

# Machine Learning Topic 1

## Introduction and Binary Classification

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## Binary Classification

- Definitions  $\mu$  and  $\eta$ : *slide 4*
- Definition of  $R(g)$  as function of  $g(X)$  and of expected loss: *slide 5*
- Definition of **Bayes Classifier**  $g^*(x)$ : *slide 5*
  - Bayes Classifier Theorem: *bottom of slide 5*
  - Proof Bayes classifier is optimal: *slide 6*
- Definition of **plug-in classifier**: *slide 7*
- Data-based classifier and its risk: *slide 8*
- Consistency, universal and strong: *slide 9*

### Notes

- How do we classify? Pick whichever class-conditional density is bigger!
- When you expand the variance of  $R(g) = \mathbb{E}[R(g) - R_n(g)]^2$ , expanding the expected value reveals only terms in  $R(g)$  and you find that the variance is small when  $R(g)$  is small

## Definitions

$\eta(x) = \frac{\mathbb{P}\{Y=1\}f_1(x)}{f(x)}$ , where  $f_1(x)$  is the conditional distribution of  $x$  given  $Y = 1$

$$f(x|Y = 1) = \frac{f(x)\mathbb{P}(Y=1|X=x)}{\mathbb{P}(Y=1)}$$

$$\mathbb{P}\{Y = 1\} = \mathbb{E}[\eta(x)]$$

$$\mathbb{P}\{X \in A\} = \mathbb{P}\{Y = 1\}f_1(x|Y = 1) + \mathbb{P}\{Y = 0\}f_0(X|Y = 0)$$

### Risk

$$R(g) = 1 - \mathbb{E}[\mathbb{I}_{g(X)=1}\eta(X)] - \mathbb{E}[\mathbb{I}_{g(X)=0}(1 - \eta(X))]$$

$$R(g_n) = \frac{1}{n} \text{Bin}(n, R(g))$$

$$\mathbb{E}[R(g_n)] = \frac{1}{n}(nR(g)) = R_g$$

$\bar{R}$ : best risk of family

$\hat{R}_n$ : empirical risk

### Bayes Risk

$$R^* = \inf_{g: \mathcal{R}^d \rightarrow \{0,1\}} \mathbb{P}\{g(X) \neq Y\}$$

$$= \mathbb{E}[\min(\eta(x), 1 - \eta(x))]$$

$$\begin{aligned}
&= \frac{1}{2} - \frac{1}{2} \mathbb{E} \left\{ |2\eta(X) - 1| \right\} \\
&= \int \min(\eta(x), 1 - \eta(x)) f(x) dx \text{ if } X \text{ has density } f(x) \\
&= \int \min((1-p)f_0(x), pf_1(x)) dx \text{ if } X \text{ has class-conditional densities } f_i(x) \\
&R^* = 0 \text{ when } \eta \in \{0, 1\} \text{ everywhere}
\end{aligned}$$

## Error Estimation

### Error-counting estimator:

(8.1) Given,  $m$  is the **testing** sequence:

$$\hat{L}_{n,m} = \frac{1}{m} \sum_{j=1}^m \mathbb{I}_{g_n(X_{n+j}) \neq Y_{n+j}}$$

Clearly unbiased:  $\mathbb{E}\{\hat{L}_{n,m}|D_n\} = L_n$

The conditional distribution of  $\hat{L}_{n,m}$  given  $D_n$  is binomial with paramters  $m$  and  $L_n$