

Last time:

- analysis of AdaBoost: bound on error rate of its final hyp. over its input sample
- start unit on PAC learning in presence of noise
- General framework

Today: Specific noise models : toy scenario {

- malicious noise (hard!) ☹
- random classification noise (easy!) ☺

→ • Learning with malicious noise is hard ☹ → RCN

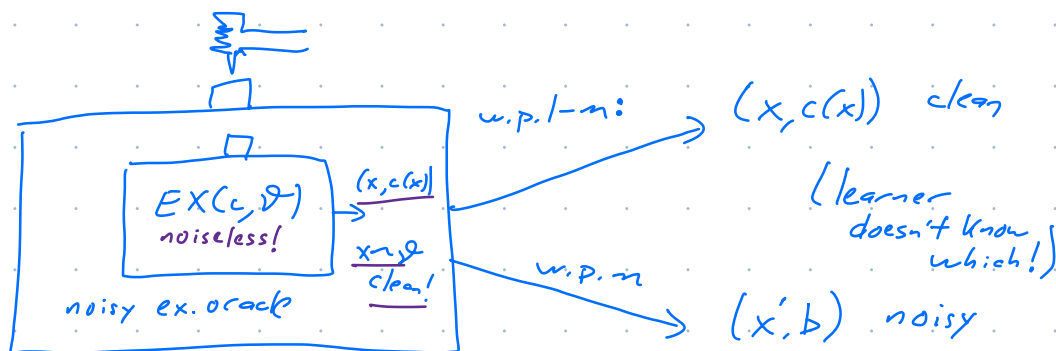
- Sad, sad positive result for
- Start discussion of learning with RCN

Admin: PS 4 due today, PS 5 out.

↳ towards new learning model: learning from **STATISTICAL QUERIES**

Questions?

Recall: we assume learner has access to a noisy example oracle: noise rate $0 \leq \eta \leq \frac{1}{2}$



Both malicious noise + random classification noise fall in this framework:

☹ Mal. noise: (x', b) can be arbitrary elt. of $X \times \{0, 1\}$.
(no assum.; can be gen. by omniscient malevolent adversary.)

😊 Rand. Class. Noise: get $(x, \overline{c(x)})$ (label flipped;
 x is not altered.)

Hi-level msg of noise unit:

☹ • Mal. noise: challenging; • if there's mal. noise at
noise rate $\eta \gtrsim 2\epsilon$, can't learn to acc. ϵ .
• best general methods to
deal w/ mal. noise: not great.

😊 • Can usually handle RCN: we'll see a general
way to convert many PAC learners to PAC
learners handling RCN at rate $\eta < \frac{1}{2}$, with
slowdown of only $\text{poly}(\frac{1}{1-2\eta})$.
($\eta = \frac{1}{2}$: imposs. to learn.)

Simple ex (cartoon):

Learning setting w/ no examples (!), just labels.
(Noise-free data)

World 1:	World 2:
$\frac{3}{8}$ of ex +	$\frac{5}{8}$ of ex +
$\frac{5}{8}$ of ex -	$\frac{3}{8}$ " " -

With noise...?

- Mal. noise at rate $\eta = 1/5$:

World 1: adv. can corrupt only - ex. to +,
+ observed data for learner:

$\frac{3}{8} +$ (true +)
and also $\frac{1}{5} \cdot \frac{5}{8}$ (true -) see +

See $\frac{1}{2} +$, $\frac{1}{2} -$ data.

World 2: adv. can corr. only + ex to -,
+ again learner sees $\frac{1}{2} +$, $\frac{1}{2} -$ data.

So learner can't tell which world it is.

- RCN at rate $\eta < \frac{1}{2}$:

• world 1: learner sees + with prob.

$$\overset{\text{true +}}{\frac{3}{8}} \cdot \overset{\text{no noise}}{(1-\eta)} + \overset{\text{true -}}{\frac{5}{8}} \cdot \overset{\text{noise}}{\eta} = \left(\frac{3}{8} + \frac{1}{4}\eta \right)$$

• world 2: learner see - with prob. $\left(\frac{3}{8} + \frac{1}{4}\eta \right)$

If $\eta < \frac{1}{2}$, this $\checkmark < \frac{1}{2}$.

→ So with enough ex., can tell if in world 1 or 2.

Lower Bound for Learning w/ Mal. Noise

Def: $\mathcal{C}$ is distinct if $\exists c_1, c_2 \in \mathcal{C} \nleftrightarrow \exists \text{ pts } u, v, w \in X$
s.t.



$$\begin{aligned} c_1(u) &= c_1(v) = 1 \\ c_2(v) &= c_2(w) = 1 \\ c_1(w) &= 0 \\ c_2(u) &= 0 \end{aligned}$$

Thm: Let $\mathcal{C}$ be distinct. If learning w/ mal. noise
at rate $\eta \geq \frac{2\epsilon}{1+2\epsilon}$, then no alg. can PAC learn
to error $< \epsilon$ & conf. $1 - \delta > \frac{1}{2}$.

Pf: Use c_1, c_2 above.
Use dist. $\mathcal{D}$:

$$\begin{aligned} \mathcal{D}(u) &= \epsilon \\ \mathcal{D}(v) &= 1 - 2\epsilon \\ \mathcal{D}(w) &= \epsilon \end{aligned}$$

Define adv. A_1 for target c_1 ,
" " A_2 " " c_2 ;

target c_1 under A_1 $\stackrel{\text{indist.}}{=} \text{target } c_2 \text{ under } A_2$.

