

ECS 171: Machine Learning

Summer 2023

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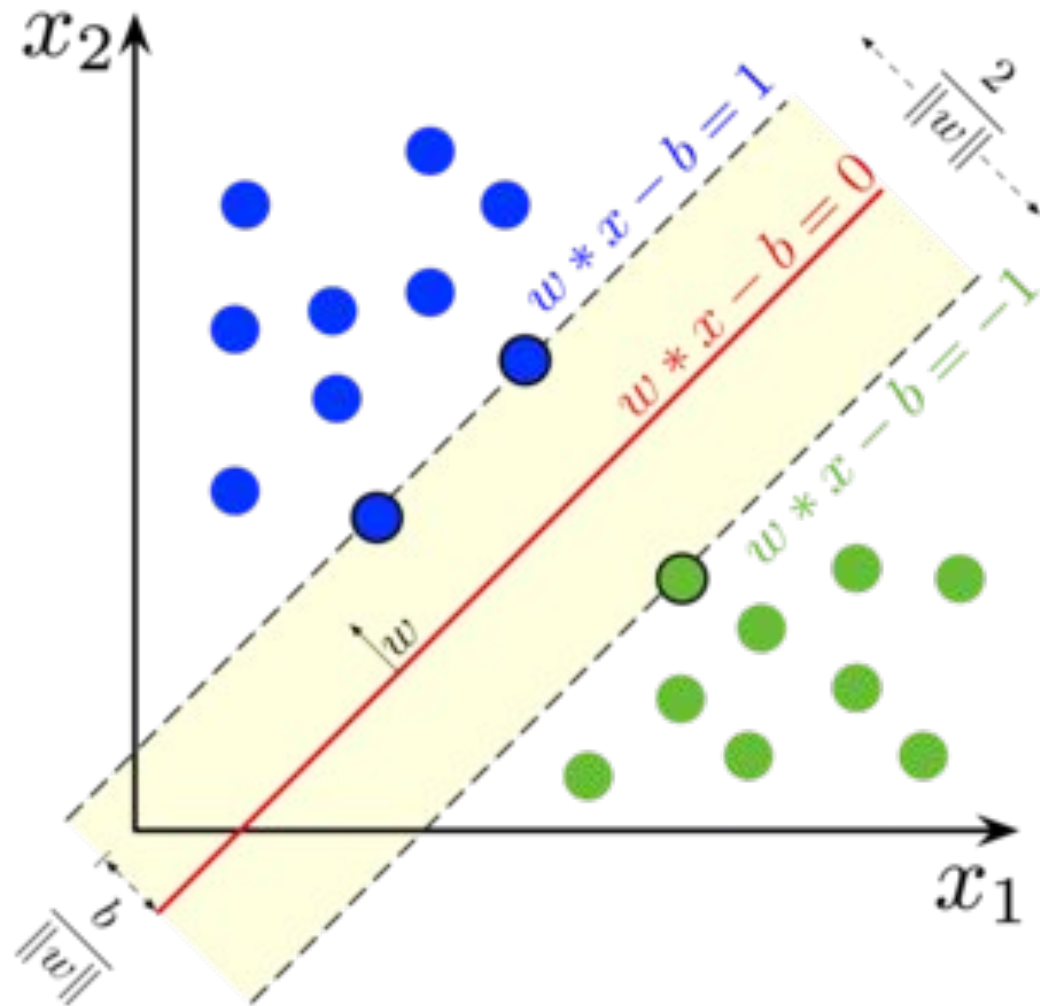
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Support Vector Machines

& Logistic Regression Again!?

