

## PAC LEARNABLE HYPOTHESES

## Why

What does it mean for an algorithm to be able to learn a concept?

## **Definition**

Let  $(X, \mathcal{X})$  and  $(Y, \mathcal{Y})$  be measurable input and output spaces.

A hypothesis class  $\mathcal{H}$  of measurable functions from X to Y is probably approximately correct learnable (or PAC learnable) if (a) there exists an inductor  $\mathcal{A}: (X\times Y)^n \to \mathcal{H}$ , so that (b) for every underlying measure  $\mu$  and labeling function  $f: X \to Y$  (c) for every  $\varepsilon, \delta \in (0,1)$  (d) there exists  $m_0 \in \mathbb{N}$  so that (e) for all  $m \geq m_0$ 

$$\mu^{m} \left[ \mu \left[ \mathcal{A}((x_{i}, f(x_{i}))_{i=1}^{n})(\xi) \neq f(\xi) \right] \leq \varepsilon \right] \geq 1 - \delta \tag{1}$$

where  $x \in X^m$  and  $\xi \in X$ . In this case we say that the inductor (or learning algorithm)  $\mathcal{A}$  PAC learns  $\mathcal{H}$ .

Many authors offer much interpretation for this condition. The usual one is: "no matter the underlying distribution and correct labeling function, if someone specifies an accuracy and confidence we can tell them the number of samples they need so that the inductor outputs a hypothesis which is probably approximately correct."

Some authors require that the hypothesis class be realizable with respect to the underlying distribution and correct labeling function. In this case they refer to the above definition as the agnostic PAC model. We emphasize here that there this definition includes the notion of realizability. In other words. We emphasize again that this definition contains to "approximation parameters." The accuracy parameter  $\varepsilon$  corresponds to the "approximately correct" piece and the confidence parameters  $\delta$  corresponds to the "probably" piece.

## Sample complexity

Note that the existence of an  $m_0$  above for each  $\varepsilon$  and  $\delta$  is equivalent to requiring that there exists  $m_0:(0,1)^2\to \mathbf{N}$  so that for all  $m\geq m_0(\varepsilon,\delta)$  the condition in Equation 1 holds. There may exist multiple such  $m_0$ , so we define  $\tilde{m}:(0,1)^2\to\mathbf{N}$  so that  $\tilde{m}(\varepsilon,\delta)$  is the smallest integer so that Equation (1) holds. We call  $\tilde{m}$  the sample complexity. Clearly it is a function of  $\varepsilon$  and  $\delta$ . It also depends on the hypothesis class  $\mathcal{H}$  and the learning algorithm  $\mathcal{A}$ .

