



Machine Learning CS F464

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Contents

Gaussian for classification

Gaussian for Classification



- Used for classifying continuous data.
- Consider a random variable x whose probability density function (pdf), given class C is a Gaussian with mean μ_c and variance σ_c^2 . Using Bayes' theorem,

$$P(C|x) \propto p(x|C) P(C)$$

$$\propto N(x; \mu_c, \sigma_c^2) P(C)$$

$$\propto \frac{1}{\sqrt{2\pi\sigma_c^2}} \exp\left(\frac{-(x - \mu_c)^2}{2\sigma_c^2}\right) P(C)$$

• Where, p(x/C) is the likelihood of class C given observation x.

•
$$\mu_c = \frac{\sum_{i=1}^n x_i}{n}, \ \sigma_c^2 = \frac{1}{n} \sum_{i=1}^n (x_i - \mu_c)^2$$

- Log Likelihood and Log Probabilities (1)
 - Use log to deal with Gaussian.
 - Log likelihood of the Gaussian probability distribution is, $LL(x|C) = LL(x|\mu_c, \sigma_c^2)$

$$LL(x|\mu_c, \sigma_c^2) = \ln p(x|\mu_c, \sigma_c^2)$$

$$= \ln \left[\frac{1}{\sqrt{2\pi\sigma_c^2}} \exp\left(\frac{-(x-\mu_c)^2}{2\sigma_c^2}\right) \right]$$

$$= -\ln\left(\sqrt{2\pi\sigma_c^2}\right) - \frac{(x-\mu_c)^2}{2\sigma_c^2}$$

$$= \frac{1}{2} \left(-\ln(2\pi) - \ln \sigma_c^2 - \frac{(x-\mu_c)^2}{\sigma_c^2}\right)$$

Using Bayes theorem Log posterior probabilities are,

$$LP(C|x) = LL(x|C) + LP(C) + \text{const.}$$

$$= \frac{1}{2} \left(-\ln(2\pi) - \ln\sigma_c^2 - \frac{(x - \mu_c)^2}{\sigma_c^2} \right) + \ln P(C) + \text{const.}$$

where LP(C) is the log prior probability of class C, and 'const.' is the log of the constant of proportionality, p(x).

Log probability ratio

• If c1 and c2 are modelled by Gaussians with means μ_a and μ_b , and variances σ_a^2 and σ_b^2 , then we can write the log odds (ratio of posterior probabilities) as follows,

$$\ln \frac{P(c_1|x)}{P(c_2|x)} = \ln P(c_1|x) - P(c_2|x)$$

$$\ln \frac{P(c_1|x)}{P(c_2|x)} = \frac{1}{2} \left(-\ln(2\pi) - \ln \sigma_a^2 - \frac{(x - \mu_a)^2}{\sigma_a^2} \right)$$

$$- \frac{1}{2} \left(-\ln(2\pi) - \ln \sigma_b^2 - \frac{(x - \mu_b)^2}{\sigma_b^2} \right) + (\ln P(c_1) - \ln P(c_2))$$

$$= -\frac{1}{2} \left(\frac{(x - \mu_a)^2}{\sigma_a^2} - \frac{(x - \mu_b)^2}{\sigma_b^2} + \ln \sigma_a^2 - \ln \sigma_b^2 \right) + \ln P(c_1) - \ln P(c_2). \tag{4}$$

Example (1)

Consider a following dataset,

- The following unlabelled data points are available: x1 = 10, x2 = 11, x3 = 6
- To which class each data points will be assigned if the two classes have equal prior probabilities.
- Step 1: Find the mean and variance

$$\hat{\mu}(S) = 10 \qquad \hat{\sigma}^2(S) = 1$$

$$\hat{\mu}(T) = 12 \qquad \hat{\sigma}^2(T) = 4$$

Example (2)

Step 2: Calculate log posterior probability ratio.

$$\ln \frac{P(S \mid X = x)}{P(T \mid X = x)} = -\frac{1}{2} \left(\frac{(x - \mu_S)^2}{\sigma_S^2} - \frac{(x - \mu_T)^2}{\sigma_T^2} + \ln \sigma_S^2 - \ln \sigma_T^2 \right) + \ln P(S) - \ln P(T)$$

$$= -\frac{1}{2} \left(\frac{(x - \mu_S)^2}{\sigma_S^2} - \frac{(x - \mu_T)^2}{\sigma_T^2} + \ln \sigma_S^2 - \ln \sigma_T^2 \right)$$

$$= -\frac{1}{2} \left((x - 10)^2 - \frac{(x - 12)^2}{4} - \ln 4 \right)$$

If the log ratio is less than 0, then assign to class T, otherwise assign to class S.



