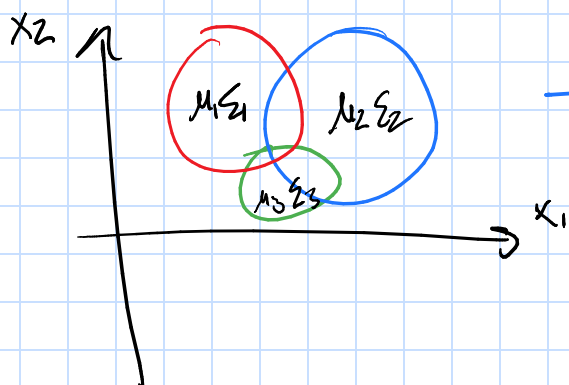


lecture 01/29/2021

How do we get the likelihood?



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

$$\vec{x} = [x_1, x_2, \dots, x_d]$$

$$p(x | w_j) = p(x_1 | w_j) p(x_2 | w_j) \dots$$

$$= \prod_{i=1}^d p(x_i | w_j)$$

What could be problematic here?

$$p(x | w_j) = \frac{1}{\sqrt{2\pi} \sigma_j} \exp\left(-\frac{(x - \mu_j)^2}{\sigma_j^2}\right)$$

$$\log p(x | w_j) = \log \prod_{i=1}^d p(x_i | w_j)$$

$$= \sum \log p(x_i | w_j)$$

Recap

We want to find a linear model

$$g(x) = w^T x + b \rightarrow y \in \{-1, 1\}$$

$$l(w) = \frac{1}{2} \sum_{i=1}^n (y_i - [w^T x_i + b])^2$$

Assume two classes $\{-1, 1\}$

$$g(x_1) = 0.125$$

$$g(x_2) = 22.95$$

$$g(x_3) = -0.01$$

We want to interpret $g(x)$ as a probability, but that is not the current form of $g(x)$.

Logistic Regression

For the recurrence relation, see Logistic map.

A logistic function or logistic curve is a common S-shaped curve (sigmoid curve) with equation

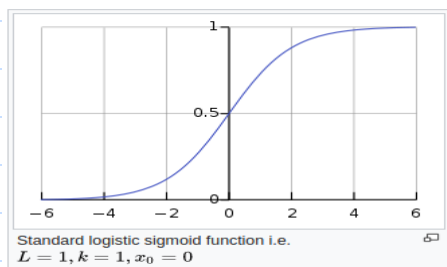
$$f(x) = \frac{L}{1 + e^{-k(x-x_0)}}$$

where

x_0 , the x value of the sigmoid's midpoint;

L , the curve's maximum value;

k , the logistic growth rate or steepness of the curve.^[1]



Assume, that we have a binary prediction task
 $y \in \{0, 1\}$ y here is bernoulli

$$P(Y=1|x) = \frac{P(X|Y=1)P(Y=1)}{P(X|Y=1)P(Y=1) + P(X|Y=0)P(Y=0)}$$

$$\frac{\frac{1}{P(X|Y=1)P(Y=1)}}{\frac{1}{P(X|Y=1)P(Y=1)} + \frac{1}{P(X|Y=0)P(Y=0)}}$$

$$= \frac{1}{1 + \exp\left\{\log\left\{\frac{P(Y=0)P(X|Y=0)}{P(Y=1)P(X|Y=1)}\right\}\right\}}$$

$$\begin{aligned} \log\left(\frac{a}{b}\right) &= \log(a) - \log(b) \\ \log(ab) &= \log(a) + \log(b) \end{aligned}$$

$$= \frac{1}{1 + \exp\left\{\log\left(\frac{P(Y=0)}{P(Y=1)}\right) + \log\left(\frac{P(X|Y=0)}{P(X|Y=1)}\right)\right\}}$$

$$= \frac{1}{1 + \exp\left(-\log\left(\frac{P(Y=1)}{P(Y=0)}\right) + \sum_{i=1}^d \log\left(\frac{P(x_i|Y=0)}{P(x_i|Y=1)}\right)\right)}$$

$$\log\left(\frac{P(Y=1)}{P(Y=0)}\right) + \log\left(\frac{P(X|Y=1)}{P(X|Y=0)}\right) = w_0 + w^T x$$