W}) = \arg \max_{y \in \mathbf{GEN}(x_1)} \mathbf{\Phi}(x_1, y) \cdot \mathbf{W}$$

  - $\Rightarrow$ each parameter in $\mathbf{W}$ gives a weight for a feature/label pair.
    e.g., $\mathbf{W}_{100} = 2.5$, $\mathbf{W}_{101} = -1.3$

A Boosting Approach to Supervised Learning

- Greedily minimize

$$L(\mathbf{W}) = \sum_i \sum_{y \neq y_i} e^{-\mathbf{m}(y_i, y, \mathbf{W})}$$

where

$$\mathbf{m}(y_i, y, \mathbf{W}) = \mathbf{\Phi}(x_i, y_i) \cdot \mathbf{W} - \mathbf{\Phi}(x_i, y) \cdot \mathbf{W}$$

- $L(\mathbf{W})$ is an upper bound on the number of ranking errors,

$$L(\mathbf{W}) \geq \sum_i \sum_{y \neq y_i} [[\mathbf{m}(y_i, y, \mathbf{W}) \leq 0]]$$

An Extension to the Cotraining Scenario

- Now build **two** linear models in parallel
  - $\mathbf{GEN}(x_1) = \mathbf{GEN}(x_2)$ is set of possible labels $\{person, location, organization\}$
  - $\mathbf{\Phi}^1(x_1, y)$ is a set of features on spelling/label pairs
  - $\mathbf{\Phi}^2(x_2, y)$ is a set of features on context/label pairs, e.g.,

$$\mathbf{\Phi}^2{}_{100}(x_2, y) \quad = \quad \begin{cases} 1 & \text{if } x_2 \text{ is } \textit{president} \text{ and } y = \textit{person} \\ 0 & \text{otherwise} \end{cases}$$

  - $\mathbf{W}^1$ and $\mathbf{W}^2$ are the two parameter vectors

$$F_1(x_1, \mathbf{W}^1) = \arg \max_{y \in \mathbf{GEN}(x_1)} \mathbf{\Phi}^1(x_1, y) \cdot \mathbf{W}^1$$

$$F_2(x_2, \mathbf{W}^2) = \arg \max_{y \in \mathbf{GEN}(x_2)} \mathbf{\Phi}^2(x_2, y) \cdot \mathbf{W}^2$$

An Extension to the Cotraining Scenario

- $n + m$ training examples $x_i = (x_{1i}, x_{2i})$
- First n examples have labels y_i
- Linear models define F_1 and F_2 as

$$F_1(x_1, \mathbf{W}^1) = \arg \max_{y \in \mathbf{GEN}(x_1)} \mathbf{\Phi}^1(x_1, y) \cdot \mathbf{W}^1$$

$$F_2(x_2, \mathbf{W}^2) = \arg \max_{y \in \mathbf{GEN}(x_2)} \mathbf{\Phi}^2(x_2, y) \cdot \mathbf{W}^2$$

- Three types of errors:

$$E_1 = \sum_{i=1}^{n} [[F_1(x_{1i}, \mathbf{W}^1) \neq y_i]]$$

$$E_2 = \sum_{i=1}^{n} [[F_2(x_{2i}, \mathbf{W}^2) \neq y_i]]$$

$$E_3 = \sum_{i=n+1}^{m+1} [[F_1(x_{1i}, \mathbf{W}^1) \neq F_2(x_{2i}, \mathbf{W}^2)]]$$

Objective Functions for Cotraining

- Define "pseudo labels"

$$z_{1i}(\mathbf{W}^1) = f_1(x_{1i}, \mathbf{W}^1) \qquad i = (n+1)\ldots(n+m)$$

$$z_{2i}(\mathbf{W}^2) = f_2(x_{2i}, \mathbf{W}^2) \qquad i = (n+1)\ldots(n+m)$$

e.g., z_{1i} is output of first classifier on the i'th example

$$\begin{aligned}
L(\mathbf{W}^1, \mathbf{W}^2) \quad = \quad & \sum_{i=1}^{n} \sum_{y \neq y_i} e^{\mathbf{\Phi}^1(x_{1i},y)\cdot\mathbf{W}^1 - \mathbf{\Phi}^1(x_{1i},y_i)\cdot\mathbf{W}^1} \\
& + \sum_{i=1}^{n} \sum_{y \neq y_i} e^{\mathbf{\Phi}^2(x_{2i},y)\cdot\mathbf{W}^2 - \mathbf{\Phi}^2(x_{2i},y_i)\cdot\mathbf{W}^2} \\
& + \sum_{i=n+1}^{n+m} \sum_{y \neq z_{2i}} e^{\mathbf{\Phi}^1(x_{1i},y)\cdot\mathbf{W}^1 - \mathbf{\Phi}^1(x_{1i},z_{2i})\cdot\mathbf{W}^1} \\
& + \sum_{i=n+1}^{n+m} \sum_{y \neq z_{1i}} e^{\mathbf{\Phi}^2(x_{2i},y)\cdot\mathbf{W}^2 - \mathbf{\Phi}^2(x_{2i},z_{2i})\cdot\mathbf{W}^2}
\end{aligned}$$

