

# Logistic Regression

## 1. Model Setup

- Sample size:  $n$
- Target variable:  $\vec{Y} = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \vdots \\ y^{(n)} \end{bmatrix}$ , where  $y^{(i)} \in \{0,1\} \rightarrow Y^{(i)} \sim \text{Bernoulli}(p_i)$ , where  $p_i = \Pr\{Y^{(i)} = 1\}$  ( $Y$  here is capitalized to reflect that it is a random variable)
- Input features:  $X = \begin{bmatrix} \vec{x}^{(1)} \\ \vec{x}^{(2)} \\ \vdots \\ \vec{x}^{(n)} \end{bmatrix}$ , where  $\vec{x}^{(i)} = [x_1^{(i)} \quad x_2^{(i)} \quad \dots \quad x_p^{(i)}]$ , for  $i \in \{1, 2, \dots, n\}$
- Goal: For each  $i$ , estimate  $p_i$  given  $\vec{x}^{(i)}$

For a given vector  $\vec{\beta} = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_m \end{bmatrix}$ , we assume the estimate of  $p_i$ , denoted as  $\hat{p}(\vec{x}^{(i)} \vec{\beta})$ , is calculated as follows:

$$\text{logit}(\hat{p}(\vec{x}^{(i)} \vec{\beta})) = \ln \left( \frac{\hat{p}(\vec{x}^{(i)} \vec{\beta})}{1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})} \right) = \vec{x}^{(i)} \vec{\beta} \Leftrightarrow \hat{p}(\vec{x}^{(i)} \vec{\beta}) = \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}}}$$

Note: the first term of the vector  $\vec{x}^{(i)}$  is typically equal to one so that  $\beta_1$  represents the intercept term

## 2. Parameter Estimation

### 2.1 Maximum Likelihood

Let  $\mathcal{L}(\vec{\beta} | (X, \vec{Y})) = \Pr\{Y^{(1)} = y^{(1)}, Y^{(2)} = y^{(2)}, \dots, Y^{(n)} = y^{(n)}\}$

Assuming an independently and identically distributed sample, we have the following expressions:

$$\begin{aligned}
\mathcal{L}(\vec{\beta}|(X, \vec{Y})) &= \prod_{i=1}^n \Pr\{Y = y^{(i)}\} = \prod_{i=1}^n \Pr\{Y = 1\}^{y^{(i)}} \times (1 - \Pr\{Y = 1\})^{1-y^{(i)}} \\
&= \prod_{i=1}^n \left(\hat{p}(\vec{x}^{(i)} \vec{\beta})\right)^{y^{(i)}} \times \left(1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})\right)^{1-y^{(i)}} \\
&= \prod_{i=1}^n \left(\frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}}}\right)^{y^{(i)}} \times \left(1 - \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}}}\right)^{1-y^{(i)}} \\
&= \prod_{i=1}^n \left(\frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}}}\right)^{y^{(i)}} \times \left(\frac{e^{-\vec{x}^{(i)} \vec{\beta}}}{1 + e^{-\vec{x}^{(i)} \vec{\beta}}}\right)^{1-y^{(i)}} \\
&= \prod_{i=1}^n \left(\frac{e^{\vec{x}^{(i)} \vec{\beta}}}{1 + e^{\vec{x}^{(i)} \vec{\beta}}}\right)^{y^{(i)}} \times \left(\frac{1}{1 + e^{\vec{x}^{(i)} \vec{\beta}}}\right)^{1-y^{(i)}} \\
&= \prod_{i=1}^n \frac{e^{y^{(i)} \vec{x}^{(i)} \vec{\beta}}}{1 + e^{\vec{x}^{(i)} \vec{\beta}}}
\end{aligned}$$

The goal is to maximize this function. This implies that if we maximize the natural logarithm of this function (which is easier to handle), we will achieve the same goal (since  $\ln(f(\cdot))$  moves in the same direction as  $f(\cdot)$ , for any function  $f(\cdot) > 0$ ).

