Sample and Computationally Efficient Active Learning

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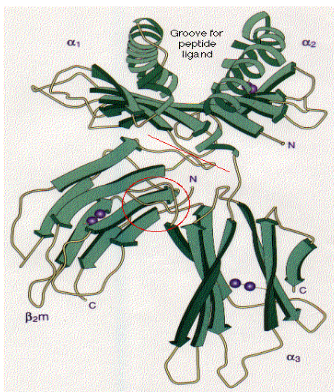
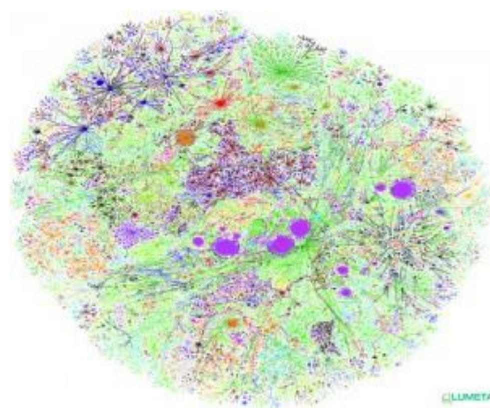
Two Minute Version

Modern applications: massive amounts of raw data.

Only a tiny fraction can be annotated by human experts.



Protein sequences



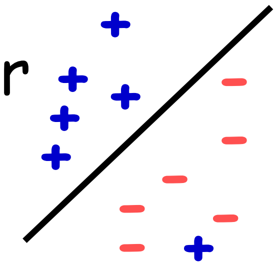
Billions of webpages

Images

Active Learning: utilize data, minimize expert intervention.

Two Minute Version

Active Learning: technique for best utilizing data while minimizing need for human intervention.



This talk: the power of aggressive localization for label efficient, noise tolerant, poly time algo for learning linear separators [Awasthi-Balcan-Long JACM'17]

[Awasthi-Balcan-Haghtalab-Urner COLT'15] [Balcan-Long COLT'13]

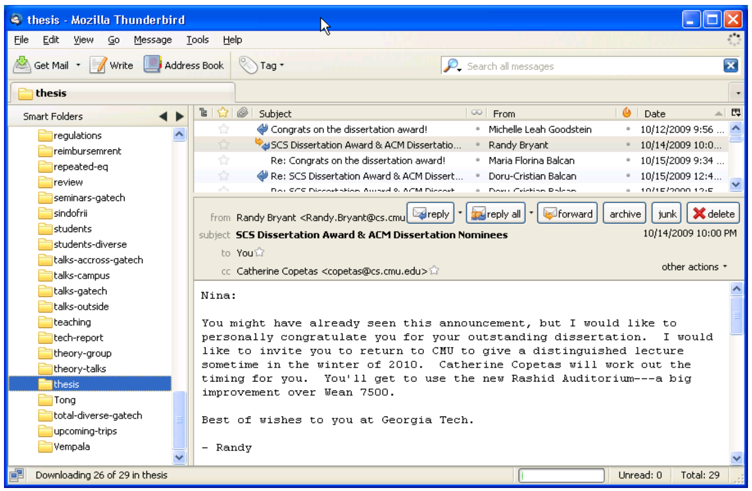
- Much better noise tolerance than previously known for classic passive learning via poly time algos. [KKMS'05] [KLS'09]
- Solve an adaptive sequence of convex optimization pbs on smaller & smaller bands around current guess for target.

Passive and Active Learning

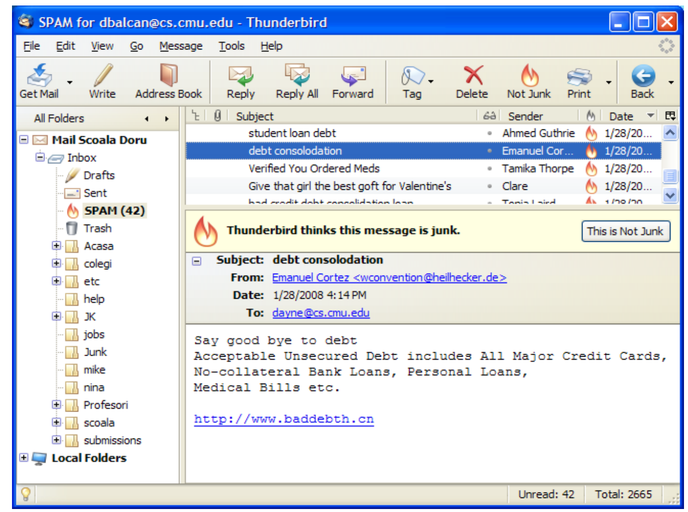
Supervised Learning

- E.g., which emails are spam and which are important.

