1) Choose hypothesis space F

2) Learn 
$$\hat{f} = \underset{f \in F}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^{n} I[y_i \neq f(x_i)]$$

$$\text{If } |F| < \infty \text{ then } P\left\{\sup_{f \in F} \bigl(P_D\bigl(y \neq f(x)\bigr) - P_S\bigl(y \neq f(x)\bigr) \geq \epsilon\bigr)\right\} \leq |F| e^{-2n\epsilon^2}$$

For  $|F| = \infty$  we have three steps:

Step 1 Double Sample Trick

$$P\left(\sup_{\phi \in \Phi} \left| \frac{1}{n} \sum_{i=1}^{n} \phi(z_i) - \frac{1}{n} \sum_{i=n+1}^{2n} \phi(z_i) \right| \ge \epsilon\right) \le 2P\left(\sup_{\phi \in \Phi} \left| \frac{1}{n} \sum_{i=1}^{n} \phi(z_i) - E[\phi(z)] \right| \ge \frac{\epsilon}{2}\right)$$

Step 2 Symmetrization

Fix 
$$\{z^{(1)} \dots z^{(2n)}\}$$

$$\begin{split} P_D \left( \sup_{\phi \in \Phi} \left| \frac{1}{n} \sum_{i=1}^n \phi(z_i) - \frac{1}{n} \sum_{i=n+1}^{2n} \phi(z_i) \right| \geq \epsilon \right) \\ & \leq N^{\Phi}(z_1 \dots z_n) P_D \left( \left| \frac{1}{n} \sum_{i=1}^n \phi(z_i) - \frac{1}{n} \sum_{i=n+1}^{2n} \phi(z_i) \right| \geq \epsilon \right) \end{split}$$

Where  $N^{\Phi}(z_1 \dots z_n) \coloneqq |\{\phi(z_1) \dots \phi(z_n), \phi \in \Phi\}| \le 2^n$ 

$$\begin{split} E_{(z^{(1)}\dots z^{(n)})} P_{z_1\dots z_n} & \left( \sup_{\phi \in \Phi} \left| \frac{1}{n} \sum_{i=1}^n \phi(z_i) - \frac{1}{n} \sum_{i=n+1}^{2n} \phi(z_i) \right| \ge \epsilon \right) \le E N^{\Phi}(z_1 \dots z_n) e^{-O(n\epsilon^2)} \\ & \le N^{\Phi}(2n) e^{-O(n\epsilon^2)} \end{split}$$

Step 3 VC-dimension

$$N^{\Phi}(n) \coloneqq \max_{z_1...z_n} N^{\Phi}(z_1 ... z_n) = \max_{z_1...z_n} |\{(\phi(z_1) ... \phi(z_n)), \phi \in \Phi\}|$$

- $\textcircled{1}\ N^\Phi(n) \leq 2^n$  But we don't know how it grows actually, maybe exponential or polynomial
- $\ensuremath{\mbox{\fontfamily{1.5}}}$  when n is small  $N^\Phi(n)$  can be exponential but when n is large it is relatively smaller

Thm

$$N^{\Phi}(n) \begin{cases} = 2^{n} & \text{if } n \leq d \\ \leq \sum_{k=0}^{d} {n \choose k} \leq \left(\frac{en}{d}\right)^{d} & \text{if } n > d \end{cases}$$

Phase change

(To prove it as homework)

So just to focus on what cases cannot be reached

Start with special case: n=d+1, if (0,0...) cannot be realized then  $N^{\Phi}(n) = \sum_{k=0}^{d} \binom{n}{k}$ 

And intuitively it is the worst case so for others it is better

Proof Fix z<sub>1</sub> ... z<sub>n</sub>

Note unrealizable patterns as (\*,\*,0,1....) but they maybe intersected. So if I change the first bit from 1 to 0 otherwise keeps the same then the union of them are smaller. So when I replace 1 with 0 then the union is that they cannot have more than d+1 zeros, then it is the special case.

Then d is called the VC-dimension of the set. And d means that there exists  $z_1$  to  $z_d$  s. t.  $\Phi$  can reach every possible results but cannot find  $z_1$  to  $z_{d+1}$ 

So:

$$P\left(\sup_{\phi \in \Phi} \left| \frac{1}{n} \sum_{i=1}^{n} \phi(z_i) - E[\phi(z)] \right| \ge \epsilon \right) \le e^{-O(n\epsilon^2)} \left(\frac{en}{d}\right)^d$$

Thm'  $\forall \delta > 0$  with prob  $1 - \delta$  over the random draw of training data  $(x_i, y_i)$ 

$$P_{D}(y \neq f(x)) \leq P_{S}(y \neq f(x)) + O(\sqrt{\frac{d\ln(n) + \ln(\frac{1}{\delta})}{n}}$$

Linear classifier: VC-dim = r+1 where  $x \in R^r$ 

For ERM  $f^*$  is the best one and  $\hat{f} = \mathop{argmin}_{f \in F} P_D(y \neq f(x))$ , then with probability  $1 - \delta$ 

$$P_{D}\left(y \neq \hat{f}(x)\right) \leq P_{D}\left(y \neq f^{*}(x)\right) + O\left(\sqrt{\frac{d\ln(n) + \ln\left(\frac{1}{\delta}\right)}{n}}\right)$$

Lecture 4 Practical Algorithms

$$\hat{f} = \underset{f \in F}{\operatorname{argmin}} \frac{1}{n} \sum_{i=1}^{n} I[y_i \neq f(x_i)]$$

But indicator function is hard to minimize

So we change classification error from 0-1 loss to other functions.

1. Linear classification

$$x \in R^d$$
,  $y \in \{\pm 1\}$ ,  $f(x) = sign(w^Tx + b)$ 

$$(1) \max_{\mathbf{w}, \mathbf{b}, \mathbf{t}} \mathbf{t} \ \text{s. t. } \mathbf{y}_{\mathbf{i}} (\mathbf{w}^{\mathsf{T}} \mathbf{x}_{\mathbf{i}} + \mathbf{b}) \ge \mathbf{t} \text{ and } ||\mathbf{w}|| = 1$$

For time limits, if it is a convex optimization and constrain is linear then it is easy to be solved.