Let  $\ell(\vec{\beta}|(X, \vec{Y})) = \ln(\mathcal{L}(\vec{\beta}|(X, \vec{Y})))$ . Thus, we have the following expression:

$$\ell(\vec{\beta}|(X, \vec{Y})) = \sum_{i=1}^n y^{(i)} \vec{x}^{(i)} \vec{\beta} - \ln(1 + e^{\vec{x}^{(i)} \vec{\beta}})$$

To obtain an optimal point, we can calculate the partial derivative of the log-likelihood function with respect to the parameter of interest and setting the derivative to zero:

For  $j \in \{0, 1, \dots, m\}$ ,

$$\begin{aligned}
\frac{\partial \ell(\vec{\beta}|(X, \vec{Y}))}{\partial \beta_j} &= \sum_{i=1}^n y^{(i)} x_j^{(i)} - \frac{x_j^{(i)} e^{\vec{x}^{(i)} \vec{\beta}}}{1 + e^{\vec{x}^{(i)} \vec{\beta}}} = \sum_{i=1}^n \left(y^{(i)} - \frac{e^{\vec{x}^{(i)} \vec{\beta}}}{1 + e^{\vec{x}^{(i)} \vec{\beta}}}\right) x_j^{(i)} \\
&= \sum_{i=1}^n \left(y^{(i)} - \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}}}\right) x_j^{(i)}
\end{aligned}$$

Thus,  $\ell(\vec{\beta}|(X, \vec{Y}))$  is at an optimal value when varying  $\beta_j$  such that  $\sum_{i=1}^n \left(y^{(i)} - \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}}}\right) x_j^{(i)} = 0$ .

If we show that  $\frac{\partial^2 \ell(\vec{\beta}|(X, \vec{Y}))}{\partial \beta_j^2} < 0$ , we will establish that  $\beta_j$ 's value that yields  $\frac{\partial \ell(\vec{\beta}|(X, \vec{Y}))}{\partial \beta_j} = 0$  maximizes  $\ell(\vec{\beta}|(X, \vec{Y}))$ . For  $j \in \{1, 2, \dots, m\}$ ,

$$\begin{aligned}
\frac{\partial \ell^2(\vec{\beta}|(X, \vec{Y}))}{\partial \beta_j^2} &= \frac{\partial}{\partial \beta_j} \left( \sum_{i=1}^n \left( y^{(i)} - \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}}} \right) x_j^{(i)} \right) \\
&= \sum_{i=1}^n \left( -\frac{-1}{(1 + e^{-\vec{x}^{(i)} \vec{\beta}})^2} \times -x_j^{(i)} e^{-\vec{x}^{(i)} \vec{\beta}} \right) x_j^{(i)} \\
&= -\sum_{i=1}^n \left( \frac{e^{-\vec{x}^{(i)} \vec{\beta}}}{(1 + e^{-\vec{x}^{(i)} \vec{\beta}})^2} \right) x_j^{(i)^2} < 0
\end{aligned}$$

To estimate  $\vec{\beta}$ , we will use the multi-variate Newton-Raphson procedure (we add a superscript  $\{t\}$ , where  $t \in \{0, 1, 2, \dots\}$ , to the variables and functions to denote that we are at iteration  $t$ ):

Set  $\vec{\beta}^{\{0\}}$  to random values.

$$t \geq 0: \vec{\beta}^{\{t+1\}} = \vec{\beta}^{\{t\}} - \left[ \frac{\partial \ell^2(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \vec{\beta}^{\{t\}^2}} \right]^{-1} \times \frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \vec{\beta}^{\{t\}}}$$

We derive  $\frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \vec{\beta}^{\{t\}}}$  and  $\frac{\partial \ell^2(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \vec{\beta}^{\{t\}^2}}$  explicitly (note: when differentiating by vector, we use the so-called numerator layout notation; source:

