

CSE 512 Spring 2021 - Machine Learning - Homework 3

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1.) 1.1.1.) For a binary classification problem,

$$r^*(x) = \min(\text{loss}(\hat{y}=0|x=1)P(x=1), \text{loss}(\hat{y}=1|x=0)P(x=0))$$

$$P(x=1) = \eta(x), \quad P(x=0) = 1 - \eta(x)$$

$$\text{loss}(\hat{y}=1|x=0) = \alpha, \quad \text{loss}(\hat{y}=0|x=1) = 1$$

$$r^*(x) = \min(1 \cdot \eta(x), \alpha(1 - \eta(x)))$$

$$\text{Optimal Bayes risk } r^*(x) = \min(\eta(x), \alpha(1 - \eta(x)))$$

1.1.2.) asymptotic risk:

$$r(x) = \underbrace{\eta(x)}_{\substack{\text{Prob of +ve class} \\ \times \text{prob of} \\ \text{-ve class}}} \underbrace{\alpha(1 - \eta(x))}_{\substack{\text{Cost of false} \\ \text{positive}}} + \underbrace{(1 - \eta(x))}_{\substack{\text{Prob of} \\ \text{-ve class}}} \underbrace{\eta(x)}_{\substack{\text{Prob of} \\ \text{+ve class}}}$$

$$1.1.3.) \quad r(x) = \alpha \eta(x)(1 - \eta(x)) + (1 - \eta(x)) \eta(x)$$

$$r(x) = (1 + \alpha) \eta(x)(1 - \eta(x)) \rightarrow \textcircled{1}$$

$$r(x) \leq (1 + \alpha) \alpha \eta(x)(1 - \eta(x)) \quad (\because \alpha > 1)$$

$$r(x) \leq (1 + \alpha) \eta(x) \alpha (1 - \eta(x))$$

$$r(x) \leq (1 + \alpha) r^*(x)(1 - r^*(x)) \quad (\text{From symmetry})$$

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$$1.1.4) \mathcal{R} = E(r(x)), \quad R^* = E(r^*(x))$$

$$r(x) \leq (1+\alpha) r^*(x) (1-r^*(x))$$

$$r(x) \leq (1+\alpha) (r^*(x) - (r^*(x))^2)$$

$$E(r^*(x)) = (E(r^*(x)))^2 + \text{Var}(r^*(x)) \geq E(r^*(x)) \Rightarrow E((r^*(x))^2) \geq E(r^*(x))$$

$$E(r(x)) \leq (1+\alpha) (E(r^*(x)) - E((r^*(x))^2))$$

$$R \leq (1+\alpha) (R^* - (R^*)^2)$$

$$R \leq (1+\alpha) R^* (1-R^*)$$

$$\left\{ \begin{array}{l} R \leq \frac{1+\alpha}{\alpha} (R^* - (R^*)^2) \quad \leftarrow \text{From (1)} \\ R \leq (1+\alpha) R^* (1-R^*) \end{array} \right. \quad \underline{\alpha > 1}$$

$$1.2.1) \quad r(x) = \eta(x) (1 - g(\eta, k)) + g(\eta, k) (1 - \eta(x))$$

$$1.2.2) \quad \text{We know, } g(\eta, k) = \sum_{i=\frac{k+1}{2}}^k k C_i \eta^i (1-\eta)^{k-i}$$

$$g(\eta, k) + g(1-\eta, k) = 1 \quad \rightarrow \quad (\eta + 1-\eta)^k = 1^k = 1$$

$$r^*(x) = \min(\eta(x) (1 - g(\eta, k)), g(\eta, k) (1 - \eta(x))) \quad \text{--- (1)}$$

$$(\because g(\eta, k) = 1 - g(1-\eta, k) \text{ \& vice versa } \dots)$$

$$r^*(x) = \min(\eta(x) g(1-\eta, k), g(\eta, k) (1 - \eta(x))) \quad \text{--- (2)}$$

$$r^*(x) = \min(\eta, 1-\eta)$$

$$r(x) = \eta(x) + g(\eta, k) - 2\eta(x) g(\eta, k) \quad (\text{via From (1)})$$

①

$$\begin{aligned}
x(x) &= \eta(x) g(1-\eta, k) + g(\eta, k) (1-\eta(x)) \\
&= \eta(x) g(1-\eta, k) + (1-g(1-\eta, k))(1-\eta(x)) \\
&= \eta(x) g(1-\eta, k) + 1 - \eta(x) - g(1-\eta, k) + \eta(x) g(1-\eta, k) \\
&= 1 - \eta(x) - g(1-\eta, k) + 2\eta(x) g(1-\eta, k) \\
&= 1 - \eta(x) + g(1-\eta, k) + 2\eta(x) g(1-\eta, k) - 2g(1-\eta, k) \\
x(x) &= 1 - \eta(x) + g(1-\eta, k) - 2(1-\eta(x))g(1-\eta, k). \quad (\text{From (2)})
\end{aligned}$$

$\Rightarrow x(x)$ is same for $x^*(x)$ being $\eta(x)$ or $1-\eta(x)$.