Not spam



spam

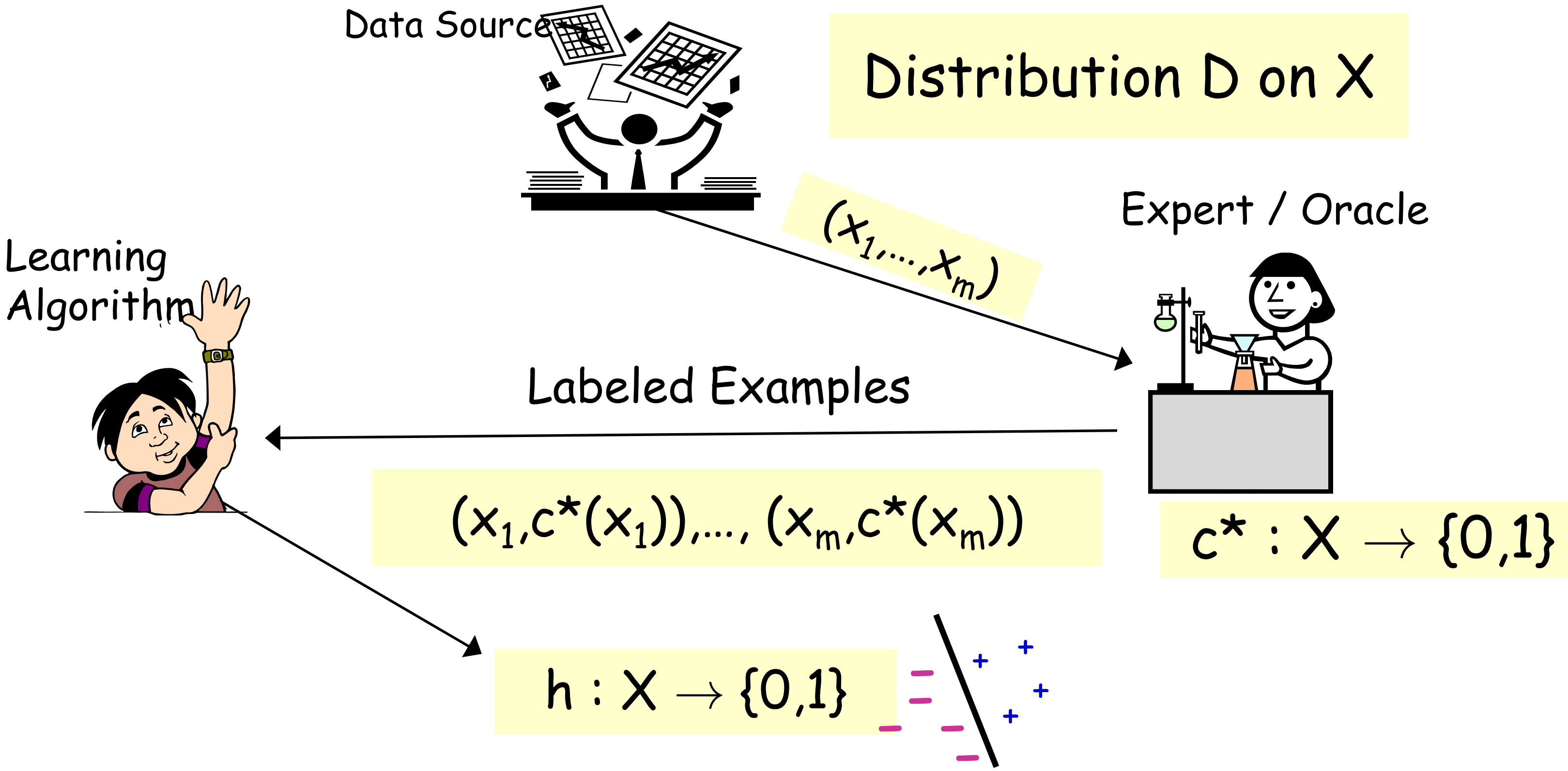


- E.g., classify objects as chairs vs non chairs.