[https://en.wikipedia.org/wiki/Matrix\\_calculus#Layout\\_conventions](https://en.wikipedia.org/wiki/Matrix_calculus#Layout_conventions)):

$$\begin{aligned}
\frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \vec{\beta}^{\{t\}}} &= \left[ \frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \beta_1^{\{t\}}} \quad \frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \beta_2^{\{t\}}} \quad \dots \quad \frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \beta_m^{\{t\}}} \right] \\
&= \left[ \sum_{i=1}^n \left( y^{(i)} - \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}}} \right) x_1^{(i)} \quad \sum_{i=1}^n \left( y^{(i)} - \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}}} \right) x_2^{(i)} \quad \dots \quad \sum_{i=1}^n \left( y^{(i)} - \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}}} \right) x_m^{(i)} \right] \\
&= X^T (\vec{y} - \vec{p}(X, \vec{\beta}^{\{t\}}))
\end{aligned}$$

$$\text{Where } \vec{p}(X, \vec{\beta}^{\{t\}}) = \begin{bmatrix} \hat{p}(\vec{x}^{(1)} \vec{\beta}^{\{t\}}) \\ \hat{p}(\vec{x}^{(2)} \vec{\beta}^{\{t\}}) \\ \vdots \\ \hat{p}(\vec{x}^{(n)} \vec{\beta}^{\{t\}}) \end{bmatrix}$$

$$\begin{aligned}
\frac{\partial \ell^2(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \vec{\beta}^{\{t\}^2}} &= \frac{\partial \ell^2(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \vec{\beta}^{\{t\}} \partial \vec{\beta}^{\{t\}^T}} \\
&= \frac{\partial}{\partial \vec{\beta}^{\{t\}^T}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \vec{\beta}^{\{t\}}} \right) \\
&= \frac{\partial}{\partial \vec{\beta}^{\{t\}^T}} \left[ \frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \beta_1^{\{t\}}} \quad \frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \beta_2^{\{t\}}} \quad \dots \quad \frac{\partial \ell(\vec{\beta}^{\{t\}}|X, \vec{Y})}{\partial \beta_m^{\{t\}}} \right]
\end{aligned}$$

$$\begin{aligned}
&= \begin{bmatrix} \frac{\partial}{\partial \beta_1^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_1^{\{t\}}} \right) & \frac{\partial}{\partial \beta_1^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_2^{\{t\}}} \right) & \cdots & \frac{\partial}{\partial \beta_1^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_m^{\{t\}}} \right) \\ \frac{\partial}{\partial \beta_2^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_1^{\{t\}}} \right) & \frac{\partial}{\partial \beta_2^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_2^{\{t\}}} \right) & \vdots & \frac{\partial}{\partial \beta_2^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_m^{\{t\}}} \right) \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial}{\partial \beta_m^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_1^{\{t\}}} \right) & \frac{\partial}{\partial \beta_m^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_2^{\{t\}}} \right) & \cdots & \frac{\partial}{\partial \beta_m^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_m^{\{t\}}} \right) \end{bmatrix} \\
&= \begin{bmatrix} \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_1^{\{t\}} \partial \beta_1^{\{t\}}} & \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_1^{\{t\}} \partial \beta_2^{\{t\}}} & \cdots & \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_1^{\{t\}} \partial \beta_m^{\{t\}}} \\ \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_2^{\{t\}} \partial \beta_1^{\{t\}}} & \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_2^{\{t\}} \partial \beta_2^{\{t\}}} & \vdots & \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_2^{\{t\}} \partial \beta_m^{\{t\}}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_m^{\{t\}} \partial \beta_1^{\{t\}}} & \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_m^{\{t\}} \partial \beta_2^{\{t\}}} & \cdots & \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_m^{\{t\}} \partial \beta_m^{\{t\}}} \end{bmatrix}, \text{ where}
\end{aligned}$$

