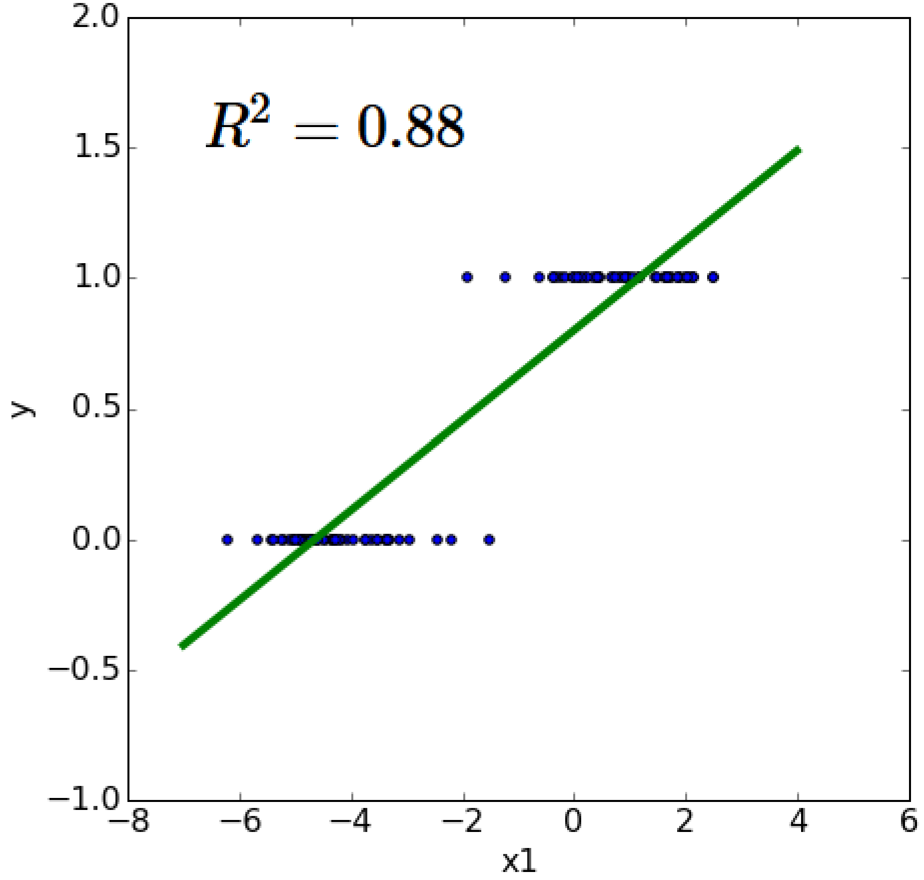
classification



We need to make

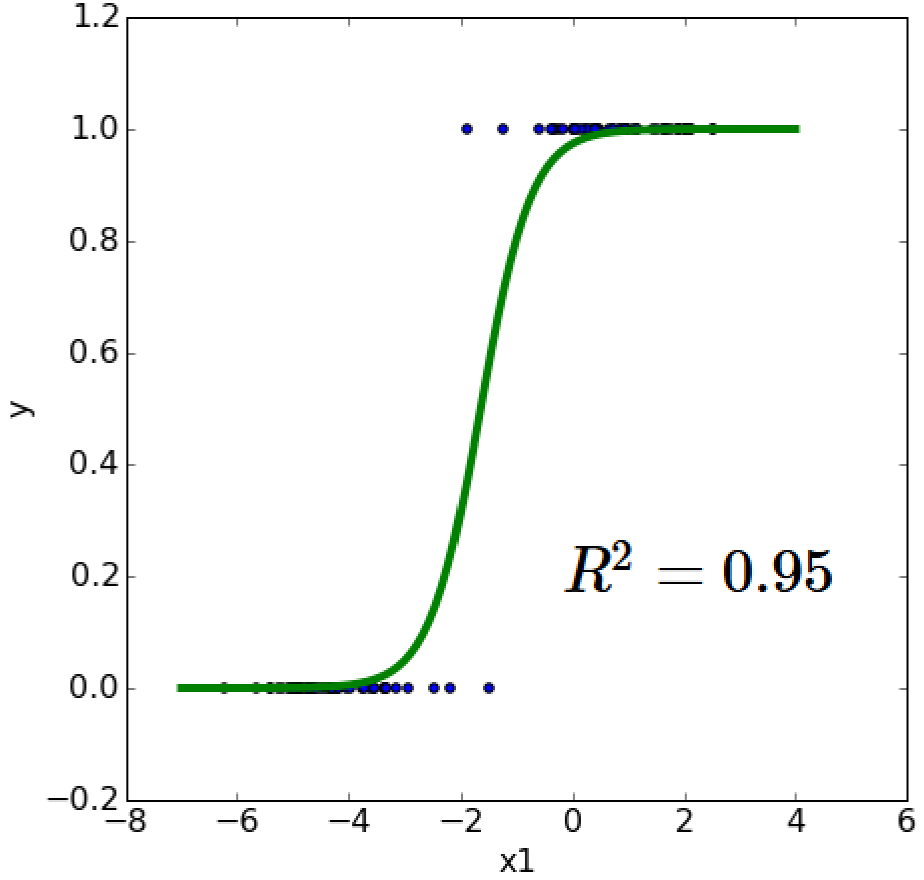
assumptions *linear relationship*

about the

model *linear model*

that generated the data.

logistic regression



We need to make

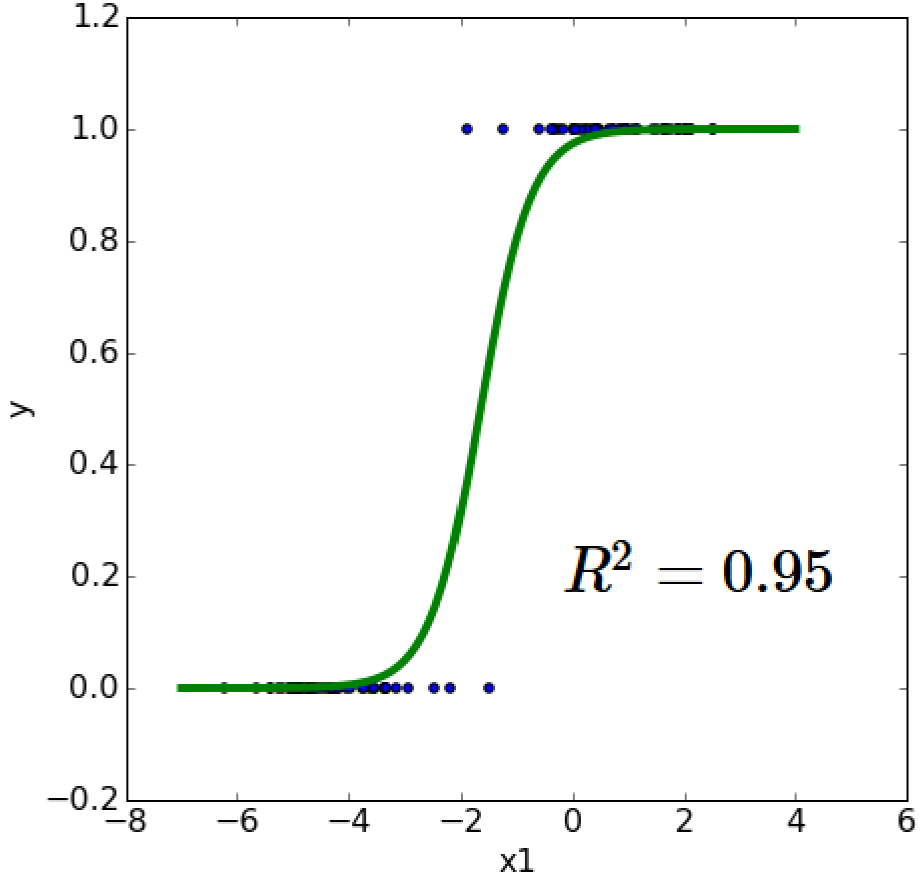
assumptions *linearly separable*

about the

model *logistic model*

that generated the data.

logistic regression



$$f(x, \theta) = g(\theta_0 + \theta_1 x_1)$$

$$g(z) = \frac{1}{1 + e^{-z}}$$

logistic regression: cost (loss function)

$$J(\theta) = -[\frac{1}{n}\sum_{i=1}^{n} y^{(i)} log(f(x^{(i)}, \theta)) + (1 - y^{(i)}) log(1 - f(x^{(i)}, \theta))]$$

We know that $y^{(i)}$ is either 0 or 1. If $y^{(i)} = 1$ then the cost function $J(\theta)$ is incremented by

$-log(f(x^{(i)}, \theta))$.

