### The logistic regression

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### Definition

We study the binary logistic model

 $Y \in \{0, 1\}$  the response X explanatory variables possibly containing factors associated with contrasts

We observe  $(X_1, Y_1), \ldots, (X_n, Y_n)$ 

We suppose that

$$\blacktriangleright Y_{i}|X_{i} = x_{i} \sim \mathscr{B}\left(\frac{\exp(x_{i}^{\mathsf{T}}\beta)}{1 + \exp(x_{i}^{\mathsf{T}}\beta)}\right)$$

▶ knowing X<sub>1</sub> = x<sub>1</sub>,..., X<sub>n</sub> = x<sub>n</sub> the variables Y<sub>i</sub> are independent

## Definition

#### We have

$$\mathbb{P}(Y = 1|X = x) = \frac{\exp(x^{T}\beta)}{1 + \exp(x^{T}\beta)} = \mathbb{E}(Y|X = x)$$
$$\mathbb{V}(Y|X = x) = \mathbb{E}(Y|X = x)(1 - \mathbb{E}(Y|X = x)) = \frac{\exp(x^{T}\beta)}{(1 + \exp(x^{T}\beta))^{2}}$$

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# We have directly modeled the distribution of $Y|X=\boldsymbol{x}$ via its expectation

This is a generalized linear model associated with the logistic link function

$$\log\left(\frac{\mathbb{E}(\mathbf{Y}|\mathbf{X}=\mathbf{x})}{1-\mathbb{E}(\mathbf{Y}|\mathbf{X}=\mathbf{x})}\right) = \mathbf{x}^{\mathsf{T}}\boldsymbol{\beta}$$

## Estimation de $\beta$

The likelihood function is

$$V(\beta) = \prod_{i=1}^{n} \left( \frac{exp(x_i^{\mathsf{T}}\beta)}{1 + exp(x_i^{\mathsf{T}}\beta)} \right)^{y_i} \left( \frac{1}{1 + exp(x_i^{\mathsf{T}}\beta)} \right)^{1-y_i}$$

The log-likelihood function is

$$L(\boldsymbol{\beta}) = \sum_{i=1}^{n} \left\{ y_{i} \boldsymbol{x}_{i}^{\mathsf{T}} \boldsymbol{\beta} - \text{log}(1 + \text{exp}(\boldsymbol{x}_{i}^{\mathsf{T}} \boldsymbol{\beta})) \right\}$$

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### Estimation de $\beta$

$$\begin{split} & \frac{\delta L}{\delta \beta}(\beta^*) = \mathbf{0}_d \\ & \Longleftrightarrow \sum_{i=1}^n \left\{ y_i x_i - \frac{x_i \exp(x_i^T \beta^*)}{1 + \exp(x_i^T \beta^*)} \right\} = \mathbf{0}_d \end{split}$$

There is no analytical solution to this system

We use an iterative algorithm derived from the Newton-Raphson procedure

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Logistic regression

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Image: A matrix

### The hessian matrix of $L(\cdot)$ is given by

$$\frac{\delta L^2}{(\delta\beta)^2}(\beta) = -\sum_{i=1}^n \frac{\text{exp}(x_i^T\beta)}{(1 + \text{exp}(x_i^T\beta))^2} x_i x_i^T$$

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The Newton-Raphson iterative procedure consists of calculating a sequence of  $\beta^{(0)}, \ldots, \beta^{(t)}, \ldots$  telle que

$$\beta^{(t)} = \beta^{(t-1)} - \left[\frac{\delta L^2}{(\delta\beta)^2}(\beta^{(t-1)})\right]^{-1} \frac{\delta L}{\delta\beta}(\beta^{(t-1)})$$

This sequence converges to a value  $\beta^*$  such that  $\frac{\delta L}{\delta \beta}(\beta^*) = 0_d$ 

Since the maximum likelihood estimator is used, it is possible to construct asymptotic confidence intervals

$$\mathbb{V}(\hat{\beta}) \approx \left[\sum_{i=1}^{n} \frac{\exp(\mathbf{x}_{i}^{\mathsf{T}}\beta)}{(1 + \exp(\mathbf{x}_{i}^{\mathsf{T}}\beta))^{2}} \mathbf{x}_{i} \mathbf{x}_{i}^{\mathsf{T}}\right]^{-1}$$

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