모두의 딥러닝 (Deep learning)

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Logistic regression

Why logistic regression

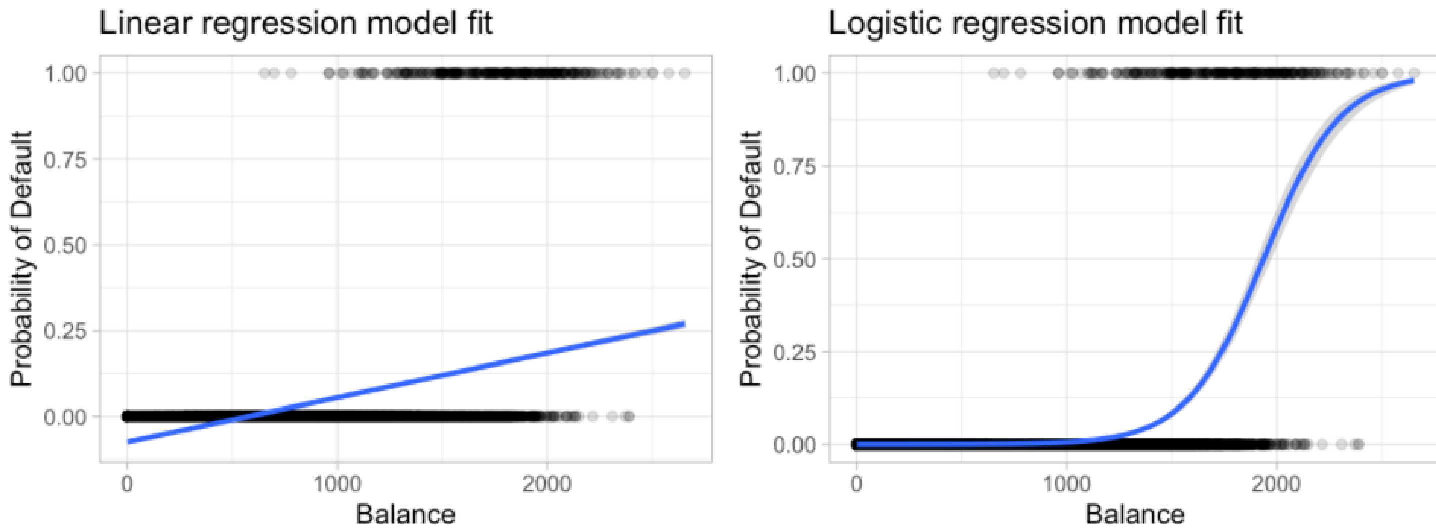


Figure 5.1: Comparing the predicted probabilities of linear regression (left) to logistic regression (right). Predicted probabilities using linear regression results in flawed logic whereas predicted values from logistic regression will always lie between 0 and 1.

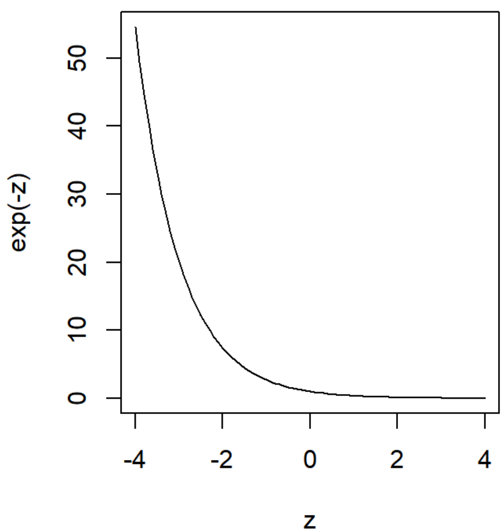
https://bradleyboehmke.github.io/HOML

시그모이드 (Sigmoid function)

