Semi-Supervised Learning

Modified from Avrim Blum’s slides
Supervised Learning = learning from labeled data. Dominant paradigm in Machine Learning.

• For example, you want to train an email classifier to distinguish spam from important messages.
Supervised Learning = learning from labeled data. Dominant paradigm in Machine Learning.

- E.g., say you want to train an email classifier to distinguish spam from important messages.
- Take sample $S$ of data, labeled according to whether they were/weren’t spam.
Supervised Learning = learning from labeled data. Dominant paradigm in Machine Learning.

- E.g., say you want to train an email classifier to distinguish spam from important messages
- Take sample $S$ of data, labeled according to whether they were/weren’t spam.
- Train a classifier (like SVM, decision tree, etc) on $S$. Make sure it’s not overfitting.
- Use to classify new emails.
Basic paradigm has many successes

• recognise speech,
• steer a car,
• classify documents
• classify proteins
• recognising faces, objects in images
• ...

[Image showing a wave form, papers, a protein structure, a steering wheel, and a diagram of a neural network.]

[Additional images: a road with a car, a neural network diagram with labels.]
However, for many problems, labeled data can be rare or expensive.

Need to pay someone to do it, requires special testing,…

Unlabeled data is much cheaper.
However, for many problems, labeled data can be rare or expensive.

Unlabeled data is much cheaper.

Speech  Customer modeling
Images   Protein sequences
Medical outcomes  Web pages
However, for many problems, labeled data can be rare or expensive.

Unlabeled data is much cheaper.

Task: speech analysis
- Switchboard dataset
- telephone conversation transcription
- 400 hours annotation time for each hour of speech

film ⇒ f ih n uh gl n m
be all ⇒ bcl b iy iy_tr ao_tr ao l_dl

[From Jerry Zhu]
However, for many problems, labeled data can be rare or expensive.

Need to pay someone to do it, requires special testing,...

Unlabeled data is much cheaper.

Can we make use of cheap unlabeled data?
Semi-Supervised Learning

Can we use unlabeled data to augment a small labeled sample to improve learning?

But unlabeled data is missing the most important info!!

But maybe still has useful regularities that we can use.

But...
Semi-Supervised Learning

Substantial recent work in ML. A number of interesting methods have been developed.

This lecture:

- Discuss several diverse methods for taking advantage of unlabeled data.
Method 1: Co-Training
Co-training

[Blum&Mitchell’98]

Many problems have two different sources of info you can use to determine label.

E.g., classifying webpages: can use words on page or words on links pointing to the page.
Co-training

Idea: Use small labeled sample to learn initial rules.

– e.g., “colleagues” pointing to a page is a good indicator it is a faculty home page.

– e.g., “I am teaching ML course” on a page is a good indicator it is a faculty home page.

Links to Co-workers

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Check out our new faculty members Ryan O’Donnell and Luis van Ahn.

My main research interests are machine learning theory, approximation algorithms, on-line algorithms, and algorithmic game theory. I was an on the Program Committee for FOCS 2008 (Workshop on Learning Theory), and was recently local organizor for COLT 2008 and FOCS 2008. I also co-organized the 2005 Foundations of Computational Mathematics Workshop on Algorithmic Game Theory and Metric Embeddings. A while back I served as Program Chair for FOCS 2006 and I’ve done some work in AI Planning. For more information on my research, see the publications and research interests links below. I am also affiliated with the Machine Learning Department.


- Publications
- AI ADDIN, Algorithms and Complexity Group
- ACO Program Home Page
- Theory Seminars, Theory Lunch, ML lunch
- Family pictures, Other pictures, My Home Page

My advisees: Saron Roth, Katrina Ligett, Niva Balan, Magdiel Rabadan, Shuhua Venkatesan.

Co-training

Idea: Use small labeled sample to learn initial rules.

Then look for unlabeled examples where one rule is confident and the other is not. Have it label the example for the other.

Training 2 classifiers, one on each type of info. Using each to help train the other.
Co-training

Turns out a number of problems can be set up this way.

