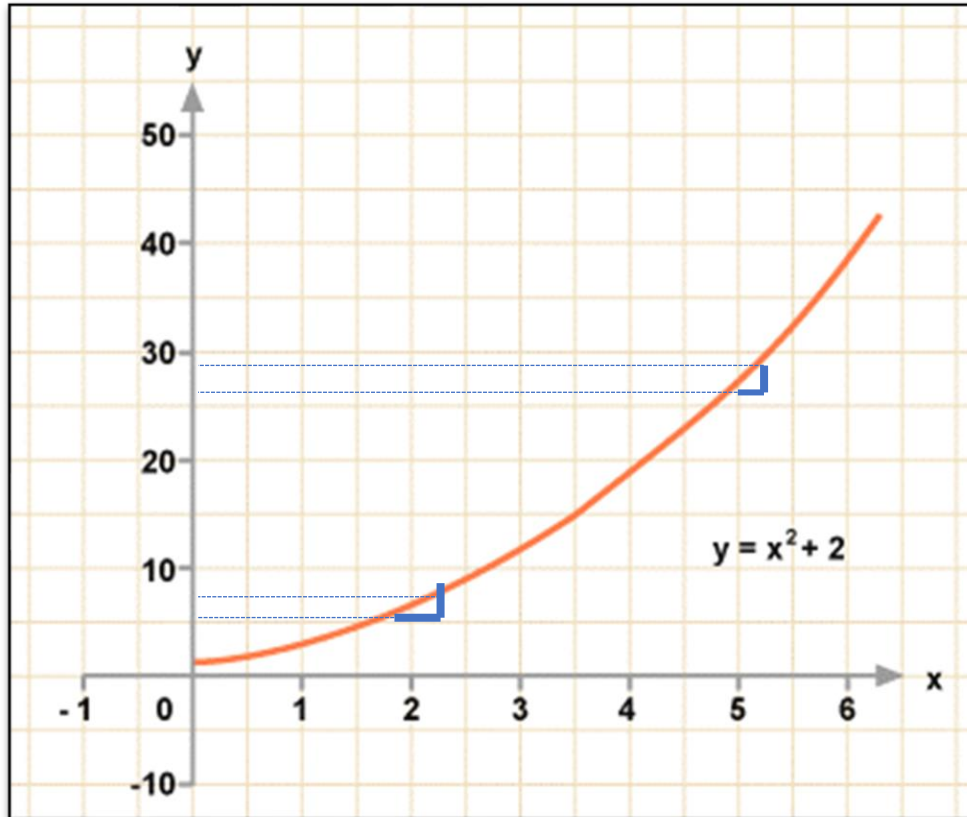


A large, solid pink triangle is positioned on the left side of the slide, pointing upwards. The text 'Gradient Descent' is overlaid on this triangle in a white, sans-serif font.

