TTIC 31250
An Introduction to the Theory of Machine Learning

Characterizing SQ-learnability

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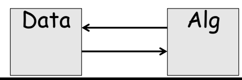
Statistical Query Recap

- Target function $c(x)$. No noise
- Algorithm asks: "what is the probability a labeled example will have property χ? Please tell me up to additive error τ."
  - Formally, $\chi{:}X \times \{0,1\} \rightarrow \{0,1\}$. Must be poly-time computable. $\tau \geq 1/\text{poly}(\ldots)$.
  - Let $P_\chi = \Pr_{x\sim D}[\chi(x,c(x))=1]$.
  - World responds with $P'_\chi \in [P_\chi - \tau, P_\chi + \tau]$.
  [can extend to $E[\chi]$ for [0,1]-valued or vector-valued χ]
- May repeat poly(…) times. Can also ask for unlabeled data. Must output h of error $\leq \varepsilon$. No δ in this model.



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Statistical Query Recap

- Examples of query:
  - What is the error rate of my current hypothesis h? [$\chi(x,y)=1$ iff $h(x) \neq y$]
- Get back answer to $\pm\tau$. Can simulate from $\approx 1/\tau^2$ examples. [That's why need $\tau \geq 1/\text{poly}(\ldots)$.]

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Characterizing what's learnable using SQ algorithms

- Say that f,g uncorrelated if $\Pr_{x\sim D}[f(x) = g(x)] = \frac{1}{2}$.

Def: the SQ-dimension of a class C wrt D is the size of the largest set $C' \subseteq C$ s.t. for all $f, g \in C'$,

$$\left|\Pr_D[f(x) = g(x)] - \tfrac{1}{2}\right| < \frac{1}{|C'|}.$$

(size of largest set of nearly uncorrelated functions in C)

- Theorem 1: if $\text{SQDIM}_D(C) \leq \text{poly}(n)$ then you can weak-learn C over D by SQ algs. [error rate $\leq \frac{1}{2} - \frac{1}{poly(n)}$]
- Theorem 2: if $\text{SQDIM}_D(C) >$ poly(n) then you can't weak-learn C over D by SQ algs.

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Characterizing what's learnable using SQ algorithms

Example: Parity functions $c(x) = c \cdot x \bmod 2$

- Let D be uniform on $\{0,1\}^n$.
- Any two parity functions are uncorrelated.
- So, SQ-dim_D({Parity functions})= 2^n
- Any parity function of size $\lg(n)$ can be described as a size-n decision tree. So, poly-sized decision trees are not SQ-learnable either.

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Characterizing what's learnable using SQ algorithms

Can anyone think of a non-SQ algorithm to learn parity functions?

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Characterizing what's learnable using SQ algorithms

Theorem 1 is easier – let's prove it first.

- Let $d = SQDIM_D(C)$.
- Let $H \subseteq C$ be a maximal subset s.t. for all $h_i, h_j \in H$, we have $|\Pr_D[h_i(x) = h_j(x)] - \frac{1}{2}| < \frac{1}{d+1}$. So, $|H| \leq d$.
- To learn, just try each $h_i \in H$ and use an SQ to estimate its error. At least one h_i (or $\neg h_i$) must be a weak predictor.

- Theorem 1: if $SQDIM_D(C) \leq poly(n)$ then you can weak-learn C over D by SQ algs. [error rate $\leq \frac{1}{2} - \frac{1}{poly(n)}$]
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Characterizing what's learnable using SQ algorithms

Now, onto Theorem 2.

To keep things simpler, will change "nearly uncorrelated" to "uncorrelated". I.e., we will assume there are more than poly(n) uncorrelated functions in C.

- Theorem 1: if $SQDIM_D(C) \leq poly(n)$ then you can weak-learn C over D by SQ algs. [error rate $\leq \frac{1}{2} - \frac{1}{poly(n)}$]
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Characterizing what's learnable using SQ algorithms

- Key tool: Fourier analysis of boolean functions.
- Sounds scary but it's a cool idea!
- Let's think of functions from $\{0,1\}^n \rightarrow \{-1,+1\}$.
- View function f as a vector of 2^n entries:

  $\left(\sqrt{D[000]}f(000), \sqrt{D[001]}f(001), \ldots, \sqrt{D[x]}f(x), \ldots\right)$
  - In other words, the truth-table of f, where entry x is weighted by the square-root of the probability of x.
- What is $\langle f, f\rangle$? What is $\langle f, g\rangle$?

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- What is $\langle f, f\rangle$? What is $\langle f, g\rangle$?
  - $\langle f, f\rangle = 1$.
  - $\langle f, g\rangle = \sum_x \Pr(x) f(x) g(x) = E_D[f(x)g(x)] =$ Pr(agree) – Pr(disagree). Call this the correlation of f and g.

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- So, functions are unit-length vectors, and uncorrelated functions are orthogonal. Dot-product equals amount of correlation.

