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## ➤ Recoding Bonte's Simplified Fixed Hessian Newton Method.

整理思路： Matlab代码>>Python代码

发现的问题：

- 设置初始权重为1会使得Sigmoid函数的输入区间很大，  
以至于很难使用多项式来替代Sigmoid函数. (SET weight = 0)
- 使用似然函数估计模型时：  $Y \in \{0, 1\}$  和  $Y \in \{-1, +1\}$  似然函数计算公式不同
- 使用似然函数衡量模型时可能出现的问题，替代方案是ROC曲线和AUC值

## ➤ 研究了一下ROC曲线和AUC值, 并用Python实现

## ➤ 使用多项式替换Sigmoid函数, 并没有很大的改变：

- 可能是Sigmoid函数的输入值区间很小，多项式在这个小区间内拟合的很好

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$Y \in \{0, 1\}$  和  $Y \in \{-1, +1\}$  似然函数计算公式不同  
 $Y = 2Y - 1$  数据预处理时容易变换类别,  $MLE$  也应该跟着变换

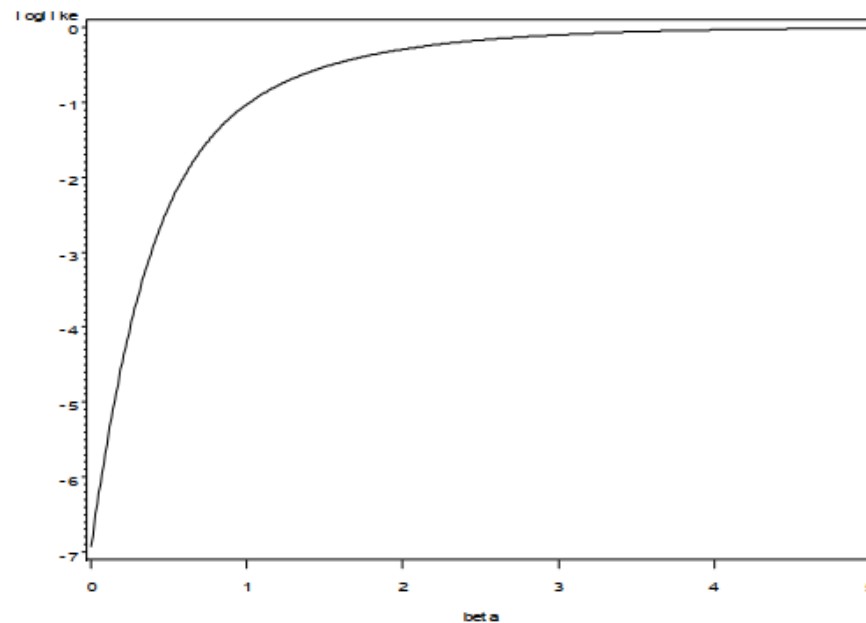
$sigm(z) = \frac{1}{1+e^{-z}} \quad sigm'(z) = sigm(z) \cdot (1 - sigm(z)) \quad h_{\theta}(x) = sigm(\theta^T x)$	
$Y \in \{0, 1\}$	$Y \in \{-1, +1\}$
$P(y = 1 x; \theta) = h_{\theta}(x)$	$P(y = +1 x; \theta) = h_{\theta}(x) = sigm(\theta^T x)$
$P(y = 0 x; \theta) = 1 - h_{\theta}(x)$	$P(y = -1 x; \theta) = 1 - h_{\theta}(x) = sigm(-\theta^T x)$
$P(y x; \theta) = (h_{\theta}(x))^y (1 - h_{\theta}(x))^{1-y}$	$P(y x; \theta) = sigm(y\theta^T x)$
$L(\theta) = \prod_{i=1}^m (h_{\theta}(x_i))^{y_i} (1 - h_{\theta}(x_i))^{1-y_i}$	$L(\theta) = \prod_{i=1}^m \frac{1}{1 + e^{-y_i \theta^T x_i}}$
$\ell(\theta) = \log L(\theta)$ $= \sum_{i=1}^m y_i \log h_{\theta}(x_i) + (1 - y_i) \log 1 - h_{\theta}(x_i)$	$\ell(\theta) = \log L(\theta)$ $= - \sum_{i=1}^m \log (1 + e^{-y_i \theta^T x_i})$
$grad = X^T (Y - h_{\theta}(X))$	$\partial \ell / \partial \theta_i = \sum_j (1 - sigm(y_j \theta^T x_j)) y_j x_j$



**Table 1. Data Exhibiting Complete Separation.**

$x$	$y$
-5	0
-4	0
-3	0
-2	0
-1	0
1	1
2	1
3	1
4	1
5	1

For these data, it can be shown that the ML estimate of the intercept is 0. Figure 1 shows a graph of the log-likelihood as a function of the slope “beta”.



**Figure 1. Log-likelihood as a function of the slope under complete separation**

It is apparent that, although the log-likelihood is bounded above by 0, it does not reach a maximum as beta increases.

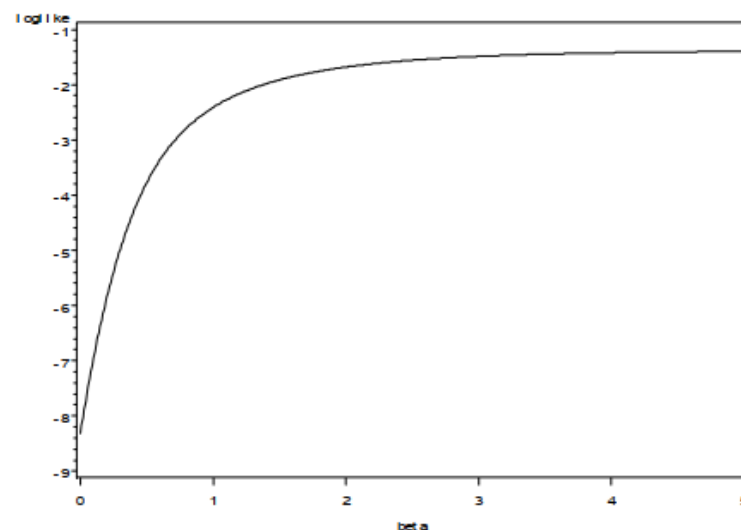


**Table 2. Data Exhibiting Quasi-Complete Separation.**

$x$	$y$
-5	0
-4	0
-3	0
-2	0
-1	0
0	0
0	1
1	1
2	1
3	1
4	1
5	1

What distinguishes this data set from the previous one is that there are two additional observations, each with  $x$  values of 0 but having different values of  $y$ .

The log-likelihood function for these data, shown in Figure 2, is similar in shape to that in Figure 1. However, the asymptote for the curve is not 0, but a number that is approximately -1.39. In general, the log-likelihood function for quasi-complete separation will not approach 0, but some number lower than that. In any case, the curve has no maximum so, again, the maximum likelihood estimate does not exist.



**Figure 1. Log-likelihood as a function of the slope, quasi-complete separation.**





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