By symmetry,

$$x(x) = x^*(x) + g(x^*, k) - 2x^*(x)g(x^*, k)$$

$$x(x) = x^*(x) + (1 - 2x^*(x))g(x^*(x), k).$$

1.2.3) Hoeffding inequality,

$$P(H(n) \geq (p+\epsilon)n) \leq \exp(-2\epsilon^2 n).$$

Here $n = k$

$$p = \eta$$

we need atleast $\frac{k+1}{2}$ +ve $\Rightarrow P(H(n) \geq \frac{k+1}{2}) = g(\eta, k)$

$$\Rightarrow (p+\epsilon)n = \frac{k+1}{2}$$

$$(\eta+\epsilon)k = \frac{k+1}{2} \Rightarrow \epsilon = \frac{1}{2} - \eta + \frac{1}{2k}$$

As $\frac{1}{2k} \rightarrow 0 \Rightarrow k \rightarrow \infty$ i.e. $\eta \rightarrow x^*$

$$g(r^*(x), k) \leq \exp(-2 \xi^2 n)$$

$$\xi = \frac{1}{2} - r^*(x)$$

$$\therefore g(r^*(x), k) \leq \exp(2(0.5 - r^*(x))^2 k)$$

(v)

$$1.2.4. \quad \pi(x) = r^*(x) + (1 - 2r^*(x)) g(r^*(x), k)$$

(vi)

$$\pi(x) - r^*(x) = (1 - 2r^*) g(r^*, k) \leq (1 - 2r^*) e^{-2(\frac{1}{2} - r^*)^2 k}$$

$$\pi(x) - r^*(x) \leq (1 - 2r^*) e^{-(1 - 2r^*)^2 k/2}$$

let's find maximum of $u e^{-u^2 k/2}$ w.r.t u . (Minimum is 0)

$$\text{Derivative} = 0 \Rightarrow e^{-u^2 k/2} + u e^{-u^2 k/2} \cdot (-2u k/2) = 0$$

(vii)

$$1 - u^2 k = 0 \Rightarrow u^* = 1/\sqrt{k}$$

$$\text{Max}(u e^{-u^2 k/2}) = \frac{1}{\sqrt{k}} \cdot e^{-\frac{1}{2}} = \frac{1}{\sqrt{k}} e^{-1/2} = \frac{1}{\sqrt{k}e}$$

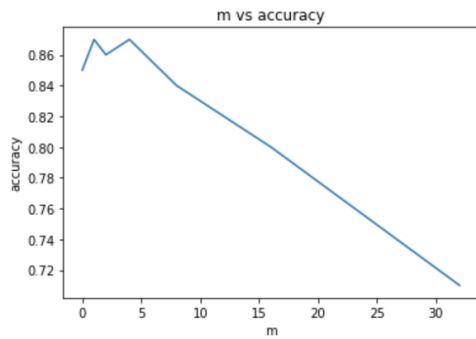
$$\therefore \pi(x) - r^*(x) \leq \text{Max}((1 - 2r^*) e^{-(1 - 2r^*)^2 k/2})$$

$$\pi(x) - r^*(x) \leq \frac{1}{\sqrt{k}e} \leq \frac{1}{\sqrt{2k}} \quad (e \approx 2.81)$$

$$\pi(x) \leq r^*(x) + \frac{1}{\sqrt{2k}}$$

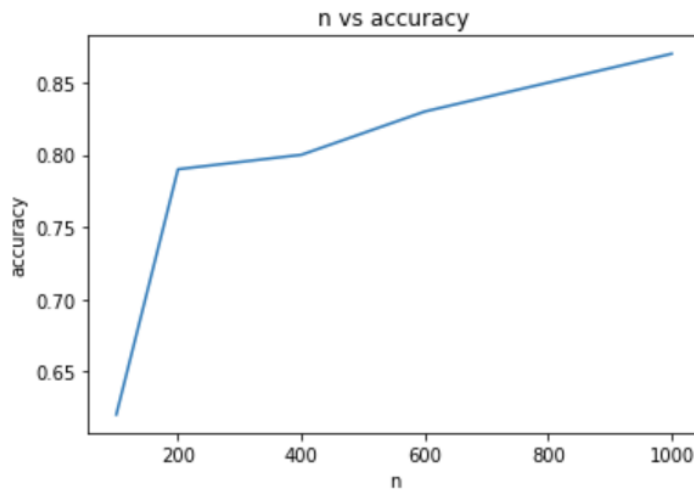
As $k \rightarrow \infty$, $\pi(x) \rightarrow r^*(x)$
Bayes risk.

→ [0, 1, 2, 4, 8, 16, 32] [0.85 0.87 0.86 0.87 0.84 0.8 0.71]



2.2.1) With increasing k value, the accuracy is getting lowered. In the beginning with increasing k value, accuracy was around 0.85 and then instantaneously decreased for $m = 16$ and kept decreasing for greater values of m.

→ [100, 200, 400, 600, 800, 1000] [0.62 0.79 0.8 0.83 0.85 0.87]



2.2.2) With increasing training data, the accuracy is increasing and settles at 0.87.

0.83

2.2.3) The accuracy is lower than accuracy using euclidean distance. The accuracy obtained is 0.83 whereas using euclidean we get 0.87 for $k=3$.



2.2.4)



Original : 2

2

5

5

5

5

5

5

5

5

Original : 8

8

3

3

9

9

4

4

9

9

Original : 2

2

7

7

3

3

7

7

9

9