

Logistic regression

ML & Bayes

↓

$$(y_i | p_i) \sim \text{Bernoulli}(p_i)$$

$$(i = 1, \dots, n)$$

AMS 206  
19 Mar 19

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{i1} + \dots + \beta_{k-1} x_{i,k-1}$$

← pregnancy  
↓ age

$$\sum_{j=1}^k \beta_j x_{ij}$$

this is a special case of generalized linear models (GLMs):

Nelder & McCulloch (1982)

$$p_i = F\left(\sum_{j=1}^k \beta_j x_{ij}\right)$$

link function

continuous CDF

$$F^{-1}(p_i) = \sum_{j=1}^k \beta_j x_{ij}$$

$$F^{-1}(p_i) = \log\left(\frac{p_i}{1-p_i}\right) \Leftrightarrow F \sim \text{logistic distribution}$$

or

2

inverse CDF of  $N(0,1)$



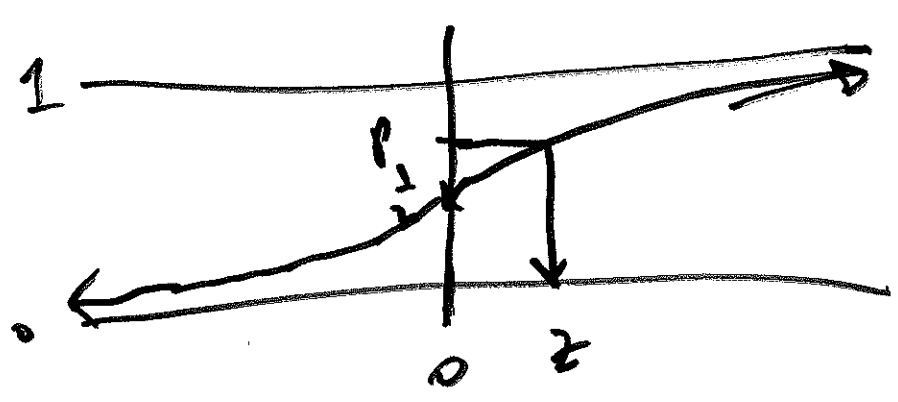
$$p_i = \sum_{j=1}^k \beta_j x_{ij}$$

K. Pearson

(1899)

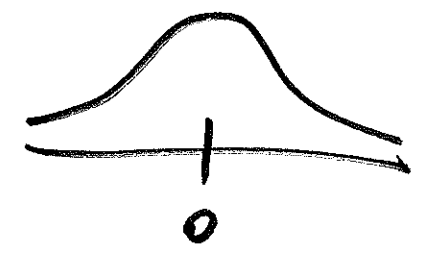
probit regression

$$\text{probit}(p_i) = \Phi^{-1}(p_i)$$



$$\Phi(z) = p$$

c) F of  $N(0,1)$



ie,  $p = \Phi(z)$

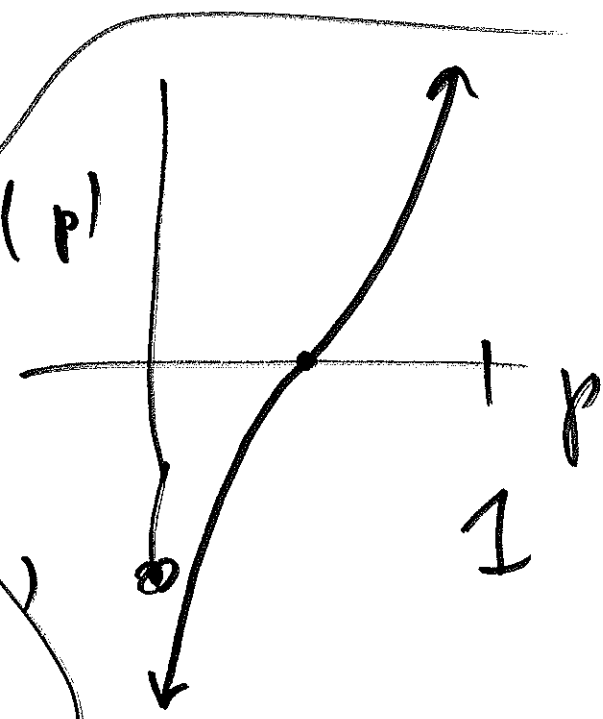
mult. lin. reg.

$$y_i = (\sum_{k=1}^k \beta_k) x_{ik} + e_i$$

$\uparrow$   
IID  
 $N(0, \sigma_e^2)$

$$\theta = (\beta_1, \dots, \beta_k, \sigma_e^2)$$

$\Phi^{-1}(p)$



$$L(\beta | y, X, Z, \mathcal{B}) =$$

$$\sum_{i=1}^n \left[ y_i \log \left\{ \frac{1}{1 + \exp[-(X\beta)_i]} \right\} \right.$$

$$\left. + (1 - y_i) \log \left\{ 1 - \frac{1}{1 + \exp[-(X\beta)_i]} \right\} \right]$$

$$\hat{\beta}_{MLE} = \underset{\beta}{\operatorname{argmax}} L(\beta | y, X, Z, \mathcal{B})$$

must be searched for numerically;  
 efficient algorithm: Fisher scoring  
 (Taylor series; Newton-Raphson)

k large: (stochastic) gradient  
descent to  $\underset{\beta}{\operatorname{argmin}} -L$

$$\left( \beta \mid N(\mu, \sigma^2) \right)$$

$$p(\beta \mid N(\mu, \sigma^2)) = c \exp\left[-\frac{1}{2\sigma^2} (\beta - \mu)^2\right]$$

$$= c \exp\left[-\frac{1}{2} (\beta - \mu)^T \left(\frac{1}{\sigma^2}\right) (\beta - \mu)\right]$$