Similarly, if $y^{(i)} = 0$ then the cost function $J(\theta)$ is incremented by

$-log(1 - f(x^{(i)}, \theta))$.

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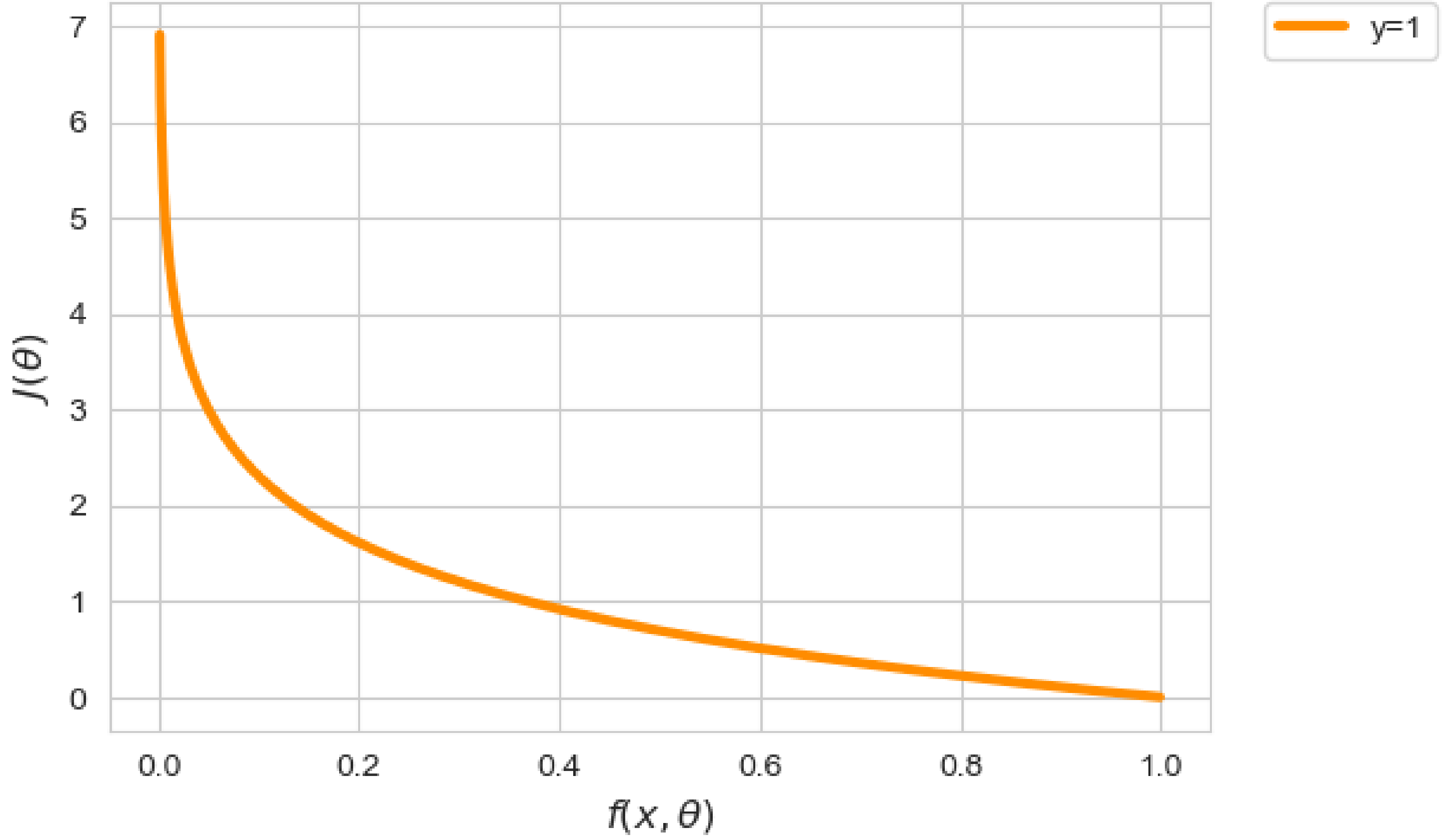

