Active Learning

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Admin

Projects and Project Presentations

- Project presentations: April 23 and April 25.
- Presentation schedule posted on Piazza last week.
- Should be in contact with TAs to discuss progress.
- Will meet with me on April 18\textsuperscript{th} or April 24\textsuperscript{th}.
- Final report: May 14\textsuperscript{th}.

Final: in class on May 2\textsuperscript{nd}. 
Classic Fully Supervised Learning Paradigm Insufficient Nowadays

Modern applications: **massive amounts** of raw data. Only a tiny fraction can be annotated by human experts.

Protein sequences  Billions of webpages  Images
Modern ML: New Learning Approaches

Modern applications: **massive amounts** of raw data.

**Active learning:** techniques that best utilize data, minimizing need for expert/human intervention.
Active Learning

Additional resources:
• Two faces of active learning. Sanjoy Dasgupta. 2011.
Batch Active Learning

Data Source

Underlying data distr. \( D \).

Unlabeled examples

Request for the Label of an Example

A Label for that Example

Request for the Label of an Example

A Label for that Example

... Algorithm outputs a classifier w.r.t \( D \)

- Learner can choose specific examples to be labeled.
- **Goal:** use fewer labeled examples [pick informative examples to be labeled].
Selective Sampling Active Learning

- **Selective sampling AL (Online AL):** stream of unlabeled examples, when each arrives make a decision to ask for label or not.
- **Goal:** use fewer labeled examples [pick informative examples to be labeled].
Can adaptive querying help? [CAL92, Dasgupta04]

- Threshold functions on the real line: $h_w(x) = 1(x \geq w)$, $C = \{h_w: w \in \mathbb{R}\}$
  - Exponential improvement.
  - $C = \{h_w: w \in \mathbb{R}\}$

**Active Algorithm**

- Get $N$ unlabeled examples
- How can we recover the correct labels with $\ll N$ queries?
- Do binary search! Just need $O(\log N)$ labels!

- Output a classifier consistent with the $N$ inferred labels.

- $N = O(1/\epsilon)$ we are guaranteed to get a classifier of error $\leq \epsilon$.

**Passive supervised:** $\Omega(1/\epsilon)$ labels to find an $\epsilon$-accurate threshold.
**Active:** only $O(\log 1/\epsilon)$ labels. Exponential improvement.
Active SVM seems to be quite useful in practice.

[Tong & Koller, ICML 2000; Jain, Vijayanarasimhan & Grauman, NIPS 2010]

**Algorithm (batch version)**

**Input** $S_u = \{x_1, ..., x_{m_u}\}$ drawn i.i.d from the underlying source $D$

**Start:** query for the labels of a few random $x_i$s.

For $t = 1, \ldots,$

- Find $w_t$ the max-margin separator of all labeled points so far.
- Request the label of the example closest to the current separator: minimizing $|x_i \cdot w_t|$.

(highest uncertainty)
Active SVM/Uncertainty Sampling

- Works sometimes....
- However, we need to be very very careful!!!
  - Myopic, greedy technique can suffer from sampling bias.
  - Bias created because of the querying strategy; as time goes on the sample is less and less representative of the true source.
  - Observed in practice too!!!!

- Main tension: want to choose informative points, but also want to guarantee that the classifier we output does well on true random examples from the underlying distribution.
Safe Active Learning Schemes

Disagreement Based Active Learning

Hypothesis Space Search

[CAL92]  [BBL06]

[Hanneke’07, DHM’07, Wang’09, Fridman’09, Kolt10, BHW’08, BHLZ’10, H’10, Ailon’12, …]
Disagreement Based Active Learning \textsuperscript{[CAL92]}

Algorithm:

Query for the labels of a few random $x_i$'s.

Let $H_1$ be the current version space.

For $t = 1, \ldots$

Pick a few points at random from the current region of disagreement $\text{DIS}(H_t)$ and query their labels.

