

Chernoff and Hoeffding Bounds

Let us consider a sequence of independent random variables

X_1, X_2, \dots, X_m such that

$$X_i = \begin{cases} 1 & \text{with probability } p \\ 0 & \text{with probability } 1-p \end{cases}$$

The sample mean is given by

$$\hat{p} = \frac{1}{m} \sum_{i=1}^m X_i.$$

Here, we want to get the upper bound of the probability

$$\Pr\{\hat{p} > q\} \quad \text{for any } q > p.$$

For any $\lambda > 0$,

$$\Pr\{\hat{p} > q\} = \Pr\{e^{m\lambda\hat{p}} > e^{m\lambda q}\}$$

since $e^{m\lambda x}$ is monotone increasing in x .

By taking the expectation of $e^{m\lambda x}$, we get

$$E[e^{m\lambda\hat{p}}] \geq e^{m\lambda q} \Pr\{e^{m\lambda\hat{p}} > e^{m\lambda q}\} + 0 \cdot \Pr\{e^{m\lambda\hat{p}} \leq e^{m\lambda q}\}.$$

This implies that

$$\Pr\{\hat{p} > q\} \leq e^{-m\lambda q} E[e^{m\lambda\hat{p}}] \quad \text{and}$$

$$\begin{aligned} E[e^{m\lambda\hat{p}}] &= E\left[e^{\lambda \sum_{i=1}^m X_i}\right] = E\left[\prod_{i=1}^m e^{\lambda X_i}\right] = \prod_{i=1}^m E[e^{\lambda X_i}] \\ &= \prod_{i=1}^m [pe^\lambda + (1-p)e^0] \\ &= [pe^\lambda + (1-p)]^m \end{aligned}$$

Thus,

$$\Pr\{\hat{p} > q\} \leq e^{-m\lambda q} [pe^\lambda + (1-p)]^m = e^{-m\lambda q + m \ln[pe^\lambda + (1-p)]} \\ \leq e^{-mf_\lambda(p,q)}$$

where

$$f_\lambda(p,q) = \lambda q - \ln[pe^\lambda + (1-p)]$$

For the tightest bounds, $f_\lambda(p,q)$ should be maximized.

Here, the optimal value of λ is given as follows:

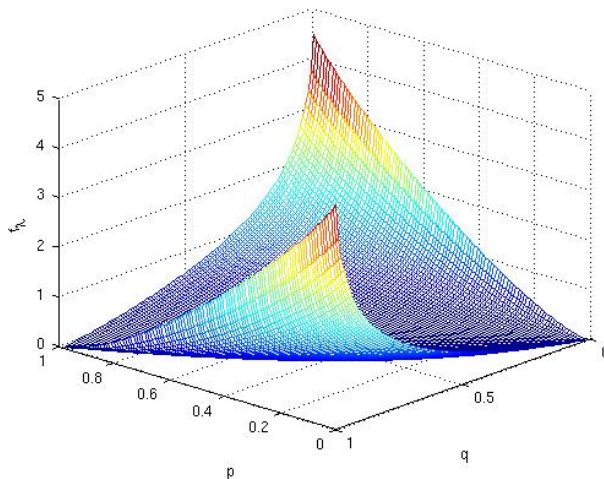
$$\frac{\partial f_\lambda}{\partial \lambda} \Big|_{\lambda^*} = 0 \rightarrow \lambda^* = \ln \frac{q(1-p)}{p(1-q)}$$

That is,

$$f_{\lambda^*}(p,q) = q \ln \frac{q}{p} + (1-q) \ln \frac{1-q}{1-p}.$$

This implies that $f_{\lambda^*}(p,q)$ is the Kullback–Leibler (KL) distance between q and p , that is,

$$f_{\lambda^*}(p,q) = D(q||p) = q \ln \frac{q}{p} + (1-q) \ln \frac{1-q}{1-p}.$$



Three important examples:

$$(1) D(q||p) \geq 2(p-q)^2$$

$$\Pr\{\hat{p} > q\} \leq e^{-2m(p-q)^2} \quad (\text{additive Chernoff bound})$$

Taking the union of two cases:

$$\hat{p} > q > p \quad \text{and} \quad \hat{p} < q < p$$

$$\Pr\{|\hat{p} - p| > \epsilon\} \leq 2e^{-2m\epsilon^2} \quad (\text{Hoeffding bound})$$

$$(2) \text{ If } q \geq p, \quad D(q||p) \geq \frac{1}{3} \frac{(q-p)^2}{p}$$

$$\Pr\{\hat{p} > q\} \leq e^{-\frac{1}{3}m \frac{(q-p)^2}{p}} \quad (\text{multiplicative Chernoff bound})$$

$$(3) \text{ If } q \leq p, \quad D(q||p) \geq \frac{1}{2} \frac{(q-p)^2}{p}$$

$$\Pr\{\hat{p} > q\} \leq e^{-\frac{1}{2}m \frac{(p-q)^2}{p}} \quad (\text{multiplicative Chernoff bound})$$

Example: Hoeffding bound

Let p and \hat{p} be the true and empirical errors. Then,

$$\Pr\{|\hat{p}-p|>\epsilon\}\leq 2e^{-2m\epsilon^2}.$$

Assuming the finite hypothesis, that is, $|H|$ is bounded by some number. What is the sufficient number of samples to assure the best hypothesis?

For PAC learning,

$$\Pr\{|\hat{p}-p|>\epsilon\}\leq 2|H|e^{-2m\epsilon^2}\leq\delta.$$

$$2|H|e^{-2m\epsilon^2}\leq\delta\rightarrow e^{-2m\epsilon^2}\leq\frac{\delta}{2|H|}\rightarrow m\geq\frac{1}{2\epsilon^2}\ln\frac{2|H|}{\delta}.$$