

Let's start with logistic regression mathematically

\hat{y} (y hat) is the %/p or probabilities.

$$\hat{y} = P(y=1 | x)$$

Read: Probability of $y=1$ - given x

$x \in \mathbb{R}^{n \times 1}$ [x is a set of Real numbers, 'm' training examples or i/p vector, $n \rightarrow$ dimension of i/p x . number of variables .]

Parameters

$$w \in \mathbb{R}^{n \times 1}$$

$$b \in \mathbb{R}$$

$$x = \begin{bmatrix} x_1 & x_2 & x_3 & \dots & m \\ 1 & 1 & 1 & \dots & 1 \end{bmatrix}^T \quad \begin{matrix} n \\ m \end{matrix}$$

$$y = [y^1 \ y^2 \ \dots \ y^m] \quad y \in \mathbb{R}^{1 \times m}$$

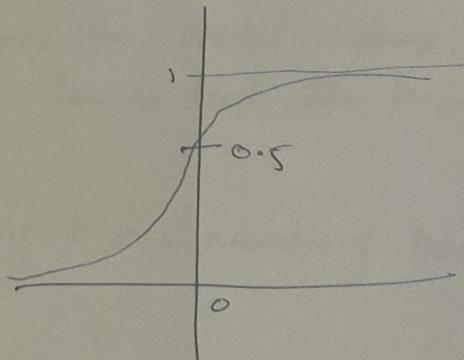
Linear reg

$$\hat{y} = w^T x + b \quad w = [w_1 \ w_2 \ w_3 \ w_4 \ \dots]$$

Logistic regression

$$\hat{y} = \sigma\left(\frac{w^T x + b}{z}\right)$$

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



If z is large

If z is small

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Loss function

A function that captures the loss between predicted and actual.

Anybody knows the loss function of linear reg?

$$L(\hat{y}, y) = -(y \log \hat{y} + (1-y) \log(1-\hat{y}))$$

we want to minimize the loss function. but how?

we want to find an optimal value for w and b which would minimize the cost function

Cost function

$$J(w, b) = \frac{1}{m} \sum_{i=1}^m L(\hat{y}_i; y_i).$$

$$= \frac{1}{m} \sum_{i=1}^m (-y_i \log \hat{y}_i + (1-y_i) \log(1-\hat{y}_i))$$

\rightarrow If $y=0$ $-\log(1-\hat{y})$ to have it minimized
 we want \hat{y} to be small

If $y=1$ $-\log \hat{y}$ to make this minimum, we
 want \hat{y} to be large

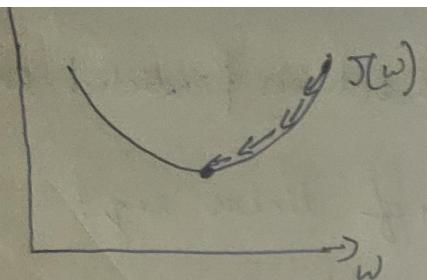
$$J(w, b) = \frac{1}{m} \sum_{i=1}^m (-y_i \log \hat{y}_i + (1-y_i) \log(1-\hat{y}_i))$$

Find w, b that minimizes $J(w, b)$



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Repeat

$$w = w - \alpha \frac{\partial J(w)}{\partial w}$$

$$\text{or } w = w - \alpha \Delta w$$

for

$$J(w, b) \quad w = w - \alpha \frac{\partial J(w, b)}{\partial w}$$

$$b = b - \alpha \frac{\partial J(w, b)}{\partial b}$$

Let's look at computational graph

In order to feedback the new computations, that come from the loss we need to know 2 things

- ① Forward propagation
- ② Backward propagation.

Let's understand this with a simple example, then we will go back to logistic reg

Suppose

$$J(a, b, c) = 3(a + bc)$$

lets store them in variables

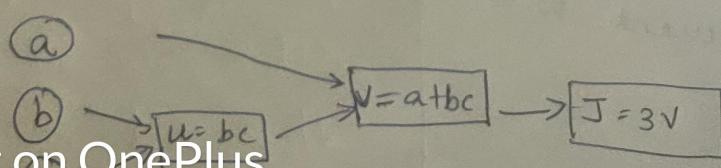
$$u = bc$$

$$v = a + bc \quad [a+u]$$

$$J = 3(a + bc) \quad [3v]$$

(a)

(b)



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a
 b
 c
 $\rightarrow u = bc$
 $v = a + bc(u)$
 $J = 3v$

Suppose $a = 5, b = 3, c = 2$

$\frac{dJ}{da} = ?$ (2)
 $a = 5$
 $\frac{dJ}{db} = ?$ (4)
 $b = 3$
 $\frac{dJ}{dc} = ?$ (5)
 $c = 2$
 $u = bc$ (6)
 $v = a + u$ (11)
 $J = 3v$ (33)

$\frac{dJ}{dv}$? [what will the change in J be if value of v is changed] that what a derivative means.

① $\boxed{\frac{dJ}{dv} = 3}$
 $J = 3v$
 $v = 11$
 if $v = 11.001$
 $J = 33.003$.