# Gradient Descent

# Derivatives



$$y=f(x)=x^2+2$$

$$\frac{df(x)}{dx} = 2x$$

$$x=2 \quad f(x)=6$$

$$x=2.0001 \quad f(x)=6.00040001$$

$$\text{Slope at } x=2 \text{ is } .0004/.0001 = 4$$

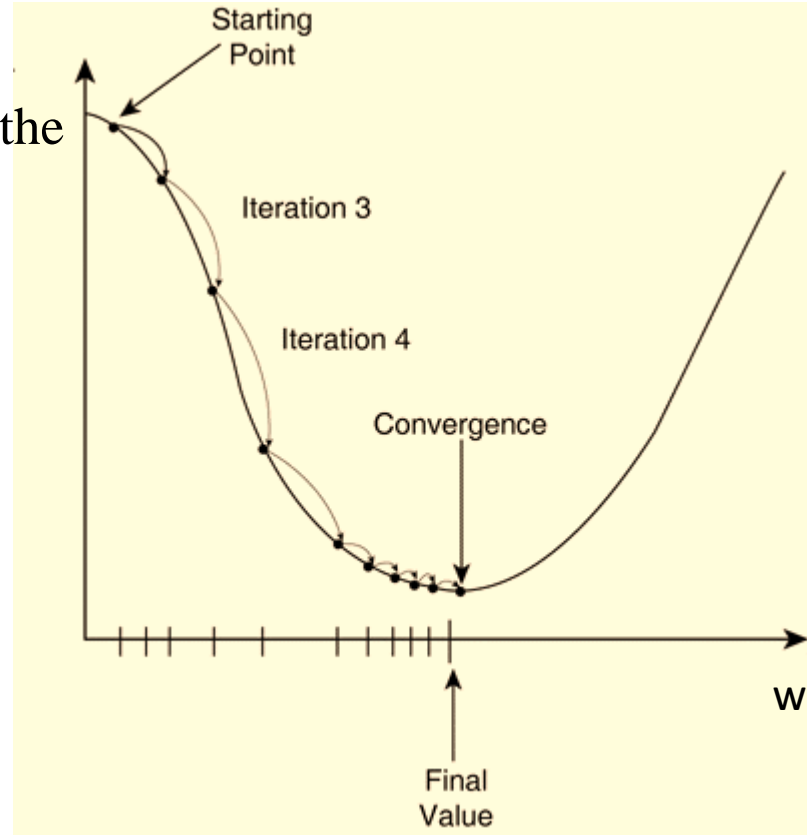
$$x=5 \quad f(x) = 27$$

$$x=5.0001 \quad f(x) = 27.00100001$$

$$\text{Slope at } a = 5 \text{ is } .0010/.0001 = 10$$

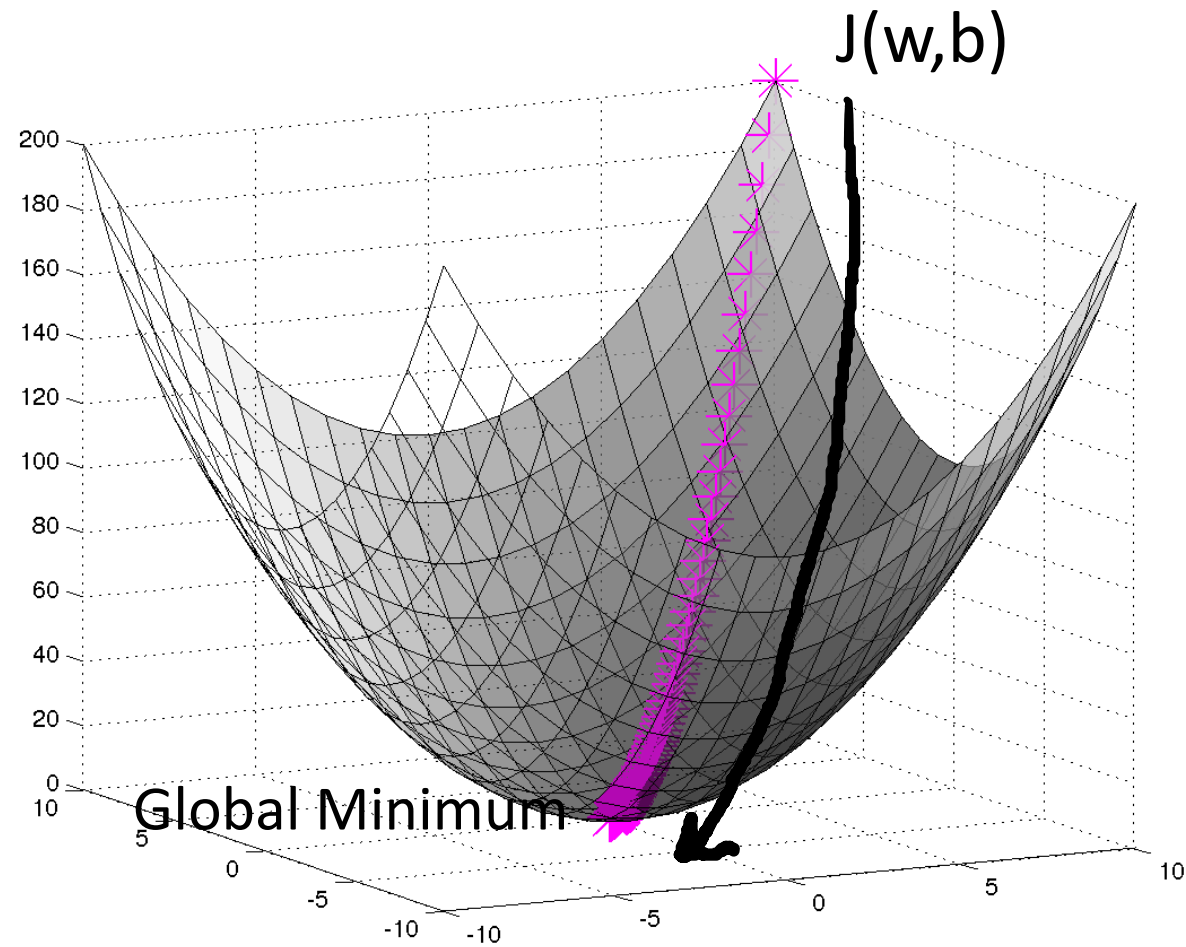
# Gradient Descent single dimension

$\frac{dj(w)}{dw}$  is less than the optimum value



$\frac{dj(w)}{dw}$  is more than the optimum value

# Gradient Descent



# How the weights will change

---

This process will repeat until we find or reach near the global minimum.