Not chair

chair

Statistical / PAC learning model



- Algo sees $(x_1,c^*(x_1)),\ldots,(x_m,c^*(x_m))$, x_i i.i.d. from D
  - Does optimization over S, finds hypothesis $h \in C$.
  - Goal: h has small error, $err(h)=Pr_{x \in D}(h(x) \neq c^*(x))$
- c^* in C, realizable case; else agnostic

Two Main Aspects in Classic Machine Learning

Algorithm Design. How to optimize?

Automatically generate rules that do well on observed data.

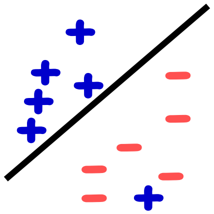
Runing time: $\mathrm{poly}\left(\mathrm{d}, \frac{1}{\epsilon}, \frac{1}{\delta}\right)$

Generalization Guarantees, Sample Complexity

Confidence for rule effectiveness on future data.

$$\mathrm{O}\left(\frac{1}{\epsilon}\left(\mathrm{VCdim(C)}\log\left(\frac{1}{\epsilon}\right) + \log\left(\frac{1}{\delta}\right)\right)\right)$$

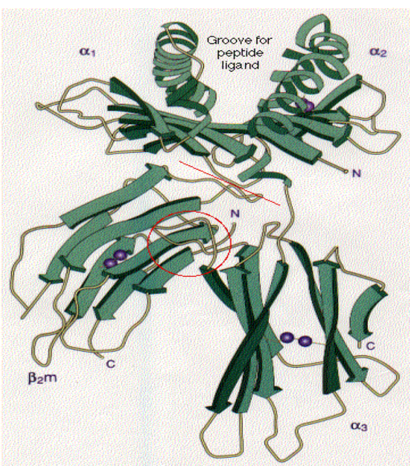
C= linear separators in R^d: $\mathrm{O}\left(\frac{1}{\epsilon}\left(\mathrm{d}\ \log\left(\frac{1}{\epsilon}\right) + \log\left(\frac{1}{\delta}\right)\right)\right)$



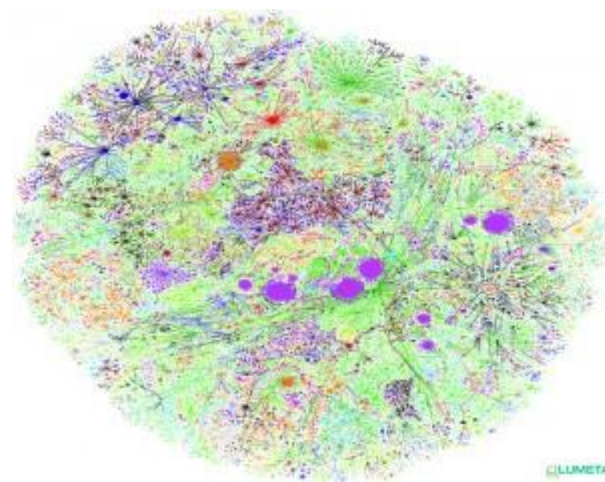
Modern ML: New Learning Approaches

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

Only a tiny fraction can be annotated by human experts.



