

# Logistic regression

Using python.

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# Logistic regression

$$\begin{aligned}P(y_i = 1) &= P_i \\P(y_i = 0) &= 1 - P_i\end{aligned}\tag{1}$$

$$P_i = \frac{1}{1 + e^{-\Theta^T x}}\tag{2}$$

# MLE

In a sample of  $n$  observations.

$$\begin{aligned} f(y_1, y_2, \dots, y_n) &= \prod_{i=1}^n f(y_i) \\ &= \prod_{i=1}^n P(y_i) \\ &= \prod_{i=1}^n P_i^{y_i} (1 - P_i)^{1-y_i} \end{aligned} \tag{3}$$

$$f(y_1, y_2, \dots, y_n) = \prod_{i=1}^n P_i^{y_i} (1 - P_i)^{1-y_i} \quad (4)$$

With logarithm is more easy, in a convenient we write  $P_i = \hat{y}_i$ .

$$\ln f(y_1, y_2, \dots, y_n) = \sum_{i=1}^n y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i) \quad (5)$$

Related with the cross binary entropy.

# Cost function

Now we need minimize the function, then could be apply

$$-\frac{1}{n} \sum_{i=1}^n y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i) \quad (6)$$

In dataset  $y_i$  and  $x_i$  are fixed quantities, we need find the values of  $\Theta$  that minimize the expression.

# Cost Function

$$\frac{\partial J(\Theta)}{\partial \Theta_j} = \sum_{i=1}^n \frac{\partial J(\Theta)}{\partial \hat{y}_i} \frac{\partial \hat{y}_i}{\partial \Theta_j} \quad (7)$$

# Derivatives

In one sample the cost for  $i$  -  $th$  pattern.

$$-\frac{1}{n} (y_i \ln(\hat{y}_i) + (1 - y_i) \ln(1 - \hat{y}_i)) \quad (8)$$

Proof

$$\frac{\partial J(\Theta)}{\partial \hat{y}_i} = -\frac{1}{n} \left( \frac{y_i}{\hat{y}_i} - \frac{(1 - y_i)}{(1 - \hat{y}_i)} \right) \quad (9)$$

# Sigmoid derivative

$$\sigma(x)' = \sigma(x)(1 - \sigma(x)) \quad (10)$$

(11)

Using quotient and chain rule we have

$$\sigma(x)' = \frac{e^{-x}}{(1 + e^{-x})^2} \quad (12)$$



$$\frac{1 + e^{-x} - 1}{(1 + e^{-x})^2} \quad (13)$$

$$\frac{1}{1 + e^{-x}} - \frac{1}{(1 + e^{-x})^2} \quad (14)$$

$$\frac{1}{1 + e^{-x}} \left( 1 - \frac{1}{1 + e^{-x}} \right) \quad (15)$$

$$\sigma(x)(1 - \sigma(x)) \quad (16)$$

$$\frac{\partial \hat{y}_i}{\partial \Theta_j} = \sigma(x)(1 - \sigma(x))x_j \quad (17)$$

$$\frac{\partial J(\Theta)}{\partial \hat{y}_i} \frac{\partial \hat{y}_i}{\partial \Theta_j} = -\frac{1}{n} \left( \frac{y_i}{\hat{y}_i} - \frac{(1 - y_i)}{(1 - \hat{y}_i)} \right) \hat{y}_i(1 - \hat{y}_i)x_{ij} \quad (18)$$

$$-\frac{1}{n} (y_i(1 - \hat{y}_i) - \hat{y}_i(1 - y_i)) x_j \quad (19)$$

$$-\frac{1}{n} (y_i - \hat{y}_i) x_j \quad (20)$$

$$\frac{1}{n} (\hat{y}_i - y_i) x_j \quad (21)$$

$$\begin{aligned}
 \frac{\partial J(\Theta)}{\partial \Theta_j} &= \sum_{i=1}^n \frac{\partial J(\Theta)}{\partial \hat{y}_i} \frac{\partial \hat{y}_i}{\partial \Theta_j} \\
 &= \frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i) x_{ij}
 \end{aligned}
 \tag{22}$$

# Gradient matricial way

$$\begin{aligned}\nabla J(\vec{\Theta}) &= \frac{1}{N} \mathbf{X}^T (\vec{\hat{y}} - \vec{y}) \\ &= \frac{1}{N} \mathbf{X}^T (\sigma(\mathbf{X}\vec{\Theta}) - \vec{y})\end{aligned}\tag{23}$$

Implementation logistic from scratch([Click here](#))

# python implementation

## Statsmodels

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```
formula = 'died ~ studytime + C(drug) ' # logit died studytime
        i.drug
model = smf.logit(formula= formula, data=df)
results = model.fit()
print(results.summary())
coefs = pd.DataFrame({
    'coef': results.params.values,
    'odds ratio': np.exp(results.params.values),
    'name': results.params.index
})
coefs
```

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# Contingency table

		Diagnose	
		Disease	No-Disease
Risk Factor	Smoke	a	b
	Not Smoke	c	d

From this table we can calculate the odds, increase the probability of a diagnose smoke, or not?

$$odds_{smoke} = \frac{a}{b} = \frac{P(D \mid smoke)}{P(ND \mid smoke)} \quad (24)$$

e

# Odds ratio

We can calculate the odds ratio as:

$$OR = \frac{odds_{smoke}}{odds_{NoSmoke}} \quad (25)$$

according to the information of the table, we can calculate the odds ratio as  $OR = \frac{\frac{a}{b}}{\frac{c}{d}}$ .

How we can interpret this  $OR$ ?



# From odds to probability

$$\frac{P(A)}{P(A^c)} + 1 = odds + 1 \quad (26)$$

$$\frac{P(A) + P(A^c)}{P(A^c)} = odds + 1 \quad (27)$$

$$\frac{1}{P(A^c)} = odds + 1 \quad (28)$$

$$\frac{odds}{odds + 1} = P(A) \quad (29)$$

# Odds Ratio

---

```
testing = pd.DataFrame({  
    'smoke': [1,1,0,1,1,0,1,1,0,1,0,0,1,1,1,0,0,1,1,1],  
    'diagnose': [1,0,1,1,0,0,1,1,0,0,0,1,1,0,0,0,0,0,1,0]})  
pd.crosstab(testing['smoke'], testing['diagnose'])
```

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```
# Odds ratio  
oddsnum = 6/7  
oddsdem = 2/5  
print(oddsnum, oddsdem, oddsnum/oddsdem)
```

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# Logistic regression

# Using statsmodels

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```
import statsmodels.formula.api as smf
model_logit = smf.logit(formula="diagnose ~ smoke", data=testing)
res = model_logit.fit()
# How we can convert to dummy variable??
res.summary()
np.exp(res.params) # This give us the odds ratio getted
                    previously.
```

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# ORs lessert than 1

$$(1 - OR) * 100 \quad (30)$$