More Intuition

- Need to minimize $L(\mathbf{W}^1, \mathbf{W}^2)$, do this by greedily minimizing w.r.t. first $\mathbf{W}^1$, then $\mathbf{W}^2$
- Algorithm boils down to:

1. Start with labeled data alone
2. Induce a contextual feature for each class
   (person/location/organization)
   from the current set of labelled data
3. Label unlabeled examples using contextual rules
4. Induce a spelling feature for each class
   (person/location/organization)
   from the current set of labelled data
5. Label unlabeled examples using spelling rules
6. Return to step 2

Optimization Method

1. Set pseudo labels z_{2i}
2. Update $\mathbf{W}^1$ to minimize

$$\sum_{i=1}^{n} \sum_{y \neq y_i} e^{\mathbf{\Phi}^1(x_{1i}, y) \cdot \mathbf{W}^1 - \mathbf{\Phi}^1(x_{1i}, y_i) \cdot \mathbf{W}^1}$$

$$+ \sum_{i=n+1}^{n+m} \sum_{y \neq z_{2i}} e^{\mathbf{\Phi}^1(x_{1i}, y) \cdot \mathbf{W}^1 - \mathbf{\Phi}^1(x_{1i}, z_{2i}) \cdot \mathbf{W}^1}$$

(for each class choose a spelling feature, weight)

3. Set pseudo labels z_{1i}

4. Update $\mathbf{W}^2$ to minimize

$$\sum_{i=1}^{n} \sum_{y \neq y_i} e^{\mathbf{\Phi}^2(x_{2i}, y) \cdot \mathbf{W}^2 - \mathbf{\Phi}^2(x_{2i}, y_i) \cdot \mathbf{W}^2}$$

$$+ \sum_{i=n+1}^{n+m} \sum_{y \neq z_{1i}} e^{\mathbf{\Phi}^2(x_{2i}, y) \cdot \mathbf{W}^2 - \mathbf{\Phi}^2(x_{2i}, z_{2i}) \cdot \mathbf{W}^2}$$

(for each class choose a contextual feature, weight)

5. Return to step 1

An Example Trace

1. Use seeds to label 8593 examples
   (4160 companies, 2788 people, 1645 locations)

2. Pick a contextual feature for each class:

COMPANY:	preposition=unit of	2.386	274/2
PERSON:	appositive=president	1.593	120/6
LOCATION:	preposition=Company of	1.673	46/1

3. Set pseudo labels using seeds + contextual features
   (5319 companies, 6811 people, 1961 locations)

4. Pick a spelling feature for each class

COMPANY:	Contains(Corporation)	2.475	495/10
PERSON:	Contains(.)	2.482	4229/106
LOCATION:	fullstring=America	2.311	91/0

5. Set pseudo labels using seeds + spelling features
   (7180 companies, 8161 people, 1911 locations)

6. Continue ...

Evaluation

- 88,962 $(spelling, context)$ pairs extracted as training data
- 7 seed rules used

contains(Incorporated)	$\Rightarrow$	Organization
full-string=Microsoft	$\Rightarrow$	Organization
full-string=I.B.M.	$\Rightarrow$	Organization
contains(Mr.)	$\Rightarrow$	Person
full-string=New_York	$\Rightarrow$	Location
full-string=California	$\Rightarrow$	Location
full-string=U.S.	$\Rightarrow$	Location

- 1,000 examples picked at random, and labelled by hand to give a test set.