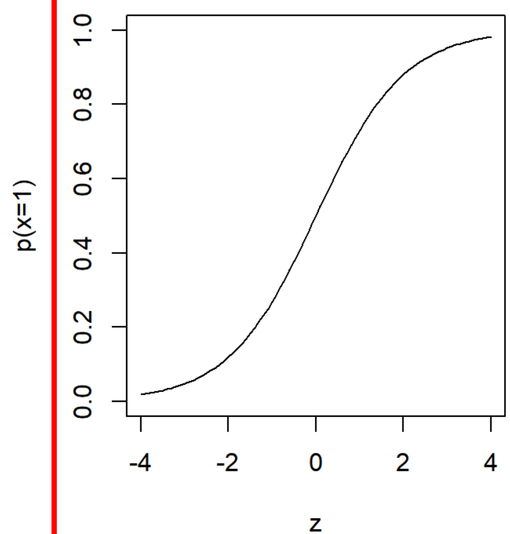
- Formula extend

$$p(X) = \frac{e^{\beta_0+\beta_1 X_1+\ldots+\beta_p X_p}}{1+e^{\beta_0+\beta_1 X_1+\ldots+\beta_p X_p}} = \frac{1}{\boxed{1+e^{-(\beta_0+\beta_1 X_1+\ldots+\beta_p X_p)}}} = \boxed{\frac{1}{1+\boxed{e^{-z}}}}$$

Exponential function



Logistic function



Logit transformation

$$g(X) = ln[\frac{p(x)}{1-p(x)}] = \beta_0 + \beta_1 X + \ldots + \beta_p X_p$$

Loss function of logistic regression

Let's see the cases of loss function of logistic regression

This equation does not have a closed-form solution

0 또는 1의 값을 가지며 암일 경우 악성, 양성의 판단을 신용의 경우 불량자인지 아닌지 결정

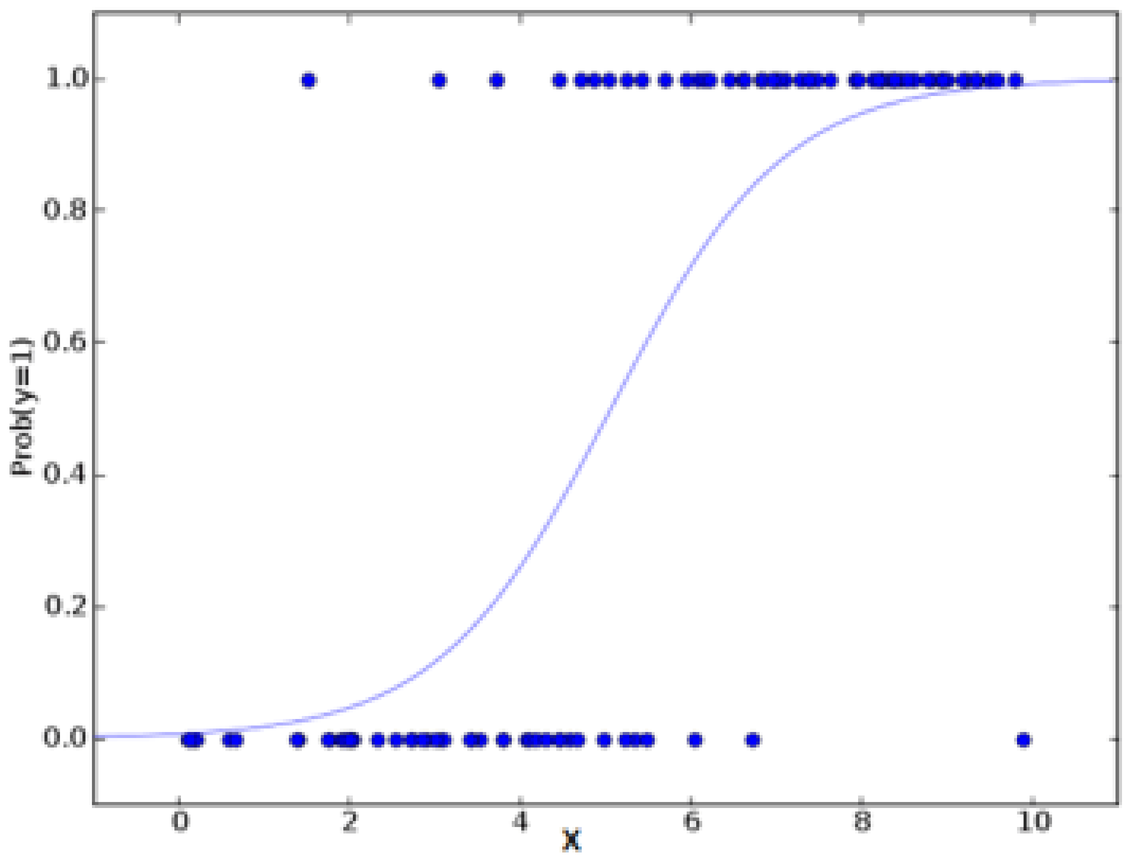
$$\boxed{J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[\boxed{y_i} log(h_\theta(x_i)) + (1-y_i)log(1-h_\theta(x_i))}$$