$$\begin{aligned}
\frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_j^{\{t\}} \partial \beta_k^{\{t\}}} &= \frac{\partial}{\partial \beta_k^{\{t\}}} \left( \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \beta_j^{\{t\}}} \right) = \frac{\partial}{\partial \beta_k^{\{t\}}} \left( \sum_{i=1}^n \left( y^{(i)} - \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}}} \right) x_j^{(i)} \right) \\
&= \sum_{i=1}^n \left( -\frac{-1}{\left( 1 + e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}} \right)^2} \times -e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}} \right) x_j^{(i)} x_k^{(i)} \\
&= -\sum_{i=1}^n \left( \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}}} \times \frac{e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}}}{1 + e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}}} \right) x_j^{(i)} x_k^{(i)} \\
&= -\sum_{i=1}^n \left( \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}}} \times \left( 1 - \frac{1}{1 + e^{-\vec{x}^{(i)} \vec{\beta}^{\{t\}}}} \right) \right) x_j^{(i)} x_k^{(i)} \\
&= -\sum_{i=1}^n \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}}) \times \left( 1 - \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}}) \right) \times x_j^{(i)} \times x_k^{(i)}
\end{aligned}$$

In matrix form,

$$\begin{aligned}
\frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{Y}))}{\partial \vec{\beta}^{\{t\}}{}^2} &= -\sum_{i=1}^n \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}}) \times \left( 1 - \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}}) \right) \times \vec{x}^{(i)T} \times \vec{x}^{(i)} \\
&= -\sum_{i=1}^n \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}}) \times \vec{x}^{(i)T} \times \left( 1 - \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}}) \right) \times \vec{x}^{(i)} \\
&= -\sum_{i=1}^n \left( \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}})^T \times \vec{x}^{(i)T} \right) \times \left( 1 - \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}}) \right) \times \vec{x}^{(i)}
\end{aligned}$$

$$\begin{aligned}
&= - \sum_{i=1}^n (\hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}}) \times \vec{x}^{(i)})^T \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{n\}})) \times \vec{x}^{(i)} \\
&= - \sum_{i=1}^n (\hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}}) \times \vec{x}^{(i)})^T \times ((1 - \hat{p}(\vec{x}^{(i)} \vec{\beta}^{\{t\}})) \times \vec{x}^{(i)}) \\
&= -(\vec{p}(X, \vec{\beta}^{\{t\}}) \circ X)^T \times ((I - \vec{p}(X, \vec{\beta}^{\{t\}})) \circ X)
\end{aligned}$$

Therefore, we have the following result for  $t \geq 0$ :

$$\vec{\beta}^{\{t+1\}} = \vec{\beta}^{\{t\}} - \left[ \frac{\partial \ell^2(\vec{\beta}^{\{t\}} | (X, \vec{y}))}{\partial \vec{\beta}^{\{t\}}^2} \right]^{-1} \times \frac{\partial \ell(\vec{\beta}^{\{t\}} | (X, \vec{y}))}{\partial \vec{\beta}^{\{t\}}}$$

$\Leftrightarrow$

$$\vec{\beta}^{\{t+1\}} = \vec{\beta}^{\{t\}} + \left[ (\vec{p}(X, \vec{\beta}^{\{t\}}) \circ X)^T \times ((I - \vec{p}(X, \vec{\beta}^{\{t\}})) \circ X) \right]^{-1} \times X^T (\vec{Y} - \vec{p}(X, \vec{\beta}^{\{t\}}))$$

## 2.2 Gradient Descent

### 2.2.1 Cross-entropy Loss Function

We choose the following loss function to minimize:

$$L(\hat{\vec{\beta}}) = - \sum_{i=1}^n y^{(i)} \ln(\hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})) + (1 - y^{(i)}) \ln(1 - \hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}}))$$

We assume that  $X$  does not have a row of all zeros.