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Characterizing what's learnable using SQ algorithms

- *Fourier analysis* is just a way of saying we want to talk about what happens when we change basis.
- An *orthonormal basis* is a set of orthogonal unit vectors that span the space.
- E.g., in 2-d, let x', y' be unit vectors in x,y directions. $v = (2,3) = 2x' + 3y'$.
- If have two other orthogonal unit vectors a, b, then could write $v = \langle v, a\rangle a + \langle v, b\rangle b$.

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Characterizing what's learnable using SQ algorithms

- We are in a 2^n–dimensional space, so an orthonormal basis is a set of 2^n orthogonal unit vectors.
- Let's fix one. $\varphi_1, \ldots, \varphi_{2^n}$.
- Given a vector f, let f_i be the ith entry in the standard basis: $f_i = f(i)\sqrt{\Pr(i)}$.
- Then $\hat{f}_i = \langle f, \varphi_i \rangle$ is the ith entry in the φ basis.
- For instance, can write vector f as $f = \sum_i \hat{f}_i \varphi_i$
- The $\hat{f}_i$ are called the "Fourier coeffs of f" in the φ basis.
- Since $f = \sum_i \hat{f}_i \varphi_i$, this means $f(x) = \sum_i \hat{f}_i \varphi_i(x)$. This is just saying the xth coordinates match.

Characterizing what's learnable using SQ algorithms

- Consider any Boolean function f. Since it's a unit-length vector, this means $\sum_i \hat{f}_i^2 = 1$. Called "Parseval's identity"
- At most t^2 of the φ_i can have $|\langle f, \varphi_i \rangle| = |\hat{f}_i| \geq \frac{1}{t}$.
- I.e, any given Boolean function can have correlation $\geq \frac{1}{t}$ with at most t^2 functions in an orthogonal set.
- In particular, any given f can be weakly correlated with at most a polynomial number of them.
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If C has $n^{\omega(1)}$ uncorrelated functions, target is a random one of them, SQs all of form "what is correlation of target with my h up to $\pm\frac{1}{poly(n)}$" then whp oracle can always answer 0.

Characterizing what's learnable using SQ algorithms

- It turns out that any SQ can be converted into a portion that looks like this, and a portion that doesn't depend on the target function at all.

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Proof of Theorem 2'

Theorem 2': If C has $n^{\omega(1)}$ uncorrelated functions, and target is random one of them, then whp any SQ algo that makes $poly(n)$ queries of tolerance $\frac{1}{poly(n)}$ will fail to weak learn.

Proof:

- Let $\varphi_1, \ldots, \varphi_m$ be orthogonal functions in C. Extend arbitrarily to a basis $\varphi_1, \ldots, \varphi_{2^n}$. (excess vectors may not be Boolean functions and may not be in C)
- Now, consider a SQ $\chi: \{0,1\}^n \times \{-1,1\} \to [-1,1]$. Can view this as a vector in 2^{n+1} dimensions.
- To apply Fourier analysis to this, need to extend our basis to this higher-dimensional space.

Proof of Theorem 2'

- Define distribution $D' = D \times uniform\ on\ \{-1, +1\}$
- Define $\varphi_i(x, y) = \varphi_i(x)$ [ignore label]

  Still orthogonal:

  $$\Pr_{D'}[\varphi_i(x,y) = \varphi_j(x,y)] = \Pr_{D}[\varphi_i(x) = \varphi_j(x)] = \frac{1}{2}$$
- Need 2^n more basis functions.
- Define $h_i(x, y) = y\varphi_i(x)$. Need to verify these work:
  - Check that h_i and h_j are orthogonal for $i \neq j$.
  - Check that h_i and φ_j are orthogonal even if $i = j$.
- Now do Fourier decomposition on $\chi(x, y)$.

Proof of Theorem 2'

- $\chi = \sum_i \alpha_i \varphi_i + \sum_i \beta_i h_i$ where $\sum_i \alpha_i^2 + \sum_i \beta_i^2 = 1$.
- So we can write the quantity we care about as:

$$E_D[\chi(x, c(x))] = \mathrm{E_D}\left[\sum_i \alpha_i \varphi_i(x) + \sum_i \beta_i h_i(x, c(x))\right]$$
$$= \sum_i \alpha_i E_D[\varphi_i(x)] + \sum_i \beta_i E_D[c(x)\varphi_i(x)]$$

- First term doesn't depend on target at all. Call it $g(\chi, D)$.
- Recall that c is random from $\{\varphi_1, \dots \varphi_m\}$. Say $c = \varphi_{i^*}$.
- What is the 2nd term?
- Ans: 2nd term $= \beta_{i^*}$. So whp, world can just return $g(\chi, D)$.
- That's it.

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Stepping back

- If C contains more than poly(n) many uncorrelated functions, then can't learn in SQ model. [holds also for "nearly uncorrelated" as in SQ-dim definition]
- Very last step of proof had adversary convert $g(\chi, D) + \mathit{tiny\ value}$ into $g(\chi, D)$. Can also make this work in "honest SQ" model, where it's estimated from a random sample.
- Can also use SQ-dim to prove that certain (C,D) pairs have no large-margin kernels (kernels where every c in C looks like a large-margin separator in the implicit space).

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