1 Logistic Regression

Log-likelihood function for logistic regression:

$$L(\theta) = \sum_{i=1}^{m} y^{(i)} log\ h_\theta(x^{(i)}) + (1 - y^{(i)})\ log(1 - h_\theta(x^{(i)}))$$

For maximizing the log-likelihood function, Newton's method is used
Update rule for newton's method:

$$\theta_{n+1} = \theta_n - H^{-1} \nabla l(\theta)$$

where H is the Hessian of L(θ) and is given by:

$$H(j,k) = -\sum_{i=1}^{m} (h_\theta(x^{(i)}))(1 - h_\theta(x^{(i)}))(x_j^{(i)})(x_k^{(i)})$$

$$h_\theta(x) = \frac{1}{1 + exp^{-z}}$$

$$z = \theta^T x$$

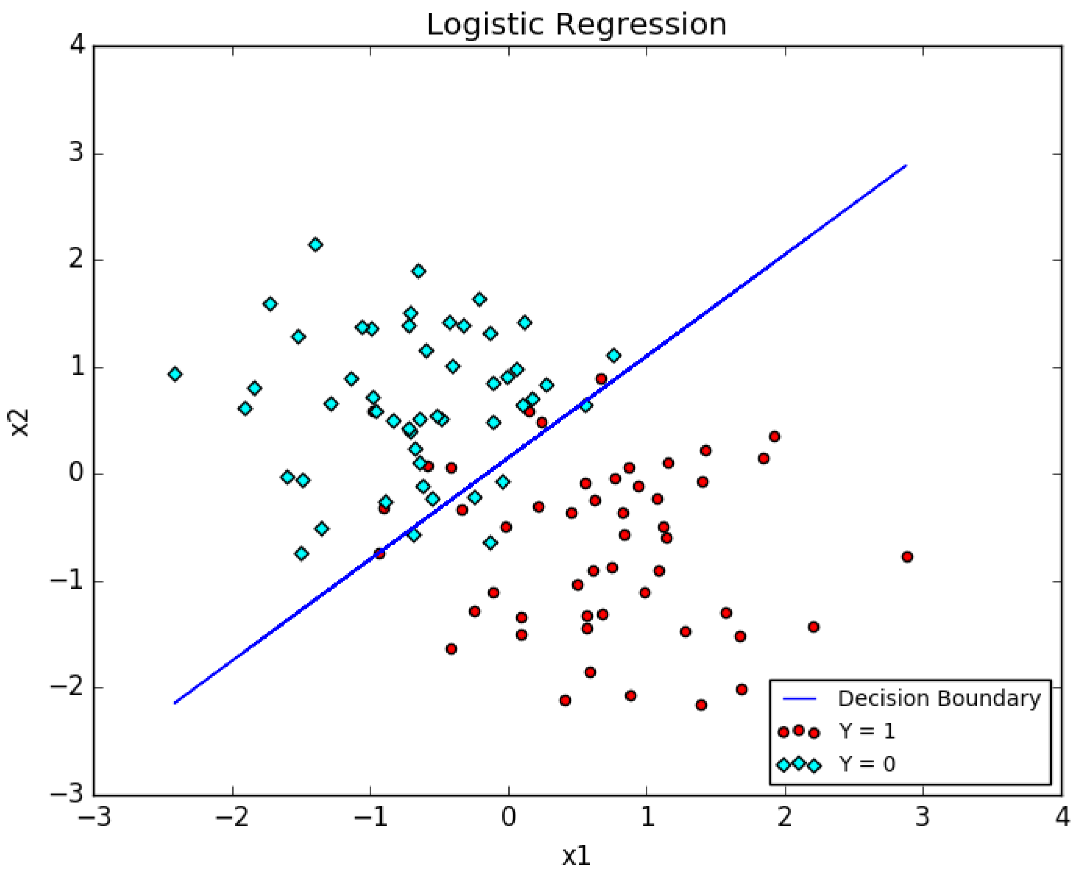
a) Coefficients θ resulting from the fit are :

$$\begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \end{bmatrix} = \begin{bmatrix} 0.40125316 \\ 2.5885477 \\ -2.72558849 \end{bmatrix}$$

b) Equation of Decision Boundary:

$$h_\theta(x) = 0.5$$

$$\theta^T x = 0$$


Logistic Regression
x2
x1
4
3
2
1
0
−1
−2
−3
−3
−2
−1
0
1
2
3
4
Decision Boundary
Y = 1
Y = 0

The End.