We begin by taking the first derivative and second derivatives with respect to  $\hat{\beta}_j$  for  $j = 1, 2, \dots, m$  and following through with the algebra:

$$\begin{aligned}
\frac{\partial L(\hat{\vec{\beta}})}{\partial \hat{\beta}_j} &= \frac{\partial \left( - \sum_{i=1}^n y^{(i)} \ln(\hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})) + (1 - y^{(i)}) \ln(1 - \hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})) \right)}{\partial \hat{\beta}_j} \\
&= - \sum_{i=1}^n y^{(i)} \frac{\partial \ln(\hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}}))}{\partial \hat{\beta}_j} + (1 - y^{(i)}) \frac{\partial \ln(1 - \hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}}))}{\partial \hat{\beta}_j} \\
&= - \sum_{i=1}^n y^{(i)} \times \frac{1}{\hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})} \times \frac{\partial \hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})}{\partial \hat{\beta}_j} + (1 - y^{(i)}) \times \frac{1}{1 - \hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})} \times \frac{\partial (1 - \hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}}))}{\partial \hat{\beta}_j} \\
&= - \sum_{i=1}^n \frac{y^{(i)}}{\hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})} \times \frac{\partial \hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})}{\partial \hat{\beta}_j} + \frac{(1 - y^{(i)})}{1 - \hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})} \times \frac{-\partial \hat{p}(\vec{x}^{(i)} \hat{\vec{\beta}})}{\partial \hat{\beta}_j}
\end{aligned}$$

Since  $\hat{p}(\vec{x}^{(i)} \vec{\beta}) = \frac{1}{1+e^{-\vec{x}^{(i)} \vec{\beta}}}$ , therefore  $\frac{\partial \hat{p}(\vec{x}^{(i)} \vec{\beta})}{\partial \hat{\beta}_j} = \frac{\partial \left( \frac{1}{1+e^{-\vec{x}^{(i)} \vec{\beta}}} \right)}{\partial \hat{\beta}_j} = -\frac{1}{(1+e^{-\vec{x}^{(i)} \vec{\beta}})^2} \times (e^{-\vec{x}^{(i)} \vec{\beta}}) \times$   
 $-x_j^{(i)} = \left( \frac{1}{1+e^{-\vec{x}^{(i)} \vec{\beta}}} \right) \times \left( \frac{e^{-\vec{x}^{(i)} \vec{\beta}}}{1+e^{-\vec{x}^{(i)} \vec{\beta}}} \right) \times x_j^{(i)} = \left( \frac{1}{1+e^{-\vec{x}^{(i)} \vec{\beta}}} \right) \times \left( 1 - \frac{1}{1+e^{-\vec{x}^{(i)} \vec{\beta}}} \right) \times x_j^{(i)} =$   
 $\hat{p}(\vec{x}^{(i)} \vec{\beta}) \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)}$

Therefore,

$$\begin{aligned} \frac{\partial L(\hat{\beta})}{\partial \hat{\beta}_j} &= -\sum_{i=1}^n \frac{y^{(i)}}{\hat{p}(\vec{x}^{(i)} \vec{\beta})} \times (\hat{p}(\vec{x}^{(i)} \vec{\beta}) \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)}) + \frac{(1 - y^{(i)})}{1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})} \\ &\quad \times (\hat{p}(\vec{x}^{(i)} \vec{\beta}) \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)}) \\ &= -\sum_{i=1}^n y^{(i)} \times ((1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)}) + (1 - y^{(i)}) \times -(\hat{p}(\vec{x}^{(i)} \vec{\beta}) \times x_j^{(i)}) \\ &= \sum_{i=1}^n -y^{(i)} \times ((1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)}) + (1 - y^{(i)}) \times (\hat{p}(\vec{x}^{(i)} \vec{\beta}) \times x_j^{(i)}) \\ &= \sum_{i=1}^n -y^{(i)} x_j^{(i)} + y^{(i)} \hat{p}(\vec{x}^{(i)} \vec{\beta}) \times x_j^{(i)} + \hat{p}(\vec{x}^{(i)} \vec{\beta}) \times x_j^{(i)} - y^{(i)} \times \hat{p}(\vec{x}^{(i)} \vec{\beta}) \times x_j^{(i)} \\ &= \sum_{i=1}^n -y^{(i)} x_j^{(i)} + \hat{p}(\vec{x}^{(i)} \vec{\beta}) \times x_j^{(i)} \\ &= -\sum_{i=1}^n (y^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta})) x_j^{(i)} \end{aligned}$$