Protein sequences



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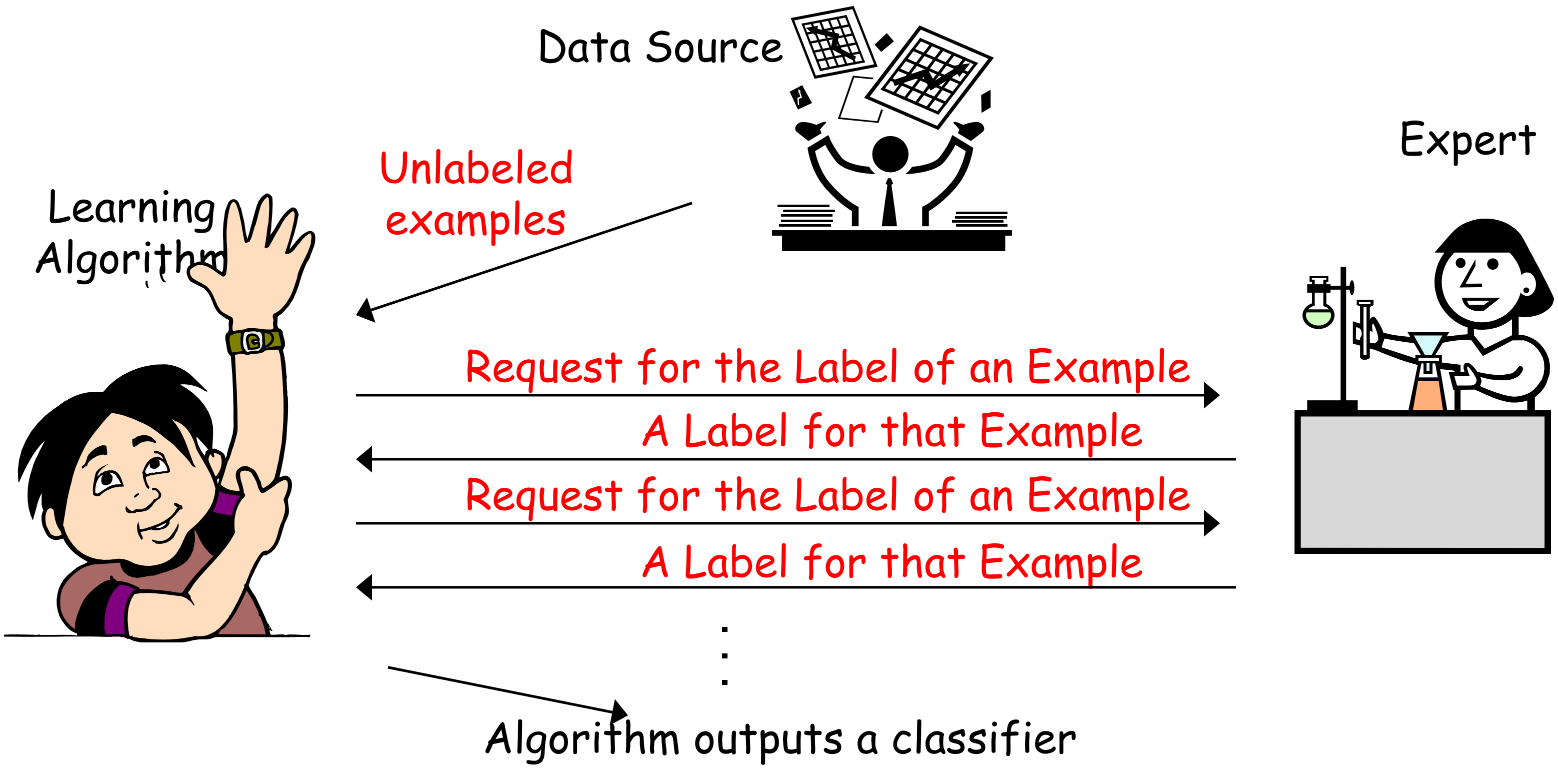
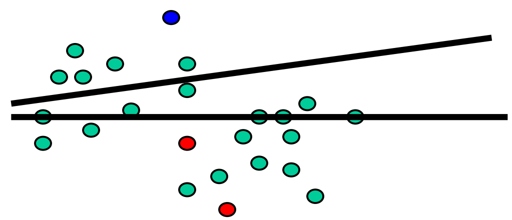
Active Learning



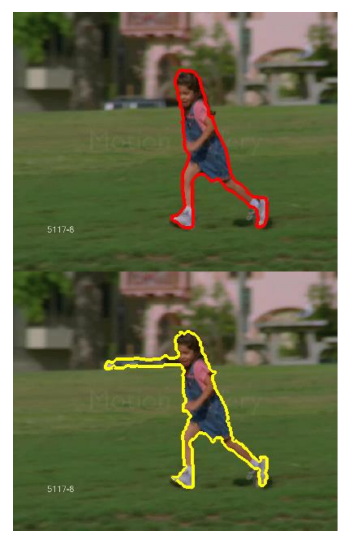
- Learner can choose specific examples to be labeled.
- Goal: use fewer labeled examples [pick informative examples to be labeled].

Active Learning in Practice

- Text classification: active SVM (Tong & Koller, ICML2000).
  - e.g., request label of the example closest to current separator.

