

Chapter 1 Chapter 1

- estimation ✓
- prediction ✓
- learning

① flip coin n times

observe $x_1, \dots, x_n$

$$P\{x_i = 1\} = \theta \in (0, 1)$$

$$\hat{\theta}(x_1, \dots, x_n) = \frac{1}{n} \sum_{i=1}^n x_i$$

Hoeffding $\Rightarrow$

$$P\{| \theta - \hat{\theta} | > \epsilon\} \leq \frac{2e^{-2n\epsilon^2}}{\delta}$$

$$2e^{-2n\epsilon^2} = \delta \quad n(\epsilon, \delta) = \left\lceil \frac{1}{2\epsilon^2} \ln(2/\delta) \right\rceil$$

If $n \geq n(\epsilon, \delta)$ then $P\{| \theta - \hat{\theta} | \leq \epsilon\} \geq 1 - \delta$

$$\epsilon = .01 \quad \delta = .01$$

$$5000 \ln 40$$

② Prediction Suppose we know θ .

$x_1, x_2, \dots$ $\text{Be}(\theta)$

$$P\{x_i = 1\} = \theta$$

$$P\{x_i = 0\} = 1 - \theta$$

$$f^* = \begin{cases} 1 & \text{if } \theta \geq 1/2 \\ 0 & \text{if } \theta < 1/2 \end{cases}$$

Optimal predictor if θ is known. .25 set $f^* = 0$

Loss $L_\theta(f^*) = P_\theta\{x_i \neq f^*\} = \min\{\theta, 1 - \theta\}$

(3) A learning algorithm maps data

$x_1, \dots, x_n$ to a predictor.

$$A_n(x_1, \dots, x_n) = \hat{f} \quad \text{where} \quad \hat{f} = \frac{1}{n} \sum_{i=1}^n \hat{f}_i$$

$$\hat{f} = \begin{cases} 0 & \text{if } \hat{G} \leq \frac{1}{2} \\ 1 & \text{if } \hat{G} > \frac{1}{2} \end{cases}$$

Idea Select the predictor that works best on the training data:

$$\hat{f} = \arg \min_{f \in \{0,1\}} \left\{ \sum_{i=1}^n 1_{\{x_i \neq f\}} \right\}$$

$$\sqrt{x_i - f} \quad (x_i - f)^2$$