Adv. A_i : w.p. $\frac{\eta}{2}$, output $(u, -)$,
" " " " $(w, +)$.

So $\rightarrow$: learner observes dist. of lab. ex.:

$(u, +)$	prob.	$\tau(1-\eta)$	} noiseless
$(v, +)$	"	$(1-\tau)(1-\eta)$	
$(w, -)$	"	$\tau(1-\eta)$	
$(u, -)$	"	$\eta/2$	} noisy
$(w, +)$	"	$\eta/2$	

Adv. A_2 : w.p. $\frac{\eta}{2}$, output $(u, +)$,
 " " " $(w, -)$.

So under $c_2 + A_2$: learner observes dist. of lab. ex.:

$(u, -)$	prob.	$\tau(1-\eta)$	} noiseless
$(v, +)$	"	$(1-\tau)(1-\eta)$	
$(w, +)$	"	$\tau(1-\eta)$	
$(u, +)$	"	$\eta/2$	} noisy
$(w, -)$	"	$\eta/2$	

If $\tau(1-\eta) = \frac{\eta}{2}$: dist's identical.
 $2\tau(1-\eta) = \eta$
 $2\tau = \eta(1+2\tau)$, $\eta = \frac{2\tau}{1+2\tau}$.

So can't achieve conf. $> \frac{1}{2}$ of having error $< \tau$.

above: bad news.

"Good" news:

How can we handle mal. noise in general?

Say have alg A that $\xrightarrow{\text{PAC}}$ learns if no noise. $\xrightarrow{\text{(efficiently)}}$

Do the foll:

- Run A . Hope no noisy example occurred.
- Repeat, "many" times.
Get $h_1, h_2, \dots, h_T$.

→ Check $h_1, \dots, h_T$ on fresh ex; output the one that did best.

Intuition: Say $m = \overset{\rightarrow \text{poly}(n)}{\# \text{ex. your noiseless PAC learner needs.}}$

- If $n \ll \frac{1}{m}$: should work! • some h_i should be good, b/c no noise;

• when we eval. how good $h_1, h_2, \dots, h_T$ are, since n tiny, adv. can't mislead too much.

Turns out: $n = \min \left\{ \frac{\epsilon}{8}, \frac{\ln m}{m} \right\}$ is "sweet spot"

if $n = \frac{\ln m}{m}$: $\left((1-x) \approx e^{-x} \right)$
x small

$\Pr[m \text{ ex. drawn for } A \text{ are all noiseless}]$

$$= \left(1 - \frac{\ln m}{m} \right)^m \approx \left(e^{-\frac{\ln m}{m}} \right)^m = \frac{1}{m}$$

For $n = \frac{\ln m}{m}$,

Take $T = m \cdot \ln\left(\frac{2}{\epsilon}\right)$, &

$$\Pr[\text{none of } T \text{ runs have noiseless data set}] \\ = \left(1 - \frac{1}{m}\right)^T = \left(1 - \frac{1}{m}\right)^{m \ln \frac{2}{\delta}} \approx \frac{\delta}{2}.$$

Random Classif. Noise (RCN)

Recall: rate η :

- w.p. $1 - \eta$, get $(x, c(x)) \quad x \sim \mathcal{D}$
- η , get $(x, \bar{c}(x)) \quad x \sim \mathcal{D}$.

Call this oracle $\boxed{EX^\eta(c, \mathcal{D})}$

Def: Alg. A PAC learns $\mathcal{C}$ with RCN if

- $\forall c \in \mathcal{C}$
- $\forall \text{dist } \mathcal{D}$,
- $\forall \eta < \frac{1}{2}$,
- $\forall \epsilon, \delta > 0$,

Efficient:

$$\text{poly}\left(\frac{1}{\epsilon}, \log \frac{1}{\delta}, n, \text{size}(c), \frac{1}{1-2\eta}\right)$$

given η, ϵ, δ & access to $EX^\eta(c, \mathcal{D})$, A outputs an h s.t.

$$\text{w.p. } \geq 1 - \delta, \quad \text{err}_{\mathcal{D}}(h, c) \leq \epsilon.$$

• Note 1: same goal: high acc. on noiseless example.

• Note 2: Sps true $\text{err}_{\mathcal{D}}(h, c) = \tau$. Then given (x, y) pairs $\sim EX^\eta(c, \mathcal{D})$, observed error rate will be

$$\begin{aligned}
 \Pr_{(x,y) \sim \mathcal{E}X^m(c,\mathcal{D})} \{h(x) \neq y\} &= \underbrace{\tau}_{\text{true error}} \underbrace{(1-\eta)}_{\Pr\{y=c\}} + \underbrace{(1-\tau)}_{\Pr\{h=c\}} \underbrace{\eta}_{\Pr\{y \neq c\}} \\
 &= \tau + \eta - 2\tau\eta \\
 &= \underbrace{\eta + \tau(1-2\eta)}_{\text{observed error}}.
 \end{aligned}$$

observed error $\eta + (1-2\tau) \cdot (\text{true error})$

Next time: old alg $\rightarrow$ make noise tol.

$\hookrightarrow$ STATISTICAL QUERY
learning model.