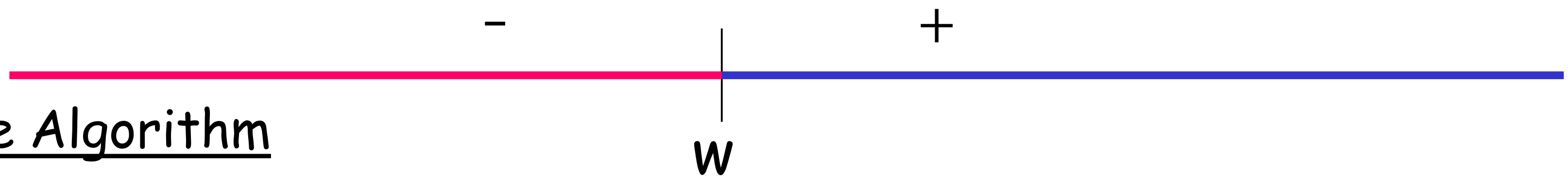


- Video Segmentation (Fathi-Balcan-Ren-Regh, BMVC 11).



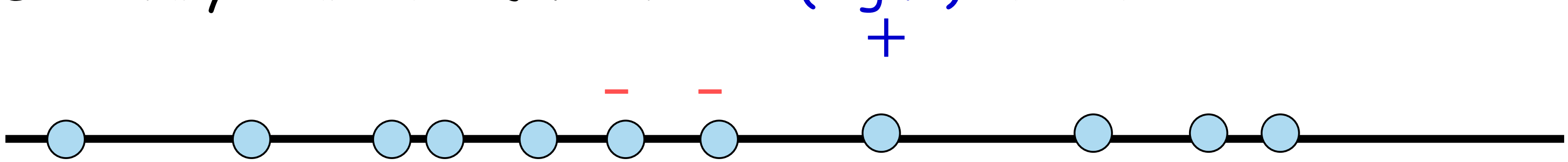
Can adaptive querying help? [CAL92, Dasgupta04]

- Threshold fns on the real line: $h_w(x) = 1(x \geq w)$, $C = \{h_w : w \in R\}$



<u>Active Algorithm</u>

- Get $N = O(1/\epsilon)$ 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.

<u>Passive supervised</u>: $\Omega(1/\epsilon)$ labels to find an ε-accurate threshold.

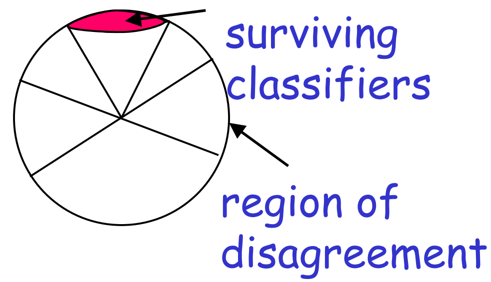
<u>Active</u>: only $O(\log 1/\epsilon)$ labels. Exponential improvement.

Active learning, provable guarantees

Lots of exciting results on sample complexity. E.g.,

- "Disagreement based" algorithms

Pick a few points at random from the current region of disagreement (uncertainty), query their labels, throw out hypothesis if you are statistically confident they are suboptimal.



[BalcanBeygelzimerLangford'06, Hanneke07, DasguptaHsuMontleoni'07, Wang'09, Fridman'09, Koltchinskii10, BHW'08, BeygelzimerHsuLangfordZhang'10, Hsu'10, Ailon'12, …]

Generic (any class), adversarial label noise.

- suboptimal in label complexity
- computationally prohibitive.

Poly Time, Noise Tolerant/Agnostic, Label Optimal AL Algos.

Margin Based Active Learning

Margin based algo for learning linear separators

- Realizable: exponential improvement, only $O(d \log 1/\varepsilon)$ labels to find w error ε when D logconcave. [Balcan-Long COLT 2013]

- Agnostic & malicious noise: poly-time AL algo outputs w with $err(w) = O(\eta)$, η = err(best lin. sep). [Awasthi-Balcan-Long JACM 2017]

  - First poly time AL algo in noisy scenarios!