If we can show that  $\frac{\partial L^2(\hat{\beta})}{\partial \hat{\beta}_j^2} > 0$ , we will establish that  $L(\hat{\beta})$  is a strictly convex function.

$$\begin{aligned} \frac{\partial L^2(\hat{\beta})}{\partial \hat{\beta}_j^2} &= \frac{\partial}{\partial \hat{\beta}_j} \left( -\sum_{i=1}^n (y^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta})) x_j^{(i)} \right) \\ &= \sum_{i=1}^n \left( 0 + \frac{\partial \hat{p}(\vec{x}^{(i)} \vec{\beta})}{\partial \hat{\beta}_j} \right) x_j^{(i)} \\ &= \sum_{i=1}^n \frac{\partial \hat{p}(\vec{x}^{(i)} \vec{\beta})}{\partial \hat{\beta}_j} x_j^{(i)} \\ &= \sum_{i=1}^n (\hat{p}(\vec{x}^{(i)} \vec{\beta}) \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)}) x_j^{(i)} \\ &= \sum_{i=1}^n \hat{p}(\vec{x}^{(i)} \vec{\beta}) \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)2} \\ &> 0 \end{aligned}$$

Therefore,  $L(\hat{\beta})$  is strictly convex function with a global minimum.

Let  $\hat{\beta}_j^{\{t\}}$  represent the estimate of  $\beta_j$  for  $j = 1, 2, \dots, n$ , at the  $t$ th iteration. Given initial values at  $t = 0$ , a learning rate  $\eta$ , we have the following expression for each  $j$ :

$$\boxed{\hat{\beta}_j^{\{t+1\}} = \hat{\beta}_j^{\{t\}} - \eta \times \frac{\partial L(\hat{\beta}^{\{t\}})}{\partial \hat{\beta}_j^{\{t\}}}}$$

Using the results and notation given in above, we proceed as follows:

$$\begin{aligned} \hat{\beta}_j^{\{t+1\}} &= \hat{\beta}_j^{\{t\}} - \eta \times \left( - \sum_{i=1}^n (y^{(i)} - \hat{p}(\tilde{x}^{(i)} \tilde{\beta}^{\{t\}})) x_j^{(i)} \right) \\ &= \hat{\beta}_j^{\{t\}} + \eta \times \sum_{i=1}^n (y^{(i)} - \hat{p}(\tilde{x}^{(i)} \tilde{\beta}^{\{t\}})) x_j^{(i)} \end{aligned}$$

In matrix form, we have the following results:

$$\begin{aligned} \tilde{\beta}^{\{t+1\}} &= \tilde{\beta}^{\{t\}} + \eta \times \sum_{i=1}^n (y^{(i)} - \hat{p}(\tilde{x}^{(i)} \tilde{\beta}^{\{t\}})) \tilde{x}^{(i)T} \\ &= \tilde{\beta}^{\{t\}} + \eta \times \sum_{i=1}^n \tilde{x}^{(i)T} (y^{(i)} - \hat{p}(\tilde{x}^{(i)} \tilde{\beta}^{\{t\}})) \\ &= \tilde{\beta}^{\{t\}} + \eta \times X^T \times (\vec{Y} - \vec{p}(X, \tilde{\beta}^{\{t\}})) \end{aligned}$$

Thus, the final expression we can use can be given as follows:

$$\boxed{\tilde{\beta}^{\{t+1\}} = \tilde{\beta}^{\{t\}} + \eta X^T (\vec{Y} - \vec{p}(X, \tilde{\beta}^{\{t\}}))}$$

Note that the derivation obtained here and the Newton-Raphson derivation are very similar. In the gradient descent formula, if we let  $\eta = \left[ (\vec{p}(X, \tilde{\beta}^{\{t\}}) \circ X)^T \times \left( (I - \vec{p}(X, \tilde{\beta}^{\{t\}})) \circ X \right) \right]^{-1}$ , then we obtain the Newton-Raphson formula.