SVM Classification

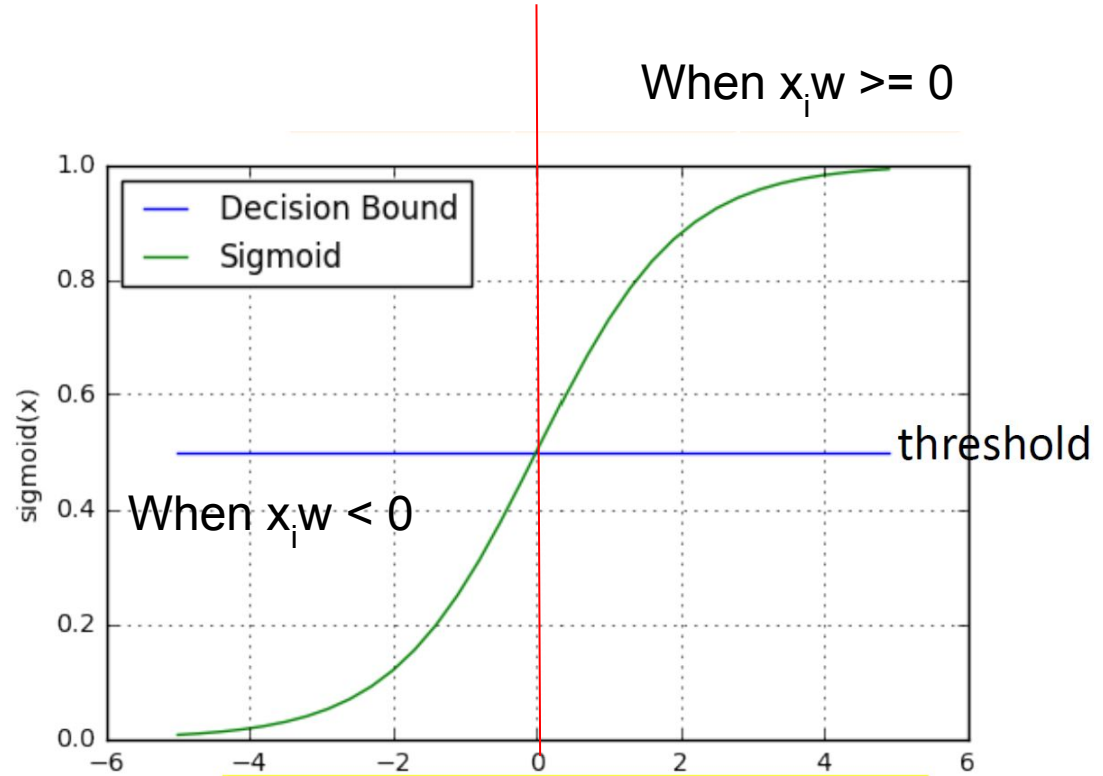
Wikipedia



Logistic Regression

\hat{y}_i Is our prediction given formula on the right, but is given a value of 0 or 1 based on the threshold of 0.5

Prior to threshold we can say our raw value is our probability. As our raw value is continuous from 0 to 1.



$$\hat{y}_i = \begin{cases} 0 & ; \text{predicted value} < \text{threshold} \\ 1 & ; \text{predicted value} \geq \text{threshold} \end{cases}$$

Logistic Regression

Where we have Bernoulli observations

And p_k is the probability of $y_k=1$ and

$1-p_k$ is the probability $y_k = 0$

The log loss for the k -th point is:

We can say p_k is our raw value, which is our probability of $y_k = 1$ given $x_i w$

$$\text{Cost} \begin{cases} -\ln p_k & \text{if } y_k = 1, \\ -\ln(1 - p_k) & \text{if } y_k = 0. \end{cases}$$

$$-y_k \ln p_k - (1 - y_k) \ln(1 - p_k)$$

log-likelihood

$$\ell = \sum_{k:y_k=1} \ln(p_k) + \sum_{k:y_k=0} \ln(1 - p_k) = \sum_{k=1}^K (y_k \ln(p_k) + (1 - y_k) \ln(1 - p_k))$$