E.g., [Levin-Viola-Freund03] identifying objects in images. Two different kinds of preprocessing.

E.g., [Collins&Singer99] named-entity extraction.
  - “I arrived in London yesterday”
  - ...

...
Results: webpages

12 labeled examples, 1000 unlabeled

<table>
<thead>
<tr>
<th></th>
<th>Page-based</th>
<th>Hyperlink-based</th>
<th>Combined</th>
</tr>
</thead>
<tbody>
<tr>
<td>Std. Supervised</td>
<td>12.9</td>
<td>12.4</td>
<td>11.1</td>
</tr>
<tr>
<td>Co-training</td>
<td>6.2</td>
<td>11.6</td>
<td>5.0</td>
</tr>
<tr>
<td>Just say neg</td>
<td>22</td>
<td>22</td>
<td>22</td>
</tr>
</tbody>
</table>

(small run)
Results: images [Levin-Viola-Freund ‘03]:

- Visual detectors with different kinds of processing

- Images with 50 labeled cars. 22,000 unlabeled images.
- Factor 2-3+ improvement.

From [LVF03]
Method 2:

Semi-Supervised (Transductive) SVM
**S³VM [Joachims98]**

- Suppose we believe target separator goes through **low** density regions of the space/ **large margin**.
- Aim for separator with large margin wrt labeled and **unlabeled** data. (L+U)
S$^3$VM [Joachims98]

- Suppose we believe target separator goes through low density regions of the space/large margin.
- Aim for separator with large margin wrt labeled and unlabeled data. (L+U)
- Unfortunately, optimization problem is now NP-hard. Algorithm instead does local optimization.
  - Start with large margin over labeled data. Induces labels on U.
  - Then try flipping labels in greedy fashion.
Suppose we believe target separator goes through low density regions of the space/large margin.

Aim for separator with large margin wrt labeled and unlabeled data. (L+U)

Unfortunately, optimization problem is now NP-hard. Algorithm instead does local optimization.

- Or, branch-and-bound, other methods (Chapelle et al. 2006)

Quite successful on text data.
Loss of S3VM
Method 3:

Graph-based methods
Graph-based methods

- Suppose we believe that very similar examples probably have the same label.
- If you have a lot of labeled data, this suggests a Nearest-Neighbor type of alg.
- If you have a lot of unlabeled data, perhaps can use them as “stepping stones”

E.g., handwritten digits [Zhu07]:

<table>
<thead>
<tr>
<th>2</th>
<th>2 2 2 2 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>not similar</td>
<td>‘indirectly’ similar with stepping stones</td>
</tr>
</tbody>
</table>
Graph-based methods

- Idea: construct a graph with edges between very similar examples.
- Unlabeled data can help “glue” the objects of the same class together.
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- Solve for:
  - Minimum cut [BC,BLRR]
  - Minimum “soft-cut” [ZGL]
  \[ \sum_{e=(u,v)}(f(u)-f(v))^2 \]
  - Spectral partitioning [J]
  - ...
Laplacian SVM

LapSVM

$$\min_w \frac{\lambda}{2} \|w\|^2 + \frac{1}{|D_l|} \sum_{(x,y) \in D_l} \max(0, 1 - y \langle w, x \rangle) +$$

$$+ \frac{\gamma}{|D_u|^2} \sum_{x \in D_u} \sum_{x' \in D_l \cup D_u} s(x, x') (\langle w, x \rangle - \langle w, x' \rangle)^2$$

Graph Laplacian

$$\min_w \frac{\lambda}{2} \|w\|^2 + \frac{1}{|D_l|} \sum_{(x,y) \in D_l} \max(0, 1 - y \langle w, x \rangle) +$$

$$+ \frac{\gamma}{|D_u|^2} \langle f, Lf \rangle$$
Conclusions

• Semi-supervised learning is an area of increasing importance in Machine Learning.

• Automatic methods of collecting data make it more important than ever to develop methods to make use of unlabeled data.

• Several promising algorithms (only discussed a few).