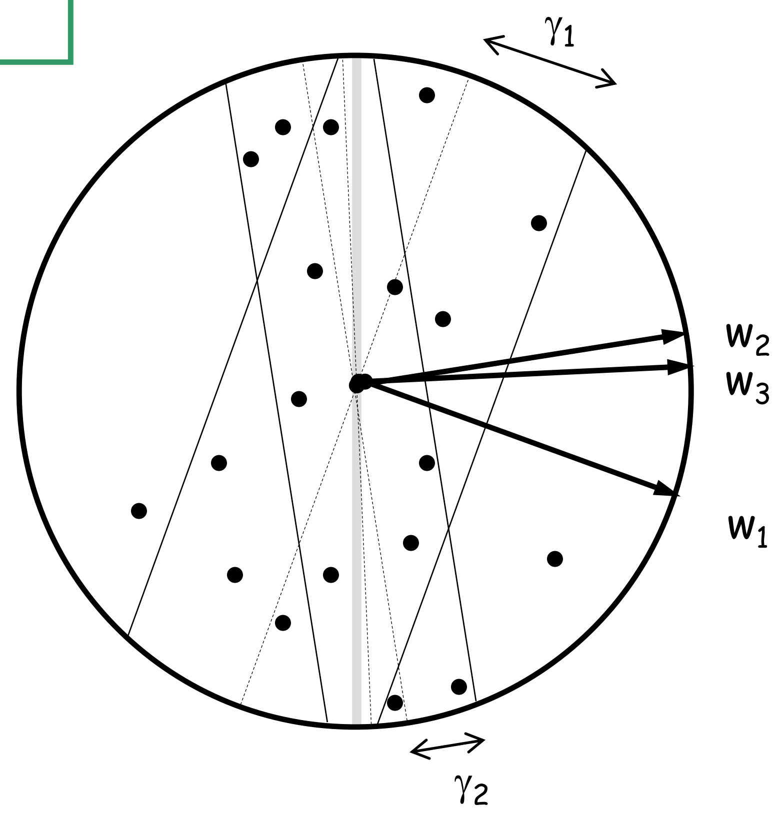
- Improves on noise tolerance of previous best passive [KKMS'05], [KLS'09] algos too!

Margin Based Active-Learning, Realizable Case

Draw m_1 unlabeled examples, label them, add them to $W(1)$.

iterate $k = 2, \ldots, s$

- find a hypothesis w_{k-1} consistent with $W(k-1)$.
- $W(k)=W(k-1)$.
- sample m_k unlabeled samples x satisfying $|w_{k-1} \cdot x| \leq \gamma_{k-1}$
- label them and add them to $W(k)$.



Margin Based Active-Learning, Realizable Case

Log-concave distributions: log of density fnc concave.

- wide class: uniform distr. over any convex set, Gaussian, etc.

$$f(\lambda x_1 + (1 - \lambda x_2)) \geq f(x_1)^{\lambda} f(x_2)^{1-\lambda}$$

Theorem D log-concave in R^d. If $\gamma_k = O\left(\frac{1}{2^k}\right)$ then $err(w_s) \leq \varepsilon$ after $s = \log\left(\frac{1}{\epsilon}\right)$ rounds using $\tilde{O}(d)$ labels per round.

Active learning

$O\left(d \log\left(\frac{1}{\epsilon}\right)\right)$ label requests

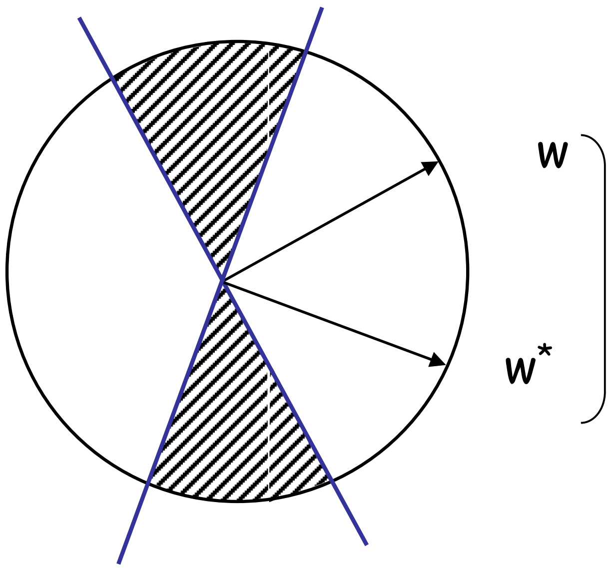
$\Theta\left(\frac{d}{\epsilon}\right)$ unlabeled examples