$$J(w) = d/dw \ell^* 1/k$$

Logistic Regression

log-likelihood

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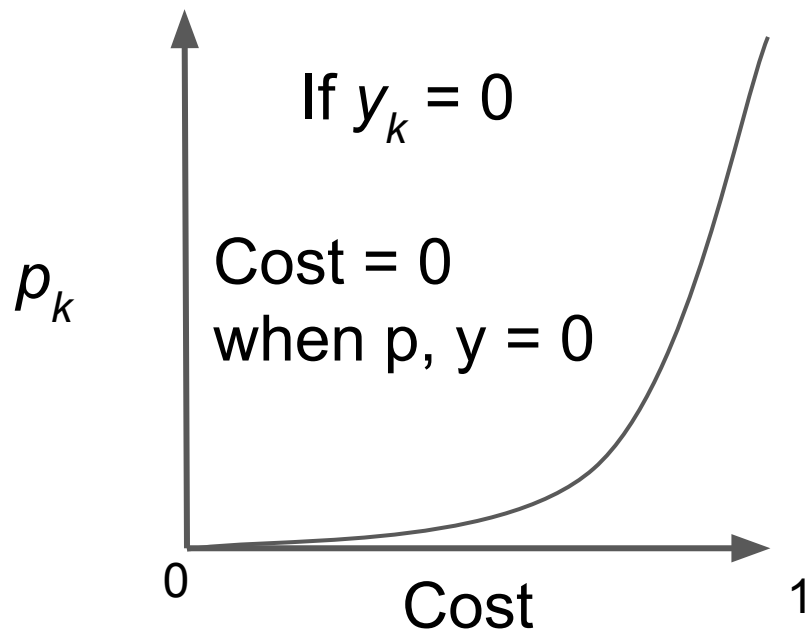
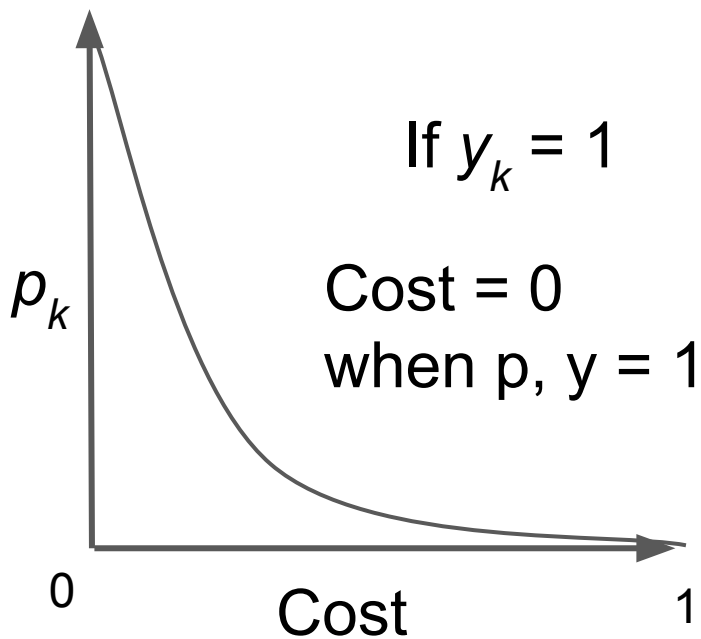
$$J(w) = 1/k \, d/dw \, \ell$$

$$d/dw \, \ell = \sum_{k=1}^K (y_k - p_k) + (y_k - p_k)x_k$$

Logistic Regression

The log loss for the k -th point is:

$$\text{Cost}(p_k, y_k) \begin{cases} -\ln p_k & \text{if } y_k = 1, \\ -\ln(1 - p_k) & \text{if } y_k = 0. \end{cases}$$



Logistic Regression

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Prior to threshold we can say our raw value is our probability. As our raw value is continuous from 0 to 1.

