

1) PAC Learning (probably approximately correct)

δ - confidence par.

ϵ - accuracy par.

$m_{\delta, \epsilon}(0, 1) \rightarrow N$

$$L_{0, f}(h) \leq \epsilon$$

$$2) P_{\mathcal{D}}[\hat{h}(x) = f(x)] = 1$$

\mathcal{D} - probability distribution over $X \times Y$

$$L_{\mathcal{D}}(h) = P_{(x, y) \sim \mathcal{D}}[h(x) \neq y] = D(\{(x, y) : h(x) \neq y\})$$

2) Agnostic PAC

$$L_{\mathcal{D}}(h) \leq \min_{h' \in H} L_{\mathcal{D}}(h') + \epsilon$$

3) Generalize Loss Function

$$L_{\mathcal{D}}(h) = E_{z \sim \mathcal{D}}[\ell(h, z)] - \text{risk function}$$

$$L_S(h) = \frac{1}{m} \sum_{i=1}^m \ell(h, z_i)$$

4) Uniform convergence

ϵ - representative sample:

$$\forall h \in H \quad |L_S(h) - L_{\mathcal{D}}(h)| \leq \epsilon$$

If $\epsilon/2$ - repr $\Rightarrow h_S \in \arg \min_{h \in H} L_S(h)$ satisfies

$$L_{\mathcal{D}}(h_S) \leq \min_{h \in H} L_{\mathcal{D}}(h)$$

$$L_{\mathcal{D}}(h_S) \leq L_S(h_S) + \epsilon/2 \leq L_S(h) + \epsilon/2 \leq L_{\mathcal{D}}(h) + \epsilon$$

m_H^{uc}

$$L_{\mathcal{D}}(h) + \epsilon/2$$

5) Finite classes are Agnostic PAC

$$D^m(\{S : \forall h \in H \quad |L_S(h) - L_{\mathcal{D}}(h)| \leq \epsilon\}) \geq 1 - \delta$$

$$\bigcup_{h \in H} \{S : |L_S(h) - L_{\mathcal{D}}(h)| > \epsilon\} \leq \sum_{h \in H} D^m(\{S : |L_S(h) - L_{\mathcal{D}}(h)| > \epsilon\}) \leq$$

$$E(L_S(h)) = E\left[\frac{1}{m} \sum_{i=1}^m \ell(h, z_i)\right] = E[\ell(h, z)] = L_{\mathcal{D}}$$

$$|L_S(h) - E(L_S(h))|$$

Use Hoeffding's ineq v

$$\leq \sum_{h \in H} 2 \exp(-2m\epsilon^2) = 2|H| \exp(-\frac{2m\epsilon^2}{\delta})$$

$$m \geq \frac{\log(2|H|/\delta)}{2\epsilon^2}$$

6) Enjoys UC-property:

$$m_H^{uc}(\epsilon, \delta) \leq \frac{\log(2|H|/\delta)}{2\epsilon^2}$$

H is pac-learnable

$$\Leftrightarrow \lim_{m \rightarrow \infty} E_{S \sim \mathcal{D}^m} [L_{\mathcal{D}}(A(S))] = 0$$