Passive learning

$\Theta\left(\frac{d}{\epsilon}\right)$ label requests

Analysis: Aggressive Localization

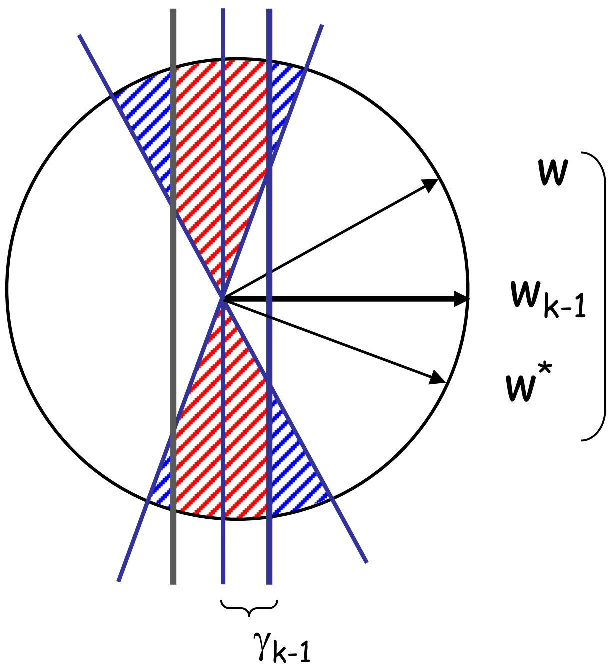
Induction: all w consistent with W(k), err(w) $\leq 1/2^k$

