# Machine Learning

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- (a)  $a = \frac{-w_1}{w_2}$
- (b)  $b = \frac{-w_0}{w_2}$

(a) 
$$E(w) = \frac{1}{n} \sum_{1}^{n} \frac{1}{1 + e^{-y_n w^T x_n}} (-y_n x_n e^{-y_n w^T x_n})$$

- (b) sigmoid is a monotonic function
- (c) boundary is still linear
- (d) monotonic

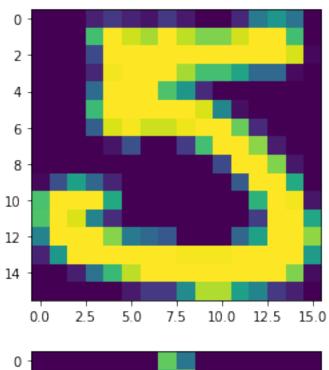
$$XW = X_1 y_1^T + ... + X_n y_n^T XW = \sum_{i=1}^{n} X_i y_i^T$$

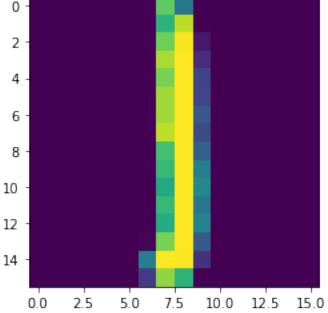
$$(a)w^{\cdot} = \frac{1}{\sigma^2} \sum_{i=1}^{n} x_i^T (y_i - x_i^T w)$$

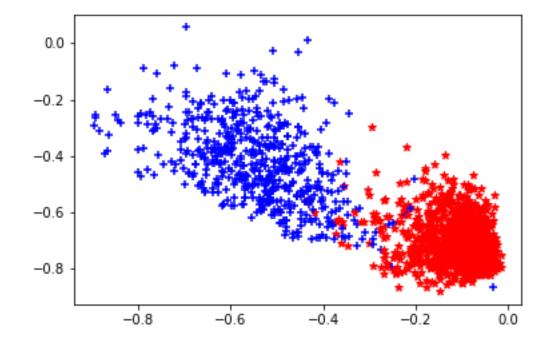
$$\sigma^{\cdot} = \frac{1}{\sigma^3} \sum_{i=1}^{n} (y_i - x_i^T w)^2 - \frac{n}{\sigma}$$

(b)  $\sigma$  optimization looks like RSS

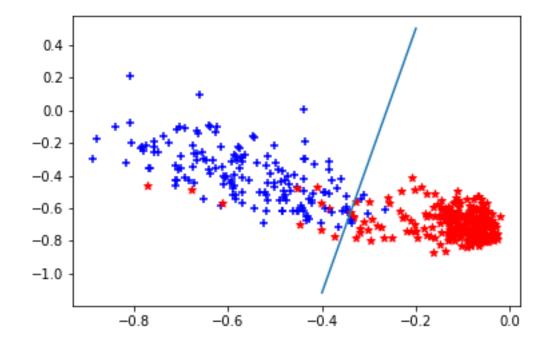
when C=2, it can be reduced to the softmax function will become sigmoid function







(b)



(d)