$$where,\ \boxed{h_\theta(x_i) = \frac{1}{1+e^{-\theta x}}},\quad y \in 0,1$$

위 페이지(시그모이드)에서 나오는 함수 = 0부터 1 사이의 값으로 확률이라고 정의할 수 있다.

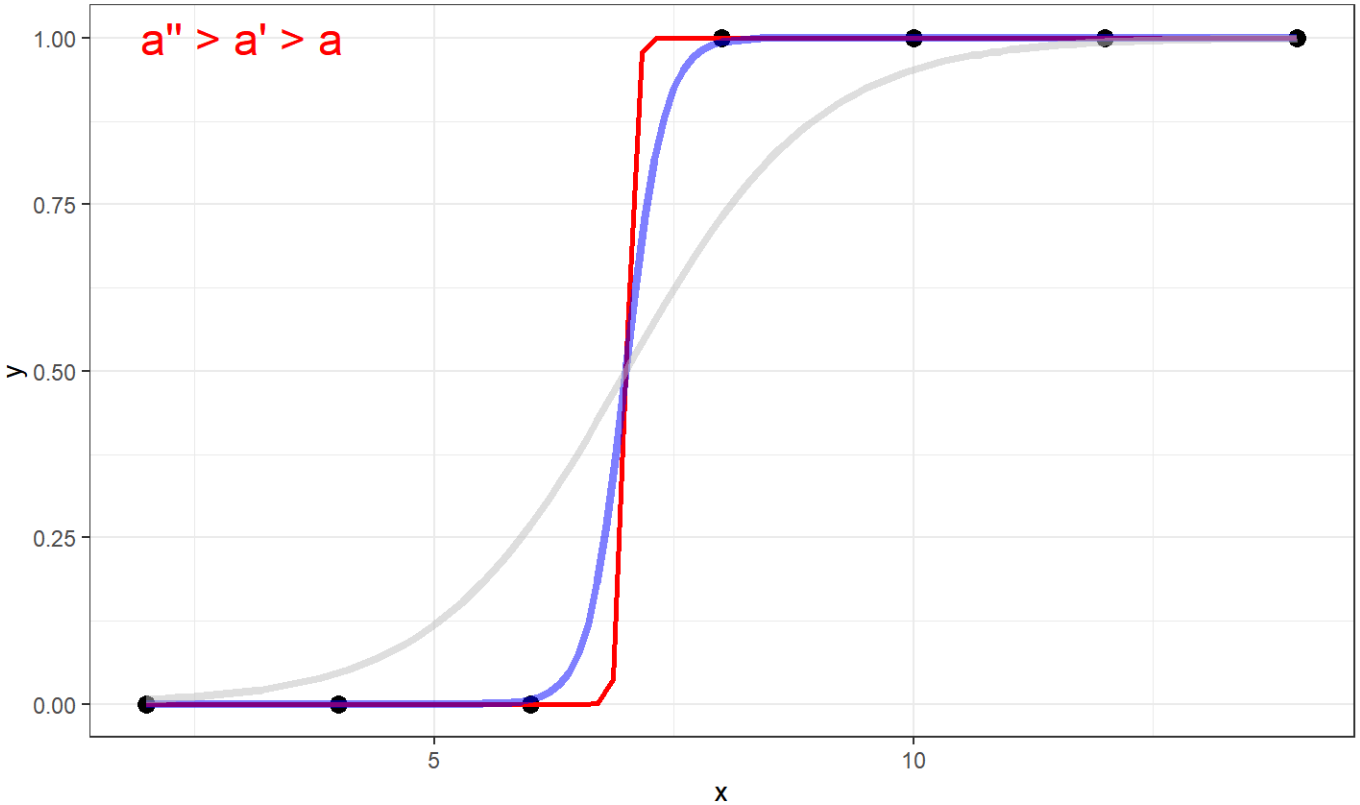
다시 말해, y_i의 값이 0 또는 1로 값이 결정되는 순간 J에 대입되면 악성(1)일 경우 악성의 확률을 양성(0)일 경우 악성이 아닐 경우의 확률을 나타낸다.