Let $H_{t+1}$ be the new version space.
Region of uncertainty [CAL92]

- Current version space: part of $C$ consistent with labels so far.
- "Region of uncertainty" = part of data space about which there is still some uncertainty (i.e. disagreement within version space)
Algorithm:

Let $H_1 = H$.

For $t = 1, \ldots,$

- Pick a few points at random from the current region of disagreement $\text{DIS}(H_t)$ and query their labels.
- Throw out hypothesis if you are statistically confident they are suboptimal.

Careful use of generalization bounds; Avoid the sampling bias!!!!
What You Should Know

- Active learning could be really helpful, could provide exponential improvements in label complexity (both theoretically and practically)!

- Common heuristics (e.g., those based on uncertainty sampling). Need to be very careful due to sampling bias.

- Safe Disagreement Based Active Learning Schemes.
  - Understand how they operate precisely in the realizable case (noise free scenarios).
Advanced additional (not required material)
Disagreement based algorithms: How about the agnostic case where the target might not belong the $H$?
Algorithm:

Let $H_1 = H$.

For $t = 1, \ldots,$

- Pick a few points at random from the current region of disagreement $\text{DIS}(H_t)$ and query their labels.
- Throw out hypothesis if you are statistically confident they are suboptimal.

Careful use of generalization bounds; Avoid the sampling bias!!!
Formal General Guarantees for Agnostic AL

**A²** is the first algorithm which is robust to noise.

[Balcan, Beygelzimer, Langford, ICML’06]  [Balcan, Beygelzimer, Langford, JCSS’08]

“Region of disagreement” style: Pick a few points at random from the current region of disagreement, query their labels, throw out hypothesis if you are statistically confident they are suboptimal.

Guarantees for **A²** [BBL’06,’08]:

- It is safe (never worse than passive learning) & exponential improvements.
  - **C** - thresholds, low noise, exponential improvement.
  - **C** - homogeneous linear separators in \( \mathbb{R}^d \),
    \( D \) - uniform, low noise, only \( d^2 \log (1/\epsilon) \) labels.

A lot of subsequent work.

[Hanneke’07, DHM’07, Wang’09, Fridman’09, Kolt10, BHW’08, BHLZ’10, H’10, Ailon’12, …]
General guarantees for $A^2$ Agnostic Active Learner

“Disagreement based”: Pick a few points at random from the current region of uncertainty, query their labels, throw out hypothesis if you are statistically confident they are suboptimal. [BBL’06]

Guarantees for $A^2$ [Hanneke’07]:

Disagreement coefficient

$$\theta_{c^*} = \sup_{r \geq \eta + \epsilon} \frac{\Pr(DIS(B(c^*, r)))}{r}$$

Theorem

$$m = \left(1 + \frac{\eta^2}{\epsilon^2}\right) VCdim(C) \theta_{c^*}^2 \log\left(\frac{1}{\epsilon}\right)$$

labels are sufficient s.t. with prob. $\geq 1 - \delta$ output $h$ with $err(h) \leq \eta + \epsilon$.

Realizable case: $$m = VCdim(C) \theta_{c^*} \log\left(\frac{1}{\epsilon}\right)$$

Linear Separators, uniform distr.: $$\theta_{c^*} = \sqrt{d}$$
Disagreement Based Active Learning

“Disagreement based” algos: query points from current region of disagreement, throw out hypotheses when statistically confident they are suboptimal.

- Generic (any class), adversarial label noise.
- Computationally efficient for classes of small VC-dimension

Still, could be suboptimal in label complex & computationally inefficient in general.

Lots of subsequent work trying to make is more efficient computationally and more aggressive too: [Hanneke07, DasguptaHsuMontleoni'07, Wang'09, Fridman'09, Koltchinskii10, BHW'08, BeygelzimerHsuLangfordZhang'10, Hsu'10, Ailon'12, …]