Machine Learning Exercise sheet 5

Linear Classification

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17/10/2019

Problem (): a) exponential distribution

$$p(y=c|x) \propto p(x|y=c) \cdot p(y=c) \Leftrightarrow$$

$$p(y=o|x) \propto \frac{30}{2} e^{-30x} \text{ (which is an exponential distribution)}$$

x is classified as L when b)

$$\rho(y=1|x) > \rho(y=0|x)$$

$$\frac{1}{2} \lambda_1 e^{-\lambda_1 x}$$

$$\frac{1}{2} \lambda_1 e^{-\lambda_1 x} + \frac{1}{2} \lambda_0 e^{-\lambda_0 x}$$

$$\rho(y=0|x) = \frac{\frac{1}{2} \lambda_0 e^{-\lambda_0 x}}{\frac{1}{2} \lambda_0 e^{-\lambda_0 x} + \frac{1}{2} \lambda_1 e^{-\lambda_1 x}}$$

$$\frac{\frac{1}{2} \lambda_{1}e^{-\lambda_{1}x}}{\frac{1}{2} \lambda_{0}e^{-\lambda_{0}x}} > \frac{\frac{1}{2} \lambda_{0}e^{-\lambda_{0}x}}{\frac{1}{2} \lambda_{0}e^{-\lambda_{0}x} + \frac{1}{2} \lambda_{1}e^{-\lambda_{1}x}} \Leftrightarrow \frac{1}{2} \lambda_{0}e^{-\lambda_{0}x} + \frac{1}{2} \lambda_{1}e^{-\lambda_{1}x} \Leftrightarrow \frac{1}{2} \lambda_{0}e^{-\lambda_{0}x} + \frac{1}{2} \lambda_{0}e^{-\lambda_{0}x} + \frac{1}{2} \lambda_{1}e^{-\lambda_{1}x} \Leftrightarrow \frac{1}{2} \lambda_{0}e^{-\lambda_{0}x} + \frac{1}{2} \lambda_{0}e^{-\lambda_{0}x} \Leftrightarrow \frac{1}{2} \lambda_{0}e^{-\lambda_{0}x} \Leftrightarrow \frac{1}{2} \lambda_{0}e^{-\lambda_{0}x} + \frac{1}{2} \lambda_{0}e^{-\lambda_{0}x} \Leftrightarrow \frac{1}{2} \lambda_{0}e$$

$$\lim_{\lambda \to \infty} \left(\frac{\lambda_1}{\lambda_0} \right)^2 > -2 \left(\frac{\lambda_0 + \lambda_1}{\lambda_0 + \lambda_1} \right) \times \iff \frac{\lambda_0 + \lambda_1 + \lambda_0}{\lambda_0 + \lambda_1 + \lambda_0} \xrightarrow{\text{of exp}}$$

$$\times \left(- \lim_{\lambda \to \infty} \left(\frac{\lambda_1}{\lambda_0} \right) \right)$$

$$= \frac{\lambda_0 + \lambda_1 + \lambda_0}{\lambda_0 + \lambda_1}$$

Problem (2):

sigmoid function: 1

1+e-wx

If we plot the sigmoid function for increasing values of w, we observe that the curve gets steeper as w increases. Steeper curve means that the model is almost sure about the class. (almost O probability or almost L), which means overfitting.

b) To prevent overtiting we want the weights to be smoul. To achieve this, instead of maximum conditional likelihood estimation we can consider maximum conditional a posterior where we assume Gaussian prior for the weight vector.

softmax :
$$\sigma(x)$$
: = $\exp(xi)$

$$\frac{\Sigma}{\sum_{k=1}^{K} \exp(X_k)}$$

$$\sigma(x)i = \frac{e^{x_0}}{e^{x_0}} = \frac{\frac{e^{x_0}}{e^{x_0}}}{\frac{e^{x_0}+e^{x_1}}{e^{x_0}}} = \frac{1}{1+\frac{e^{x_1}}{e^{x_0}}} = \frac{1}{1+\frac{e^{x_1}}{e^{x_0}}}$$

$$\frac{1}{1+e^{X_1-X_0}}$$
 (1) . Set $X_1-X_0=Z$

$$(L) = \frac{1}{1 + e^2} = sigmoid(2) = sigmoid(x_1 - x_0)$$

Problem 4: X1 X2

We notice that circles have negative negative positive positive crosses have positive negative

so if the transformation is q(X1X2, X2) one group (circles) will have positive x while the other group (crosses) megactive.