Logistic estimation

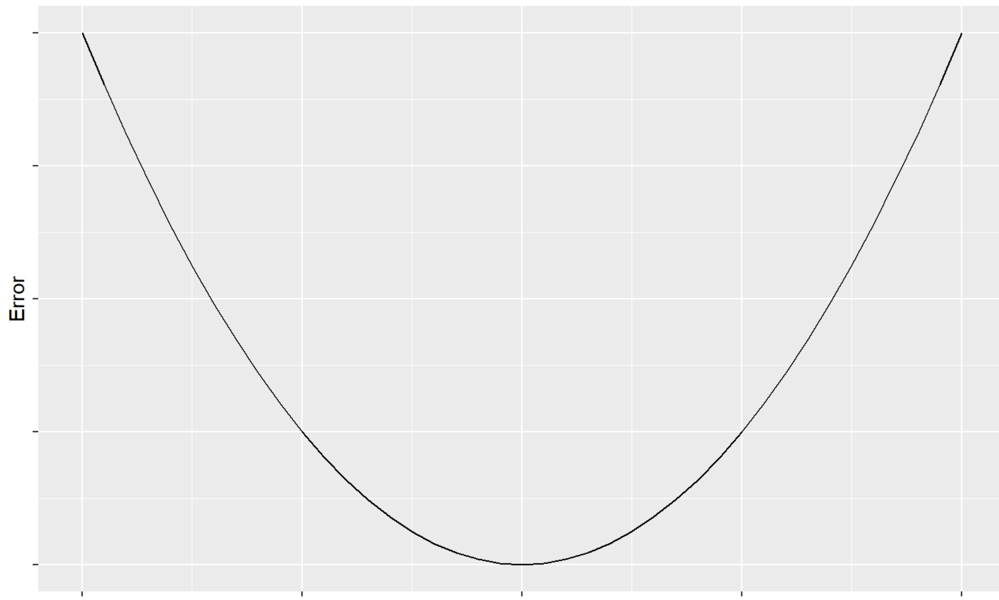


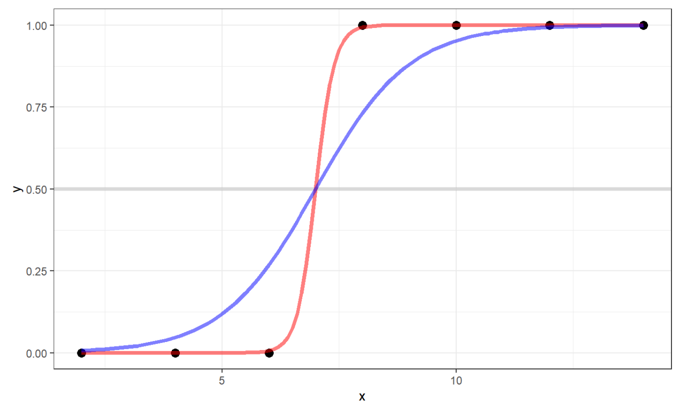
https://www.analyticsvidhya.com/blog/2015/11/beginners-guide-on-logistic-regression-in-r/

