

PERCEPTRON / ARTIFICIAL NEURON

- 3 inputs :
- (1) learning rate
 - (2) n_iter (epoch)
 - (3) random state - for initialize.

fit method

- 2 inputs :
- (1) X - can be multiple dimension
 - (2) y - label

- algorithm :
1. Make a random number generator using `np.random.RandomState`
 2. Initialise w, b randomly.
 - ↳ w is initialized using normal distribution w/ mean 0 and s.d 0.01
 - ↳ b is initialized as 0
 3. Iterate through epoch, take note of error each epoch
 4. Iterate through training data
 5. Update w, b
 6. Increment error / epoch
 7. Append epoch's error into a list of errors attribute of perception
 8. return the model (self)

net_input & predict

`net_input` takes in X and returns the dot product output

`predict` takes in X and return 1/0 based on output of `net_input`.

`np.where (condition, value-if-true, value-if-false)` ternary operator!

Some notes

- since b is used, the threshold is always 0!
- some imp't eqⁿ

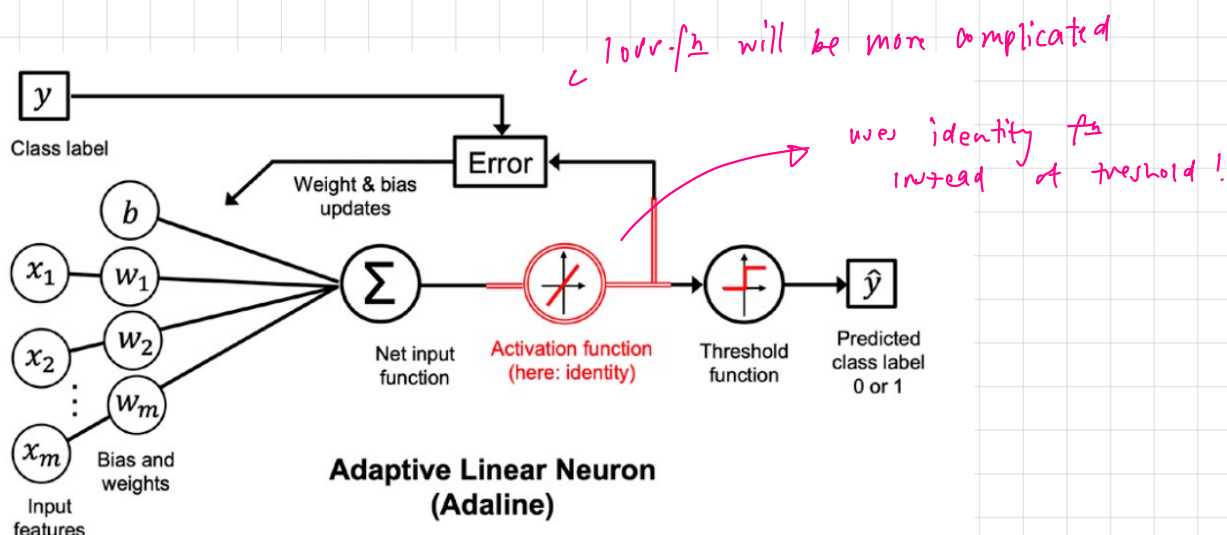
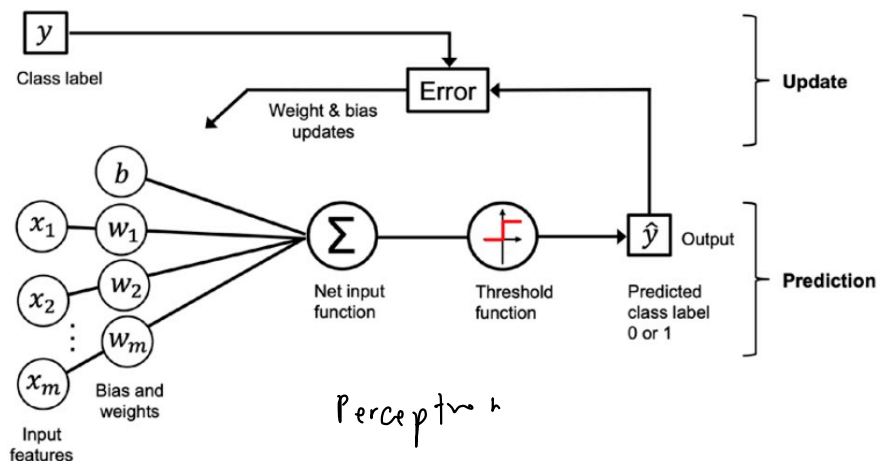
$$z = w_1 x_1 + w_2 x_2 + \dots + w_n x_m + b = \underline{w}^T \underline{x} + b$$

$$\sigma(z) = \begin{cases} 1 & \text{if } z \gg 0 \\ 0 & \text{otherwise} \end{cases}$$

note that $x_j^{(i)}$ means
 i^{th} example
 j^{th} dimension / feature

$$\begin{aligned} \Delta w_1 &= \alpha (y^{(i)} - \hat{y}^{(i)}) x_1^{(i)} \\ \Delta w_2 &= \alpha (y^{(i)} - \hat{y}^{(i)}) x_2^{(i)} \\ \Delta b &= \alpha (y^{(i)} - \hat{y}^{(i)}) \end{aligned}$$

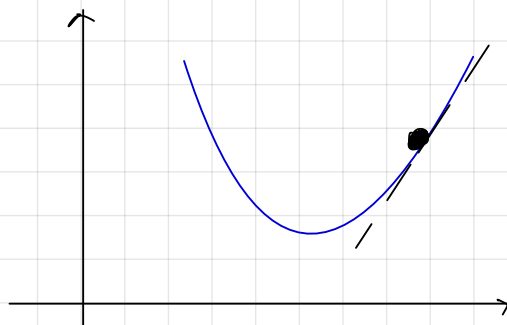
PERCEPTRON vs ADALINE



minimizing loss fn w/ gradient descent

In Adaline, the loss fn is the mean squared error (MSE)

$$L(w, b) = \frac{1}{2n} \sum_{i=1}^n (y^{(i)} - \sigma(z^{(i)}))^2$$



∇_N is the same as $\frac{\partial L}{\partial w}$!

if the $\frac{d}{dx} > 0$, you want to go down ↓

$$\Delta w = -\alpha \nabla_w L(w, b)$$

$$\Delta b = -\alpha \nabla_b L(w, b)$$

$$\frac{\partial L}{\partial w} = -\frac{2}{n} \sum (y^{(i)} - \sigma(z^{(i)})) x_j^i$$

$$\frac{\partial L}{\partial b} = -\frac{2}{n} \sum (y^{(i)} - \sigma(z^{(i)}))$$