$$\hat{y} = \frac{1}{1 + e^{(\mu - x)/s}}$$

$$\hat{y} = \frac{1}{1 + e^{-(w_0 + w_1 x)}}$$

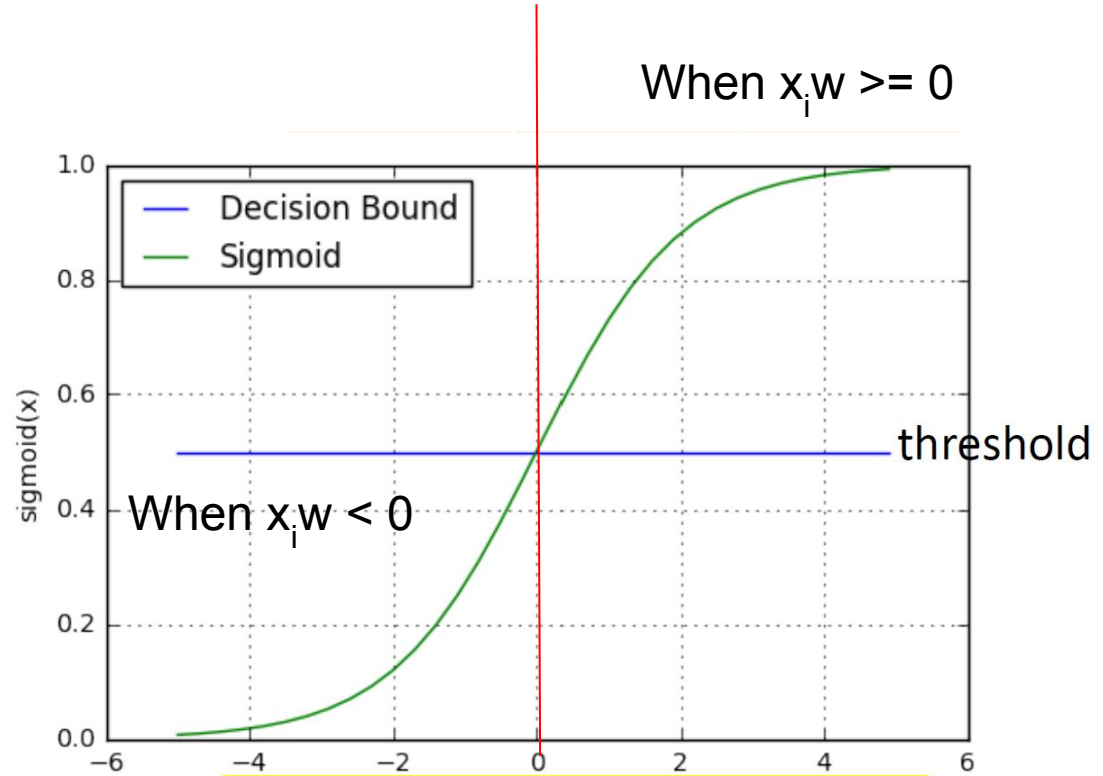
where $w_0 = -\mu/s$ and $w_1 = 1/s \therefore$ we can solve for μ and s