---

$\alpha$  is the learning rate which will decide that how fast or slow we are going towards the global minima. How big or small steps we want to take. Both have their own limitations and advantages.

# Derivatives in logistic regression

Original Value of  $y=1$

$x_1=5$   $w_1=0.5$   
 $b=1$   
 $x_2=3$   $w_2=0.5$

$$z = w_1 x_1 + w_2 x_2 + b \rightarrow \hat{y} = a = \sigma(z) \rightarrow L(a, y)$$

$z = 0.5 * 5 + 0.5 * 3 + 1 = 5$        $a = 0.99307 \approx 0.0023$

$$dz = \frac{dL(a, y)}{dz} = \frac{dL}{da} \frac{da}{dz} = \left( \frac{-y}{a} + \frac{1-y}{1-a} \right) * a(1-a) = a - y = -0.00693$$

$$da = \frac{dL(a, y)}{da} = \frac{-y}{a} + \frac{1-y}{1-a} = -1.006978$$

$$dw_1 = \frac{dL(a, y)}{dw_1} = x_1 \cdot dz = 5 * -0.00693 = -0.03465$$

$$dw_2 = \frac{dL(a, y)}{dw_2} = x_2 \cdot dz = 3 * -0.00693 = -0.02079$$

$$db = dz$$

$$w_1 = w_1 - \alpha dw_1 = 0.5 - (0.01 * -0.03465) = 0.503465$$

$$w_2 = w_2 - \alpha dw_2 = 0.5 - (0.01 * -0.02079) = 0.502079$$

$$b = b - \alpha db = 1 - (0.01 * -0.00693) = 1.00693$$

$$\alpha = 0.01$$

# Logistic Regression on whole training set

$J=0, dw_i=0, db=0$

for  $i=1$  to  $m$

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

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

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

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

for  $k=1$  to  $n$

#no of features

$$dw_k += x_k^{(i)} dz^{(i)}$$

$$db += dz^{(i)}$$

$J/=m$

$db/=m$

for  $i=1$  to  $n$

$$dw_i /= m$$

$$w_i = w_i - \alpha dw_i$$

$$b = b - \alpha db$$

# Vectorized

for iteration (epoch) in range (1000)

$Z = w^T X + b$  (In python `np.dot(w.T,X)+b`)