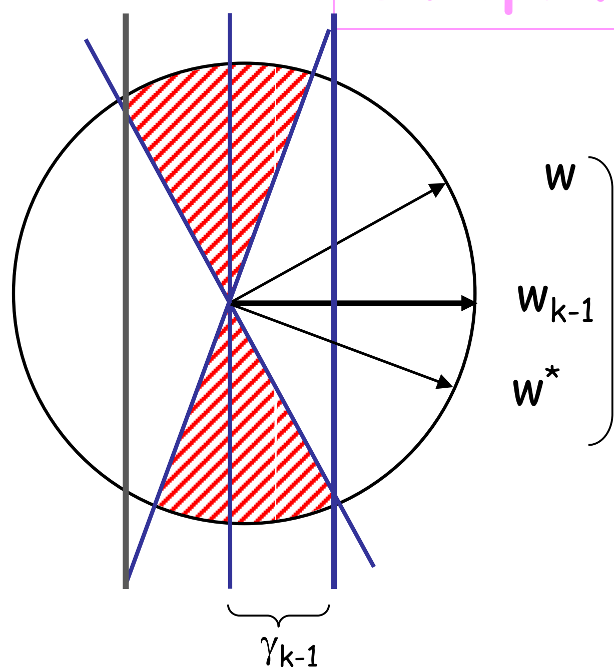


Analysis: Aggressive Localization

Induction: all w consistent with W(k), err(w) $\leq 1/2^k$

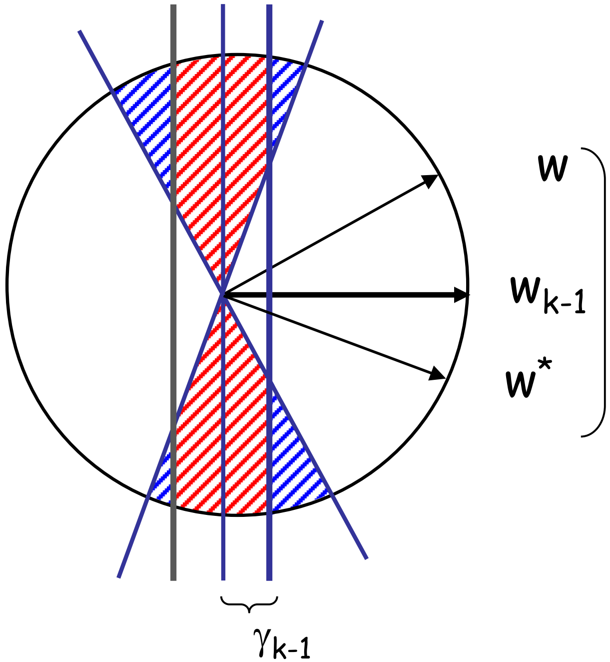
Suboptimal





Analysis: Aggressive Localization

Induction: all w consistent with W(k), err(w) $\leq 1/2^k$



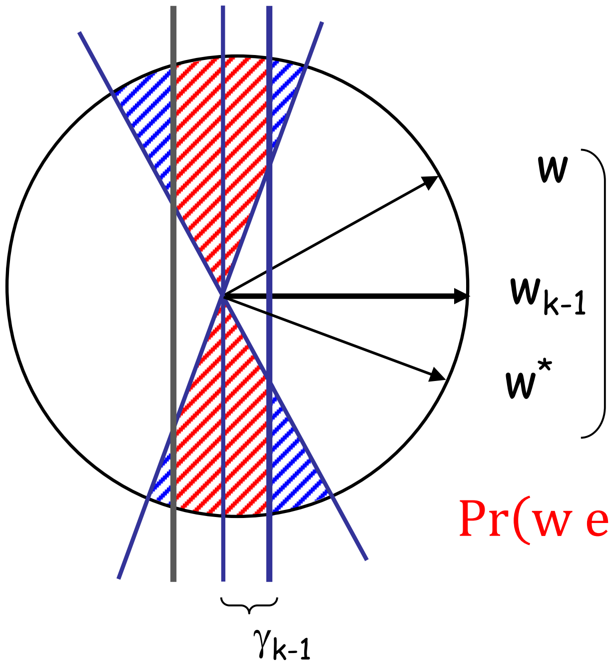
$\leq 1/2^{k+1}$

$$\mathrm{err}(w) = \Pr(w \text{ errs on } x, |w_{k-1} \cdot x| \geq \gamma_{k-1}) +$$

$$\Pr(w \text{ errs on } x, |w_{k-1} \cdot x| \leq \gamma_{k-1})$$

Analysis: Aggressive Localization

Induction: all w consistent with W(k), $err(w) \leq 1/2^k$



$\leq 1/2^{k+1}$

$$err(w) = Pr(w \text{ errs on } x, |w_{k-1} \cdot x| \geq \gamma_{k-1}) +$$

$$Pr(w \text{ errs on } x \mid |w_{k-1} \cdot x| \leq \gamma_{k-1}) Pr(|w_{k-1} \cdot x| \leq \gamma_{k-1})$$

Enough to ensure $Pr(w \text{ errs on } x \mid |w_{k-1} \cdot x| \leq \gamma_{k-1}) \leq C$

Need only $m_k = \tilde{O}(d)$ labels in round k.

Key point: localize aggressively, while maintaining correctness.

Margin Based Active-Learning, Agnostic Case

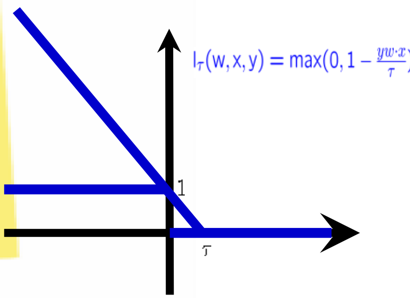
Draw m_1 unlabeled examples, label them, add them to W.

iterate k=2, …, s

- find w_{k-1} in $B(w_{k-1}, r_{k-1})$ of small τ_{k-1} hinge loss wrt W.
    - Clear working set.
    - sample m_k unlabeled samples x satisfying $|w_{k-1} \cdot x| \leq \gamma_{k-1}$;
    - label them and add them to W.

end iterate

Localization in concept space.



Localization in instance space.

<u>Analysis, key idea:</u>

- Pick $\tau_k \approx \gamma_k$
- Localization & variance analysis control the gap between hinge loss and 0/1 loss (only a constant).

Improves over Passive Learning too!

Passive Learning	**Prior Work**	**Our Work**
Malicious	$\text{err}(w) = O(\eta d^{1/4})$ [KKMS'05] $\text{err}(w) = O\left(\sqrt{\eta \log(d/\eta)}\right)$ [KLS'09]	$\text{err}(w) = O(\eta)$ Info theoretic optimal [Awasthi-Balcan-Long'17]
Agnostic	$\text{err}(w) = O\left(\eta\sqrt{\log(1/\eta)}\right)$ [KKMS'05]	$\text{err}(w) = O(\eta)$ [Awasthi-Balcan-Long'17]
Bounded Noise $\lvert P(Y=1\lvert x) - P(Y=-1\lvert x)\rvert \geq \beta$	NA	$\eta + \epsilon$ [Awasthi-Balcan-Haghtalab-Urner'15]
Active Learning [agnostic/malicious/bounded]	NA	same as above! Info theoretic optimal [Awasthi-Balcan-Long'14]

Slightly better results for the uniform distribution case.

Localization both algorithmic and analysis tool!

Useful for active and passive learning!

Discussion, Open Directions

- Active learning: important modern learning paradigm.
- First poly time, label efficient AL algo for agnostic learning in high dimensional cases.
- Also leads to much better noise tolerant algos for passive learning of linear separators!

Open Directions

- More general distributions, other concept spaces.
- Exploit localization insights in other settings (e.g., online convex optimization with adversarial noise).