$$\mu = w_0 / w_1 \text{ and } s = 1 / w_1$$

Logistic Regression

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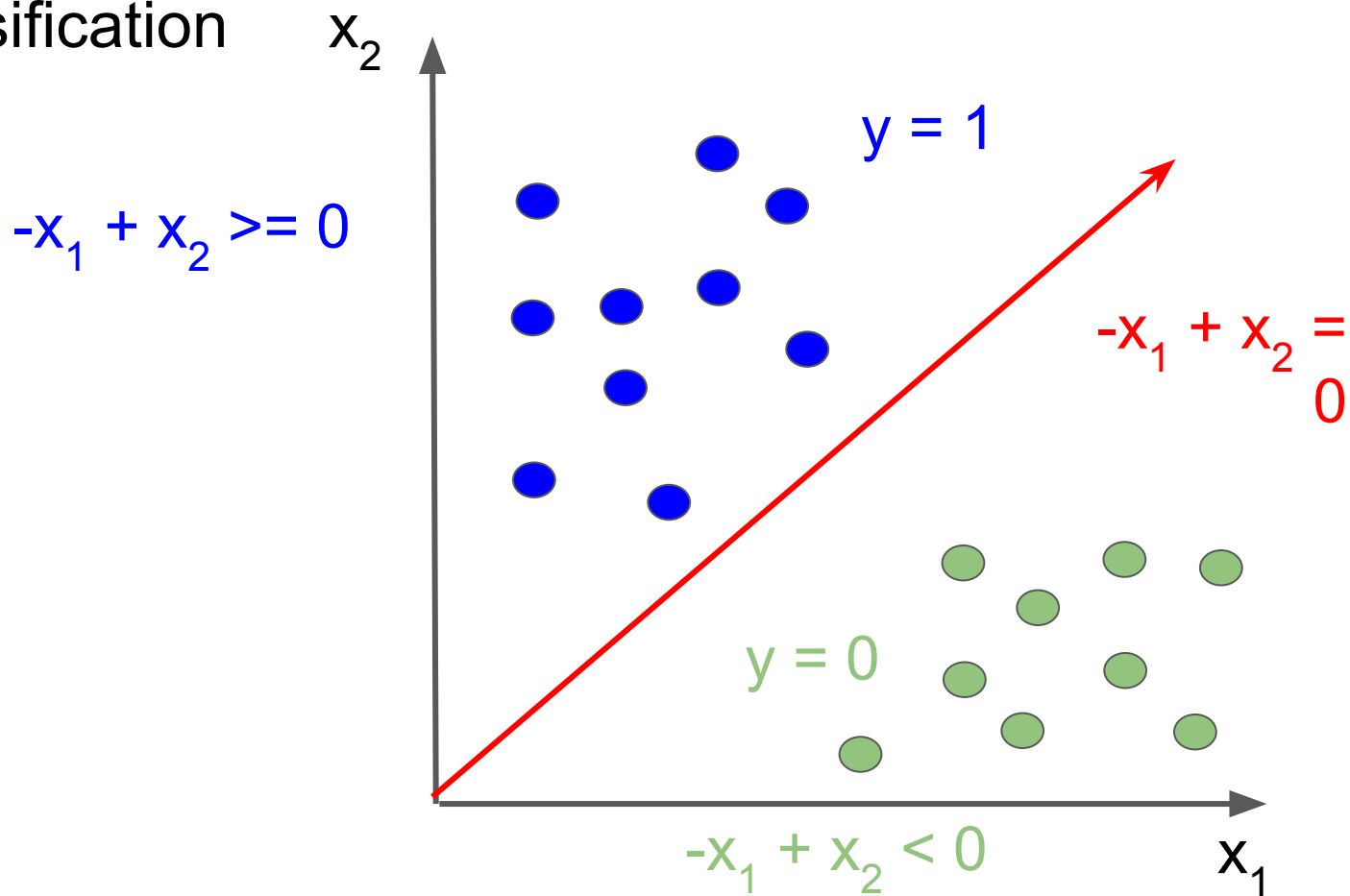
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Logistic Classification