Step 3: Consider each value of x and calculate log posterior probability ratio.

$$x_1 = 10$$
:

Example (3)

$$\ln \frac{P(S \mid X = x_1)}{P(T \mid X = x_1)} = -\frac{1}{2} \left((x_1 - 10)^2 - \frac{(x_1 - 12)^2}{4} - \ln 4 \right)$$
$$= -\frac{1}{2} (0 - 1 - \ln 4)$$
$$= 1.19$$
Class S

$$x_2 = 11$$
:

$$\ln \frac{P(S \mid X = x_2)}{P(T \mid X = x_2)} = -\frac{1}{2} \left((x_2 - 10)^2 - \frac{(x_2 - 12)^2}{4} - \ln 4 \right)$$
$$= -\frac{1}{2} (1 - 0.25 - \ln 4)$$
$$= 0.32$$
 Class S





$$x_3 = 6$$
:

$$\ln \frac{P(S \mid X = x_3)}{P(T \mid X = x_3)} = -\frac{1}{2} \left((x_3 - 10)^2 - \frac{(x_3 - 12)^2}{4} - \ln 4 \right)$$
$$= -\frac{1}{2} (16 - 9 - \ln 4)$$
$$= -2.81$$
Class T

Practice Problem:

Consider different probabilities, P (S) = 0.3 and P(T) = 0.7. Including this prior information, to which class should each of the above test data points $\{x1, x2, x3\}$ be assigned?

Hint: The log posterior probability ratios is,

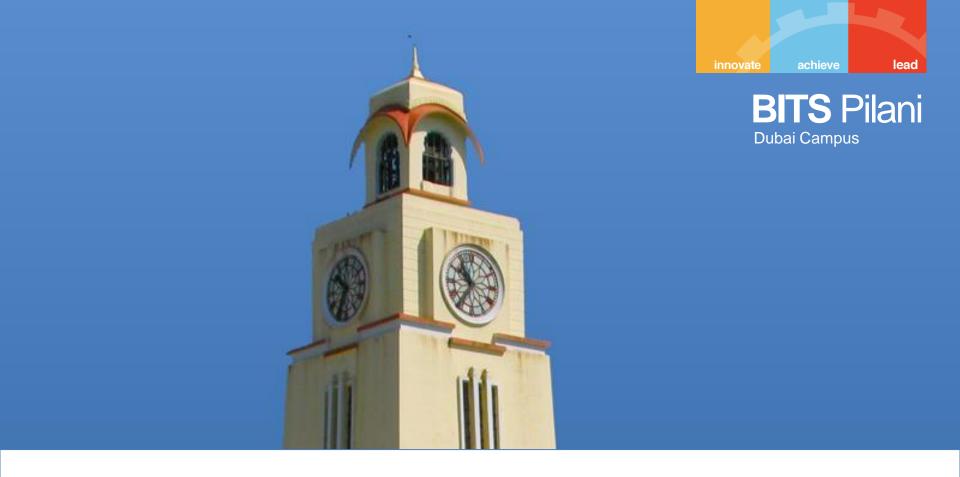
$$\ln \frac{P(S \mid X = x)}{P(T \mid X = x)} = -\frac{1}{2} \left(\frac{(x - \mu_S)^2}{\sigma_S^2} - \frac{(x - \mu_T)^2}{\sigma_T^2} + \ln \sigma_S^2 - \ln \sigma_T^2 \right) + \ln P(S) - \ln P(T)$$

$$= -\frac{1}{2} \left((x - 10)^2 - \frac{(x - 12)^2}{4} - \ln 4 \right) + \ln P(S) - \ln P(T)$$

$$= -\frac{1}{2} \left((x - 10)^2 - \frac{(x - 12)^2}{4} - \ln 4 \right) + \ln(3/7)$$

Sources

- http://people.cs.ksu.edu/~hankley/d764/Slides07/C hou_Reasoning.ppt
- http://www.inf.ed.ac.uk/teaching/courses/inf2b/learn notes/
- Chapter 6, Tom M. Mitchell, Machine Learning, The McGraw-Hill Companies, 1st edition 2013.
- https://www.udemy.com/course/python-for-datascience-and-machine-learning-bootcamp



Thank You!