② $\frac{dJ}{da} = ?$ [what does that mean]
 $a = 5 \rightarrow 5.001$
 $v = 11 \rightarrow 11.001$
 $J = 33 \rightarrow 33.003$ So, if you change a , it would change v , which will change J

$\Rightarrow \frac{dJ}{da} = \frac{dJ}{dv} \cdot \frac{dv}{da} \xrightarrow[1]{3} \xrightarrow[3]{1}$
 = (chain rule).

③ $\frac{dJ}{du} = ?$
 $\frac{dJ}{dv} \cdot \frac{dv}{du}$
 $\frac{3}{3} \cdot \frac{1}{1} = 1$

$u = 6 \rightarrow 6.001$
 $v = 11 \rightarrow 11.001$
 $J = 33 \rightarrow 33.003$

④ $\frac{dJ}{dc} = ?$
 $\frac{dJ}{dv} \cdot \frac{dv}{dc}$
 $\frac{3}{1} \cdot \frac{1}{2} = 1.5$

⑤ $\frac{dJ}{dc} = 1.5$

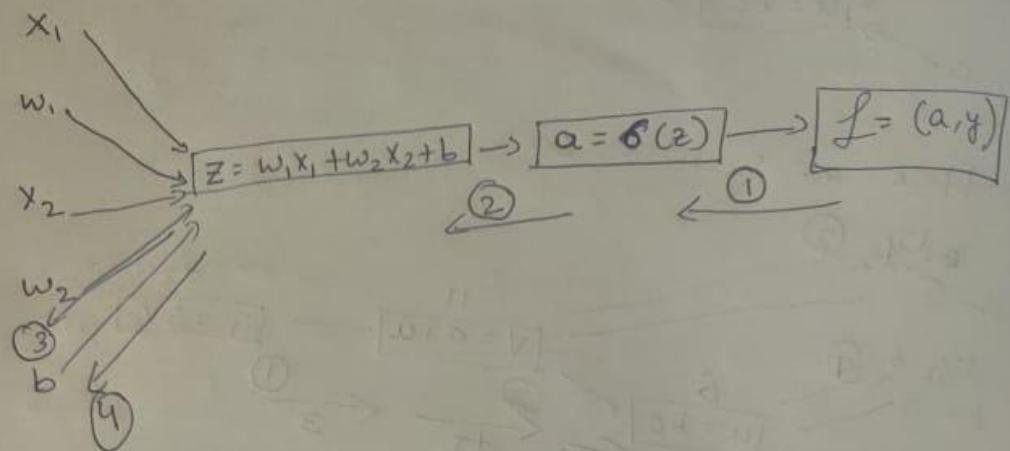


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Let's see the same for logit

Suppose we have 2 variables:



$$\textcircled{1} \quad \frac{dL}{da} = -\frac{y}{a} + \frac{1-y}{1-a}$$

lets call it ' da' ' = $-\frac{y}{a} + \frac{1-y}{1-a}$

$$\textcircled{2} \quad \frac{dL}{dz} = a-y \quad \left[\frac{dL}{da} \cdot \frac{da}{dz} \right] \rightarrow a(1-y)$$

lets call it ' dz' '

$$\textcircled{3} \quad \cancel{\frac{dz}{db}} = \frac{1}{a} \quad \text{lets call } 'db'$$

$$\textcircled{4} \quad \frac{dL}{dw_2} = x_2 \cdot dz \quad \text{lets call } dw_2$$

$$\frac{dL}{dw_1} = x_1 \cdot dz \quad \text{lets call } dw_1$$

$$w_1 = w_1 - \alpha dw_1$$

$$w_2 = w_2 - \alpha dw_2$$



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Now all that was being done on one row/training example we have to do it for all. for that we will minimize the cost function

$$J = \frac{1}{m} \sum_{i=1}^m L(a^{(i)}, y^{(i)}). \quad \begin{aligned} a^{(i)} &= \hat{y}^{(i)} = \sigma(z^{(i)}) \\ &= \sigma(w^T x + b) \end{aligned}$$

$i \rightarrow$ Training examples.

In computer [Pseudo algo]
 $J = 0, dw = 0, dw_2 = 0, db = 0$] Random initialization

for $i = 1$ to m

$$z^{(i)} = w^T x^{(i)} + b^{(i)}$$

$$a^{(i)} = \sigma(z^{(i)})$$

$$J += -[y^{(i)} \log(a^{(i)}) + (1 - y^{(i)}) \log(1 - a^{(i)})]$$

$$dz^{(i)} = a^{(i)} - y^{(i)}$$

$dw_1 += x_1^{(i)} dz^{(i)}$ $dw_2 += x_2^{(i)} dz^{(i)}$ $db += dz^{(i)}$	$\uparrow n=2$
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$$J / m \quad db / m$$

$$dw_1 / m \quad dw_2 / m$$

update

$$w_1 = w_1 - \alpha dw_1$$

$$w_2 = w_2 - \alpha dw_2$$

$$b = b - \alpha db$$



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