$$\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$

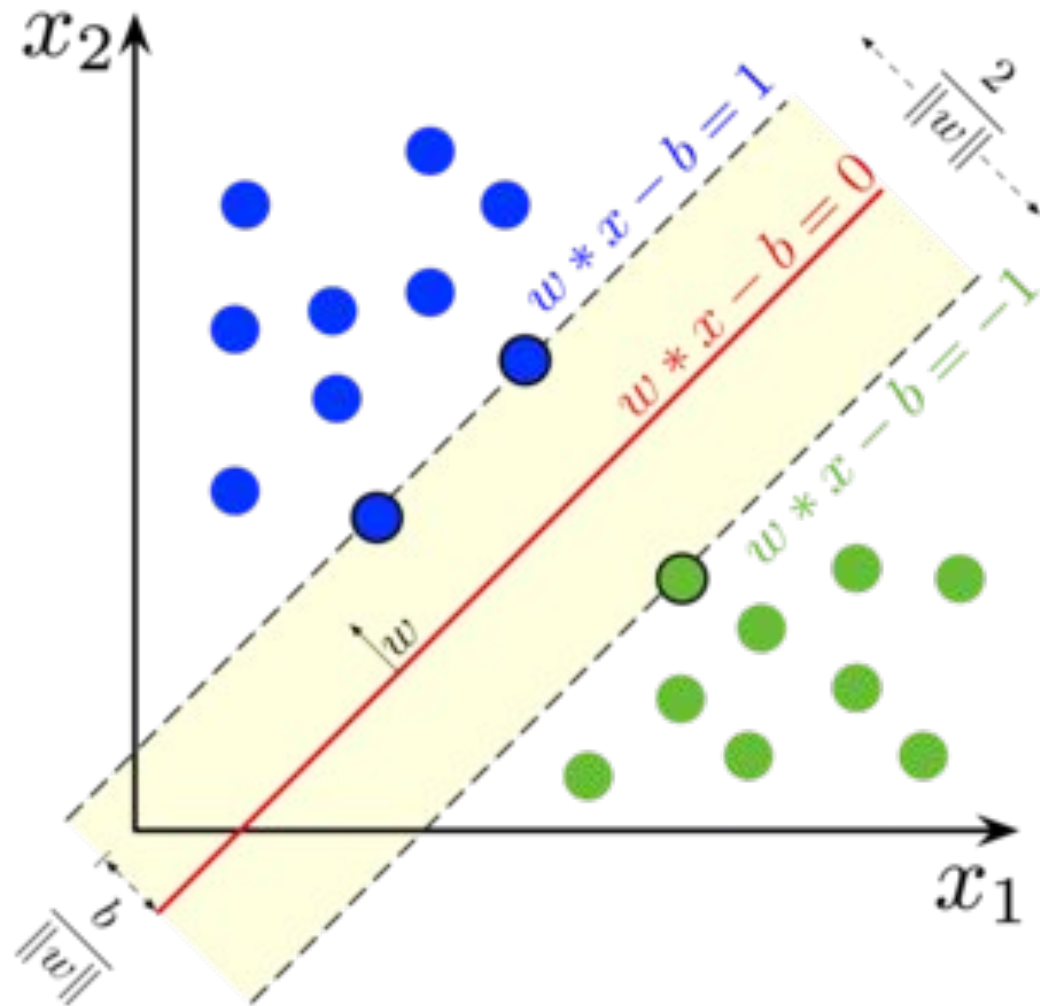
$$\mathbf{w} = \begin{bmatrix} -1 \\ +1 \end{bmatrix}$$