- Around 9% of examples were “noise”, not falling into any of the three categories

- Two measures given: one excluding all noise items, the other counting noise items as errors

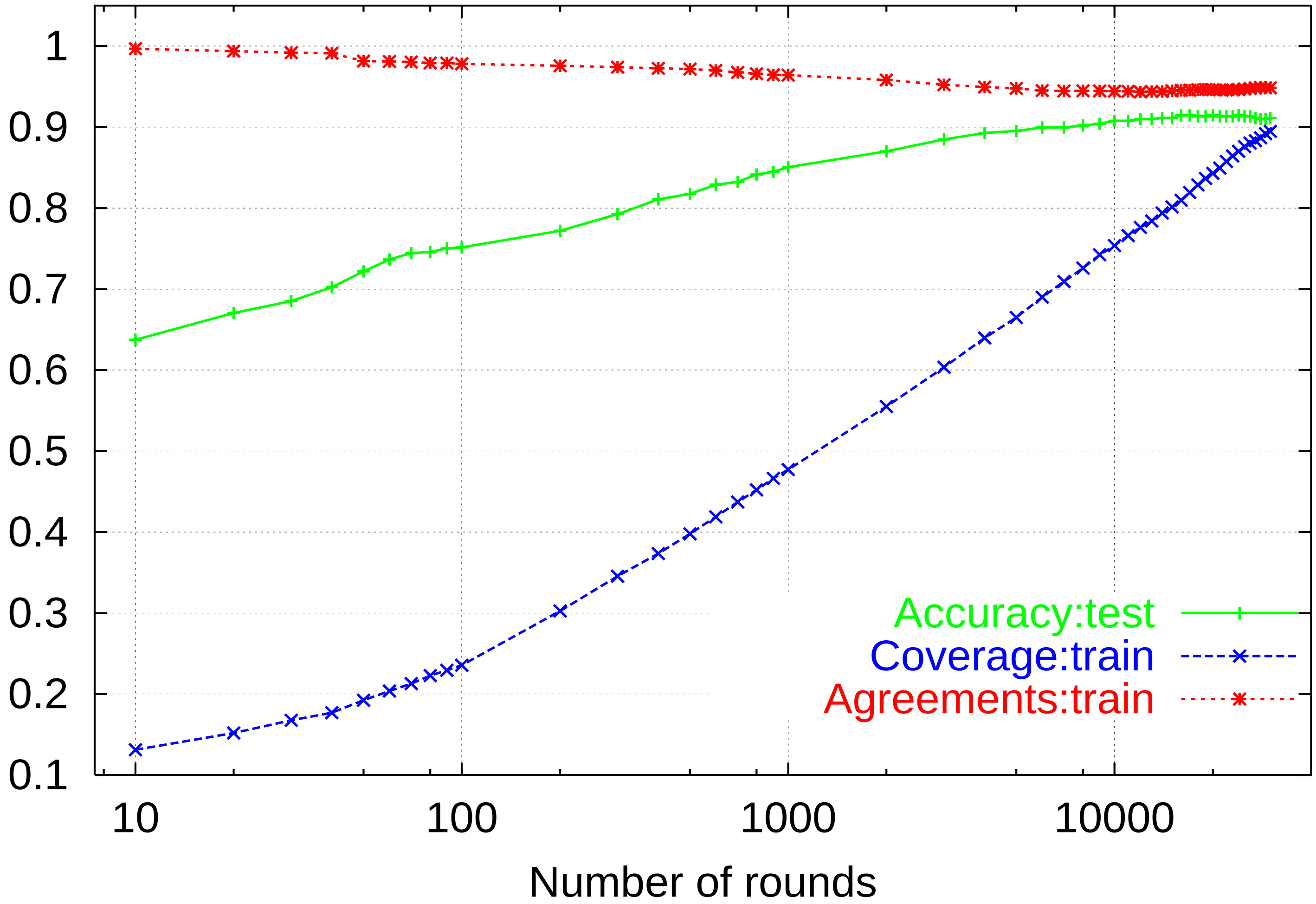
Other Methods

- EM approach
- Decision list (Yarowsky 95)
- Decision list 2 (modification of Yarowsky 95)
- DL-Cotrain:
  decision list alternating between two feature types

Results

Learning Algorithm	Accuracy (Clean)	Accuracy (Noise)
Baseline	45.8%	41.8%
EM	83.1%	75.8%
Decision List	81.3%	74.1%
Decision List 2	91.2%	83.2%
DL-CoTrain	91.3%	83.3%
CoBoost	91.1%	83.1%

Learning Curves for Coboosting



Summary

- Appears to be a complex task: many features/rules required
- With unlabeled data, supervision is reduced to 7 “seed” rules
- Key is **redundancy** in the data
- Cotraining suggests training two classifiers that “**agree**” as much as possible on unlabeled examples
- **CoBoost** algorithm builds two additive models in parallel, with an objective function that bounds the rate of agreement