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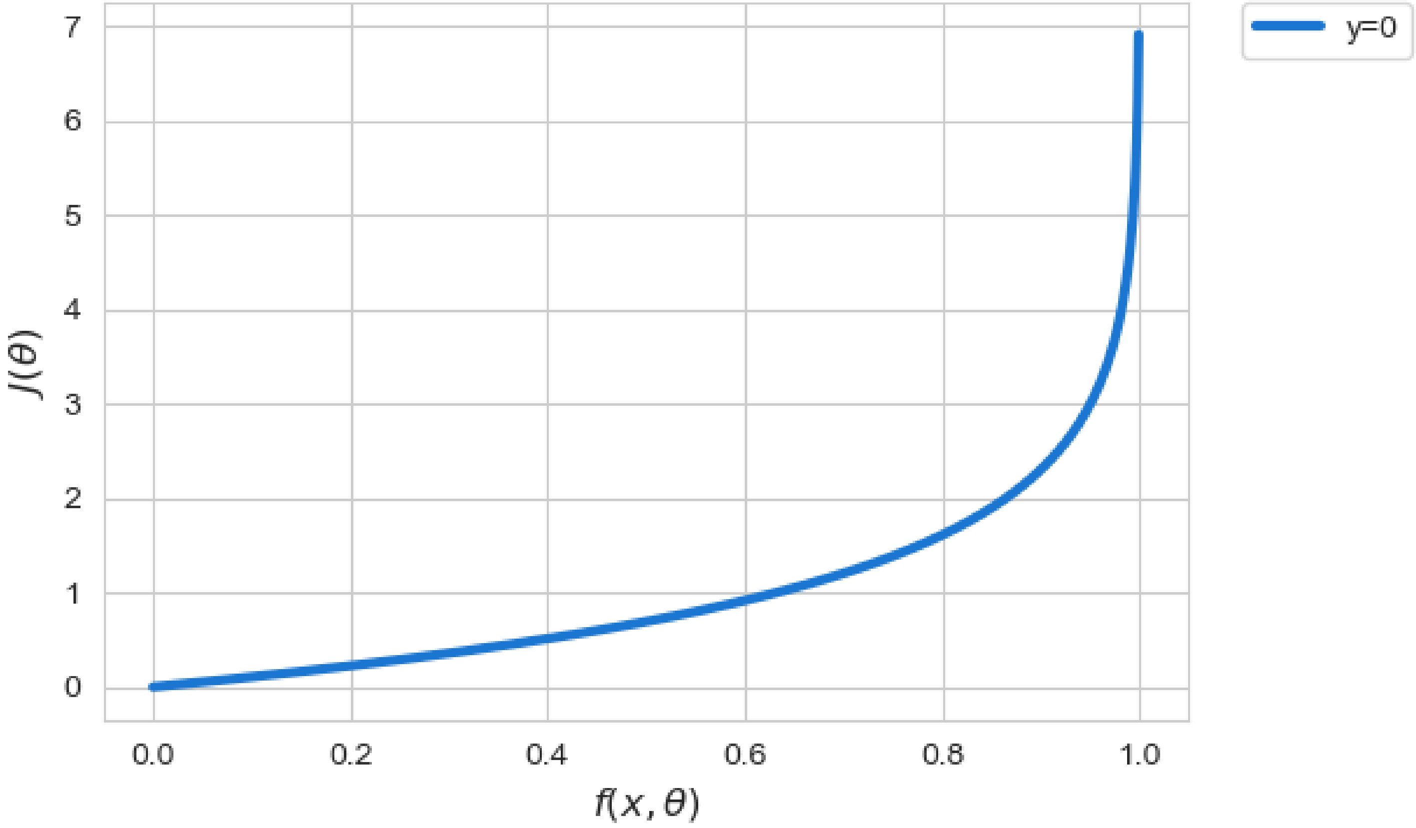

logistic regression

Fit a logistic model

$$f(x, \theta) = g(\theta_0 x_0 + \theta_1 x_1 + \theta_2 x_2 + \ldots + \theta_m x_m) = g(\theta' x)$$

to the data set such that the cost function

$$J(\theta) = -[\frac{1}{n} \sum_{i=1}^{n} y^{(i)} log(f(x^{(i)}, \theta)) + (1 - y^{(i)}) log(1 - f(x^{(i)}, \theta))]$$

is minimal using gradient descent

$$\theta_j := \theta_j - \alpha \frac{1}{n} \sum_{i=1}^{n} (f(x^{(i)}, \theta) - y^{(i)}) x_j^{(i)}$$

multiclass classification: one-against-all

Fit a binary classifier for each class.

Each binary classifier computes a probability prediction.

The class with the highest probability is predicted.