Predict $y = 1$ given $x_1 w_1 + x_2 w_2 + w_0$



SVM Classification

Wikipedia

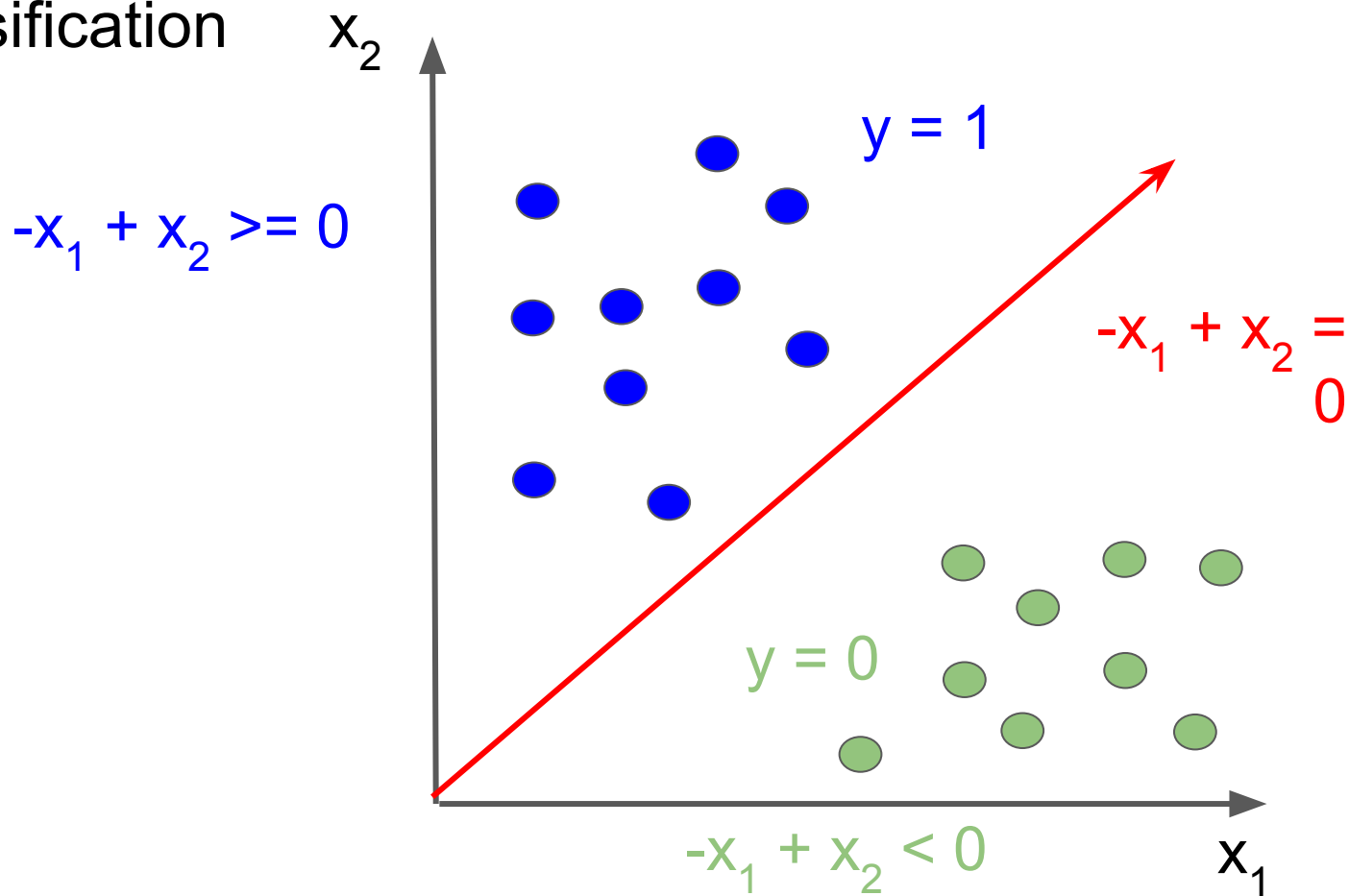


Logistic Classification

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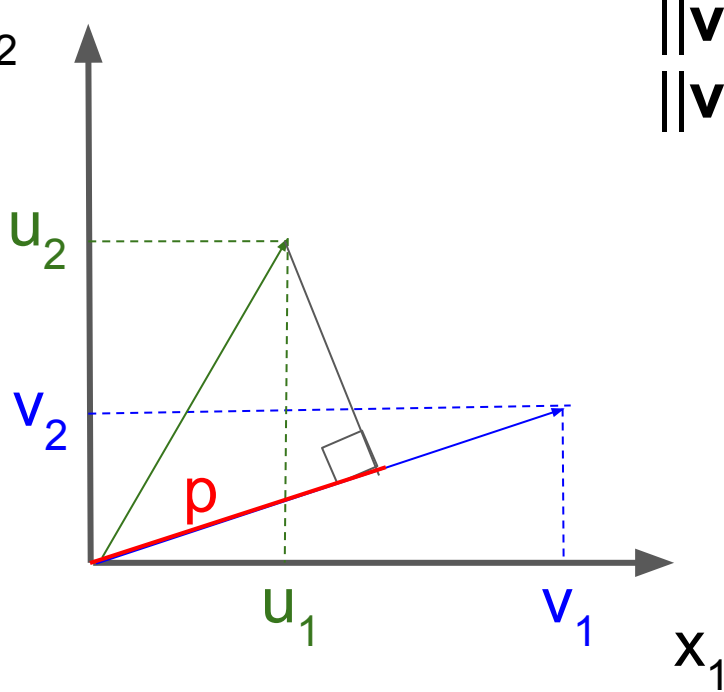


