## **Rigorous Bounds to Retarded Learning**

Using an elegant approach, Herschkowitz and Opper [1] established rigorous bounds on the information inferable (learnable) from a set of data (*m* points  $\in \mathbb{R}^N$ ) when the latter are drawn from a distribution  $P(\mathbf{x}) = P_0(\mathbf{x}) \times$  $exp[-V(\lambda)]$ , where  $P_0(\mathbf{x})$  is a spherical normal law and  $exp[-V(\lambda)]$  is a modulation along an unknown anisotropy axis  $\lambda = \mathbf{w} \cdot \mathbf{x}$ , for some direction **w**. They show in particular that if  $P(x)$  has zero mean, it is impossible to learn the direction of anisotropy below a critical fraction of data  $\alpha^*$ , and claim that  $\alpha^* = \alpha_{lb} \equiv (1 - \overline{\lambda^2})^{-1}$  *only* depends on  $\lambda^2$ , the second moment of the distribution along  $\lambda$ , on  $\lambda^2$ , the second moment of the  $P(\lambda) \equiv e^{-\lambda^2/2} \exp[-V(\lambda)]/\sqrt{2\pi}$ .

The authors reach this conclusion by an expansion at small *q* of the upper bound to  $\Delta R$ , the difference between the trivial risk and the cumulative Bayes risk. In the thermodynamic limit ( $m \to \infty$ ,  $N \to \infty$ , with  $\alpha = m/N$  finite) the upper bound (min<sub>q</sub> erroneously stands for max<sub>q</sub> in Eq. (7) of [1]) is given by  $\max_{q} G_{\alpha}(q) = G_{\alpha}(q^*)$ , with  $G_{\alpha}(q) = \ln(1 - q^2)^{1/2} + \alpha \ln F(q)$  where

$$
F(q) = \iint Dx \, Dy \, e^{[-V(x) - V(xq + y\sqrt{1 - q^2})]}, \qquad (1)
$$

and  $Dx = e^{-x^2/2} dx/\sqrt{2}$  $2\pi$ . The authors show that  $q = 0$ is always a maximum for  $\alpha \leq \alpha_{lb}$ . In the case of highly anisotropic data distributions, when the learning task is simple enough that only the variance matters, this leads to  $\alpha^* = \alpha_{lb}$ . However, they disregarded the possibility of having other extrema, which we expect to exist [2,3] if there is some structure in the data along  $\lambda$ . We show here that the global maximum may jump from  $q^* = 0$  to a *finite* value  $q^* \equiv q_1$ , at  $\alpha^* = \alpha_1 < \alpha_{lb}$ . Consider data with components along  $\lambda$  drawn according to

$$
P(\lambda) = \frac{1}{2\sigma\sqrt{2\pi}} \left[ e^{-(\lambda-\rho)^2/2\sigma^2} + e^{-(\lambda+\rho)^2/2\sigma^2} \right].
$$
 (2)

A straightforward calculation shows that  $G_\alpha(q)$  has indeed a maximum at  $q_1 > 0$ , which may overcome the one at  $q = 0$  for some values of  $\rho$  and  $\sigma$ . This *first order* phase transition of the upper bound signals the onset of a phase where learning is possible at  $\alpha_1 < \alpha_{lb}$ . In Fig. 1 we represent  $\alpha_1$  and  $\alpha_{lb}$  as a function of  $\rho$ , for  $\sigma = 0.5$ . It may be seen that  $\alpha_1(\rho)$  leaves  $\alpha_{lb}(\rho)$  with a discontinuous slope at  $\rho = 0.7023(7)$  [ $\alpha_1 = \alpha_{lb} = 15.177(9), q_1 =$ 0.900(5)] [the inset shows the two maxima of  $G(q)$ ], but smoothly at  $\rho = 1.338(1)$  ( $q_1 = 0, \alpha_1 = \alpha_{lb} = 0.96$ ). In the latter case, both the second and fourth order coefficients of the *q* expansion of  $G_{\alpha}(q)$  vanish at the transition. The other inset represents  $G_{\alpha}(q)$  for  $\rho = 1$ ; the transition occurs at  $\alpha_1 = 4.477(5) < \alpha_{1b} = 16$ , at which  $q^*$  jumps from 0 to  $q_1 \sim 0.876(4)$ .

In some limiting cases, the first order transition may occur with a jump of  $q^*$  from 0 directly to  $q^* = 1$  at



FIG. 1. Lower bound to the fraction of examples  $\alpha$  below which learning is impossible, as a function of  $\rho$  for  $\sigma = 0.5$ . Insets:  $G(q)$  showing the maxima at  $q = 0$  and at  $q_1 > 0$ , for the two particular values of  $(\alpha_1, \rho)$  indicated by the arrows.

 $\alpha^* = \alpha_1 = 1$ . This arises, for example, for  $P(\lambda) =$ 2  $\sum_{\tau=\pm 1} \delta(\lambda - \tau \rho) + \frac{1-a}{2}$  $\sum_{\tau=\pm 1}$   $\delta(\lambda - \tau \rho')$ , when  $a = 0.2, \rho = 0.5, \rho' = 1.4.$ 

One of the main conclusions of Ref. [1], based on this upper bound, is that retarded learning exists whenever  $\lambda = 0$ . This conclusion is not invalidated by the present analysis: although there is no simple and general expression for  $\alpha^*$ , it can be shown that  $0 < \alpha^* \leq \alpha_{1b}$ .

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