### 2.2.2 Sum of Squared Error Loss Function

We choose the following loss function to minimize:

$$L(\hat{\beta}) = (\vec{Y} - \vec{p}(X, \tilde{\beta}^{\{t\}}))^T \times (\vec{Y} - \vec{p}(X, \tilde{\beta}^{\{t\}}))$$

We assume that  $X$  does not have a row of all zeros.

We begin by taking the first derivative and second derivatives with respect to  $\hat{\beta}_j$  for  $j = 1, 2, \dots, m$  and following through with the algebra:

$$\begin{aligned}
\frac{\partial L(\hat{\vec{\beta}})}{\partial \hat{\beta}_j} &= \frac{\partial \left( (\vec{Y} - \vec{p}(X, \vec{\beta}))^T \times (\vec{Y} - \vec{p}(X, \vec{\beta})) \right)}{\partial \hat{\beta}_j} \\
&= \frac{\partial \left( \sum_{i=1}^n (y^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta}))^2 \right)}{\partial \hat{\beta}_j} \\
&= \sum_{i=1}^n \frac{\partial \left( y^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta}) \right)^2}{\partial \hat{\beta}_j} \\
&= \sum_{i=1}^n 2 \times \left( y^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta}) \right) \times \frac{\partial \left( -\hat{p}(\vec{x}^{(i)} \vec{\beta}) \right)}{\partial \hat{\beta}_j} \\
&= \sum_{i=1}^n 2 \left( y^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta}) \right) \times \frac{-\partial \hat{p}(\vec{x}^{(i)} \vec{\beta})}{\partial \hat{\beta}_j} \\
&= \sum_{i=1}^n 2 \left( y^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta}) \right) \times \frac{-\partial \hat{p}(\vec{x}^{(i)} \vec{\beta})}{\partial \hat{\beta}_j} \\
&= - \sum_{i=1}^n 2 \left( y^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta}) \right) \times \left( \hat{p}(\vec{x}^{(i)} \vec{\beta}) \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)} \right) \\
&= -2 \sum_{i=1}^n y^{(i)} \hat{p}(\vec{x}^{(i)} \vec{\beta}) x_j^{(i)} - y^{(i)} \hat{p}(\vec{x}^{(i)} \vec{\beta})^2 x_j^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta})^2 x_j^{(i)} + \hat{p}(\vec{x}^{(i)} \vec{\beta})^3 x_j^{(i)} \\
&= -2 \sum_{i=1}^n \hat{p}(\vec{x}^{(i)} \vec{\beta})^3 x_j^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta})^2 \{y^{(i)} x_j^{(i)} + x_j^{(i)}\} + \hat{p}(\vec{x}^{(i)} \vec{\beta}) y^{(i)} x_j^{(i)}
\end{aligned}$$

If we can show that  $\frac{\partial L^2(\hat{\vec{\beta}})}{\partial \hat{\beta}_j^2} > 0$ , we will establish that  $L(\hat{\vec{\beta}})$  is a strictly convex function.