파라메터와 오차



Loss function

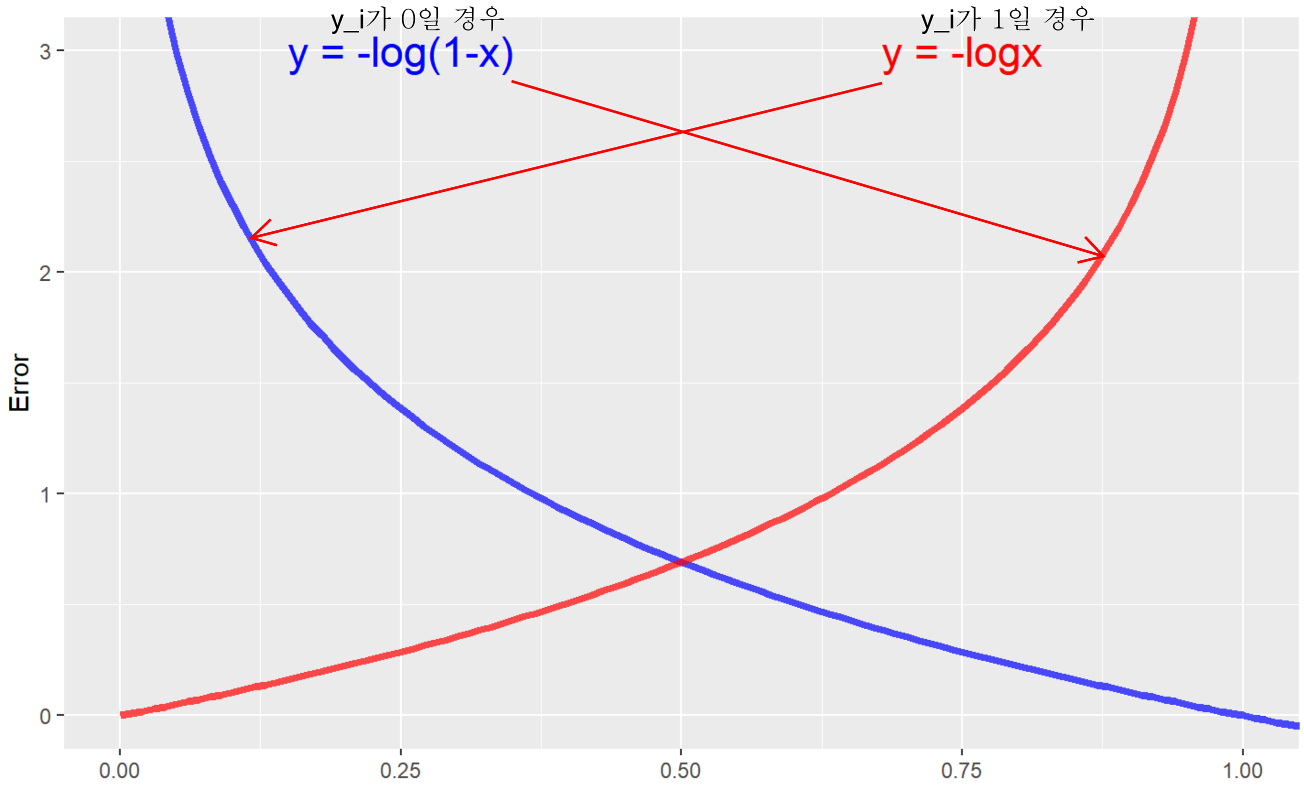




로그 함수

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y_i log(h_\theta(x_i)) + (1-y_i)log(1-h_\theta(x_i))$$

$$where,\ h_\theta(x_i) = \frac{1}{1+e^{-\theta x}},\ \ y \in 0, 1$$



로지스틱 회귀와 perceptron

$$f(X) = \frac{1}{1+e^{-(a_1x_1+a_2x_2+b)}}$$

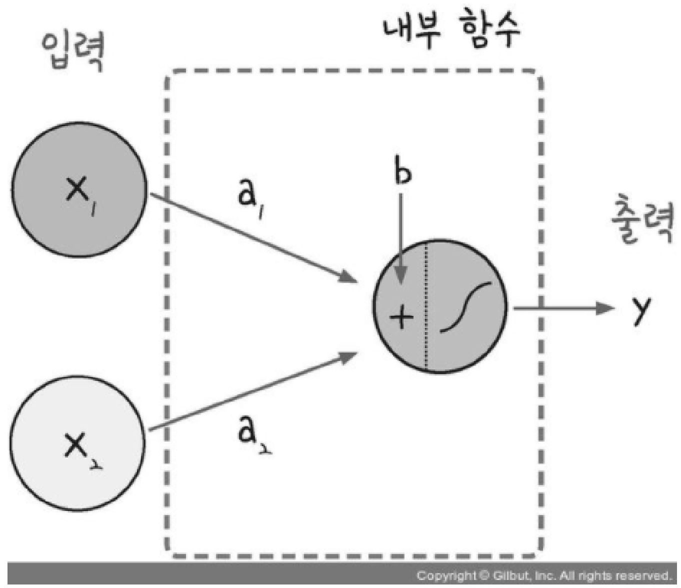


그림 5-11

로지스틱 회귀를 퍼셉트론 방식으로 표현한 예