$A = \sigma Z$

$dZ = A - Y$

$dw = \frac{1}{m} X dZ^T$

$db = \frac{1}{m} \text{np.sum}(dz)$

$w = w - \alpha dw$

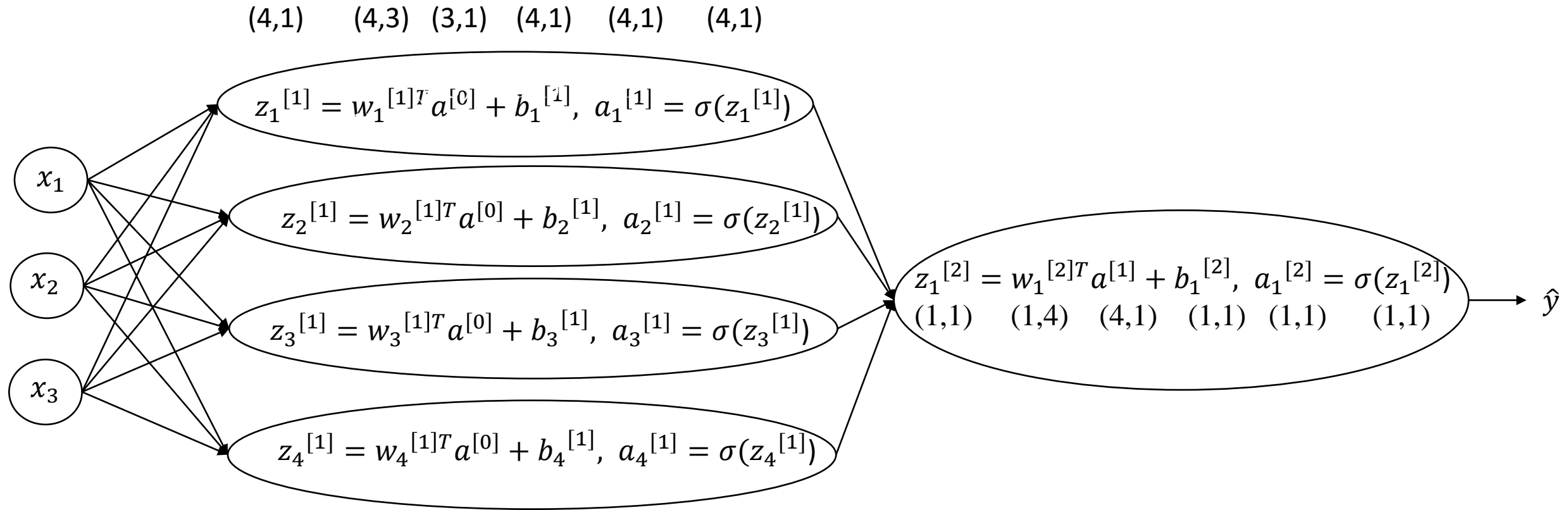
$b = b - \alpha db$



# Neural Network Representation

## 2 layer neural network

$$a_i^l \quad a_{\text{node in layer}}^{\text{layer}}$$

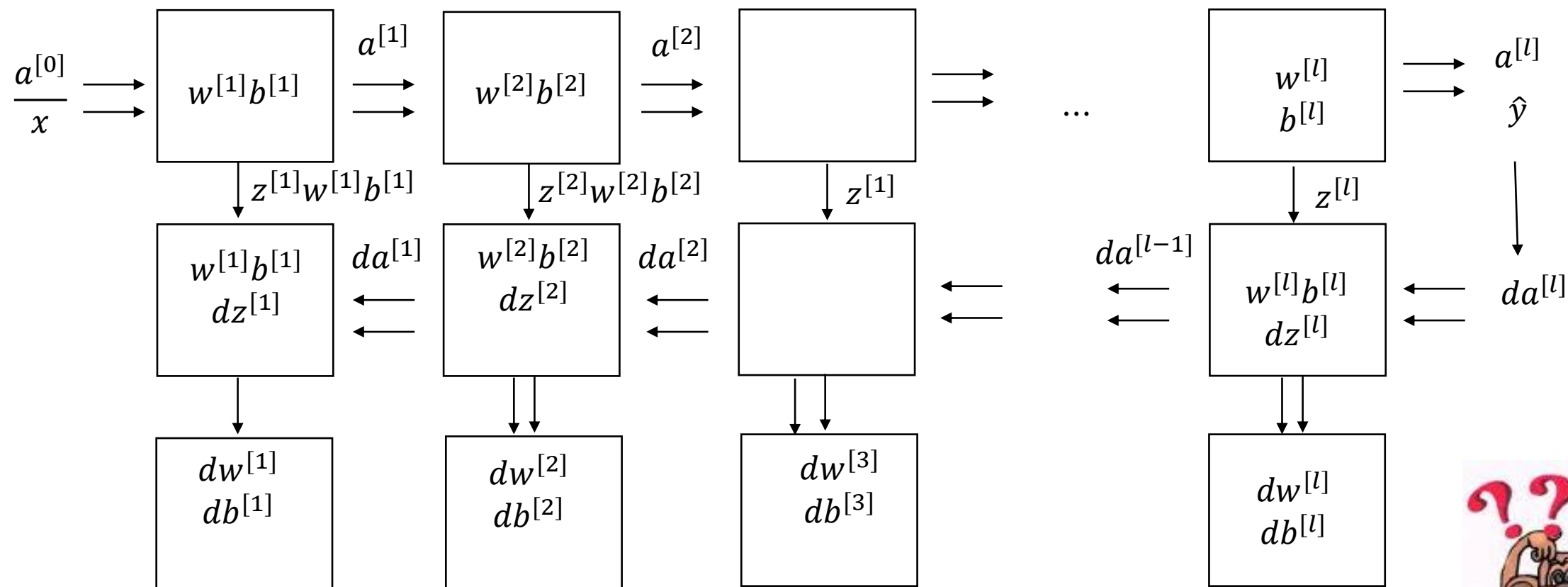


$a^{[0]}$  Layer 0  
Input Layer

$a^{[1]}$  Layer 1  $w^{[1]} \quad b^{[1]} \quad z^{[1]}$   
Hidden Layer

$a^{[2]}$  Layer 2  $w^{[2]} \quad b^{[2]} \quad z^{[2]}$   
Output Layer

# Forward and Backward Functions



$$w^{[l]} = w^{[l]} - \alpha dw^{[l]}$$

$$b^{[l]} = b^{[l]} - \alpha db^{[l]}$$

When to stop the training?