$$\begin{aligned}
\frac{\partial L^2(\hat{\vec{\beta}})}{\partial \hat{\beta}_j^2} &= \frac{\partial}{\partial \hat{\beta}_j} \left( -2 \sum_{i=1}^n \hat{p}(\vec{x}^{(i)} \vec{\beta})^3 x_j^{(i)} - \hat{p}(\vec{x}^{(i)} \vec{\beta})^2 \{y^{(i)} x_j^{(i)} + x_j^{(i)}\} + \hat{p}(\vec{x}^{(i)} \vec{\beta}) y^{(i)} x_j^{(i)} \right) \\
&= -2 \sum_{i=1}^n 3 \hat{p}(\vec{x}^{(i)} \vec{\beta})^2 \frac{\partial \hat{p}(\vec{x}^{(i)} \vec{\beta})}{\partial \hat{\beta}_j} x_j^{(i)} - 2 \hat{p}(\vec{x}^{(i)} \vec{\beta}) \{y^{(i)} x_j^{(i)} + x_j^{(i)}\} \frac{\partial \hat{p}(\vec{x}^{(i)} \vec{\beta})}{\partial \hat{\beta}_j} \\
&\quad + y^{(i)} x_j^{(i)} \frac{\partial \hat{p}(\vec{x}^{(i)} \vec{\beta})}{\partial \hat{\beta}_j}
\end{aligned}$$



$$\begin{aligned}
&= -2 \sum_{i=1}^n 3\hat{p}(\vec{x}^{(i)} \vec{\beta})^2 \left( \hat{p}(\vec{x}^{(i)} \vec{\beta}) \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)} \right) x_j^{(i)} \\
&\quad - 2\hat{p}(\vec{x}^{(i)} \vec{\beta}) \{y^{(i)} x_j^{(i)} + x_j^{(i)}\} \left( \hat{p}(\vec{x}^{(i)} \vec{\beta}) \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)} \right) \\
&\quad + y^{(i)} x_j^{(i)} \left( \hat{p}(\vec{x}^{(i)} \vec{\beta}) \times (1 - \hat{p}(\vec{x}^{(i)} \vec{\beta})) \times x_j^{(i)} \right) \\
&= -2 \sum_{i=1}^n 3\hat{p}(\vec{x}^{(i)} \vec{\beta})^3 x_j^{(i)^2} - 3\hat{p}(\vec{x}^{(i)} \vec{\beta})^4 x_j^{(i)^2} - 2\hat{p}(\vec{x}^{(i)} \vec{\beta})^2 \{y^{(i)} x_j^{(i)^2} + x_j^{(i)^2}\} \\
&\quad + 2\hat{p}(\vec{x}^{(i)} \vec{\beta})^3 \{y^{(i)} x_j^{(i)^2} + x_j^{(i)^2}\} + \hat{p}(\vec{x}^{(i)} \vec{\beta}) y^{(i)} x_j^{(i)^2} - \hat{p}(\vec{x}^{(i)} \vec{\beta})^2 y^{(i)} x_j^{(i)^2} \\
&= \sum_{i=1}^n 6\hat{p}(\vec{x}^{(i)} \vec{\beta})^4 x_j^{(i)^2} - 2\hat{p}(\vec{x}^{(i)} \vec{\beta})^3 (5x_j^{(i)^2} - 2y^{(i)} x_j^{(i)^2}) + 2\hat{p}(\vec{x}^{(i)} \vec{\beta})^2 (2x_j^{(i)^2} - 3y^{(i)} x_j^{(i)^2}) \\
&\quad - 2\hat{p}(\vec{x}^{(i)} \vec{\beta}) y^{(i)} x_j^{(i)^2}
\end{aligned}$$

The sign of this expression  $(\frac{\partial L^2(\hat{\beta})}{\partial \hat{\beta}_j^2})$  will ultimately be determined by the values of  $\hat{p}(\vec{x}^{(i)} \vec{\beta})$  and  $y^{(i)}$ , and therefore, we cannot guarantee a strictly convex function, implying that we cannot guarantee a global minimum. Also note that finding  $\hat{\beta}_j$  by plugging  $\frac{\partial L(\hat{\beta})}{\partial \hat{\beta}_j} = 0$  will likely yield several possible values further suggesting the existence of more than one optimum point.