Adding Margin (Recall Inner Products)

$$\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$$

$$\|\mathbf{v}\| = \text{Length of } \mathbf{v}$$
$$\|\mathbf{v}\| = \sqrt{v_1^2 + v_2^2}$$

$$\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \end{bmatrix}$$



$$\mathbf{v}^T \mathbf{u} = \|\mathbf{v}\| p$$

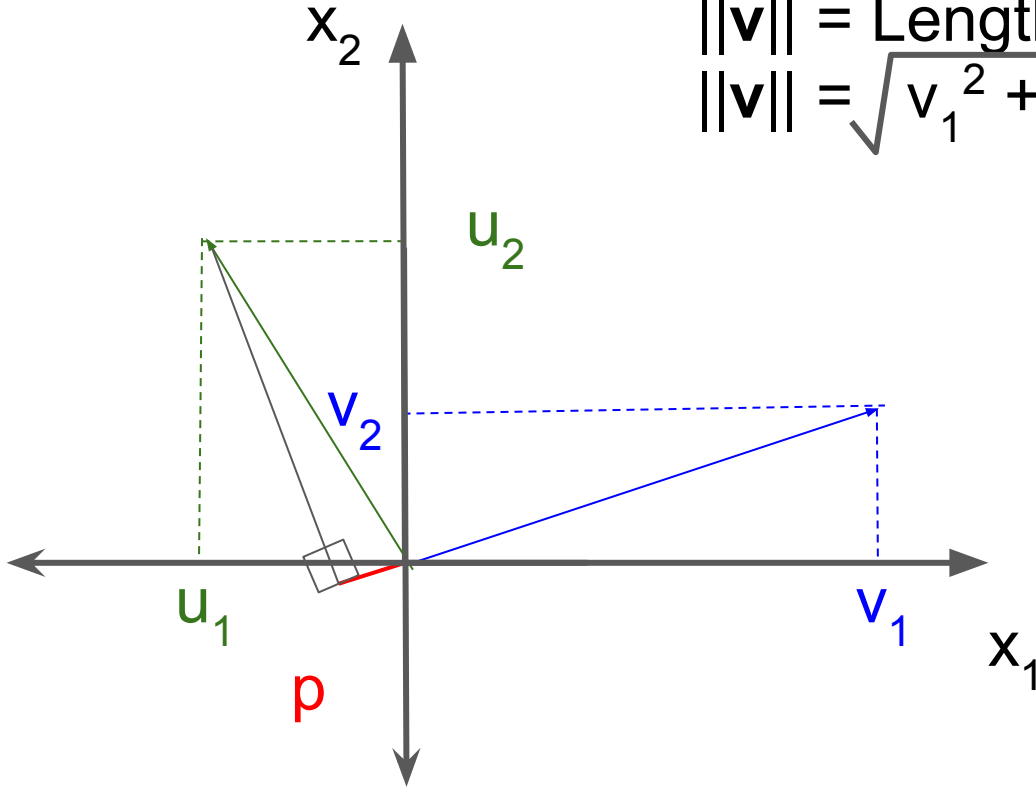
Where p is the
projection of \mathbf{u} onto \mathbf{v}

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Where p is the
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SVM with Margin

We want large \mathbf{p}

Since it will be our margin

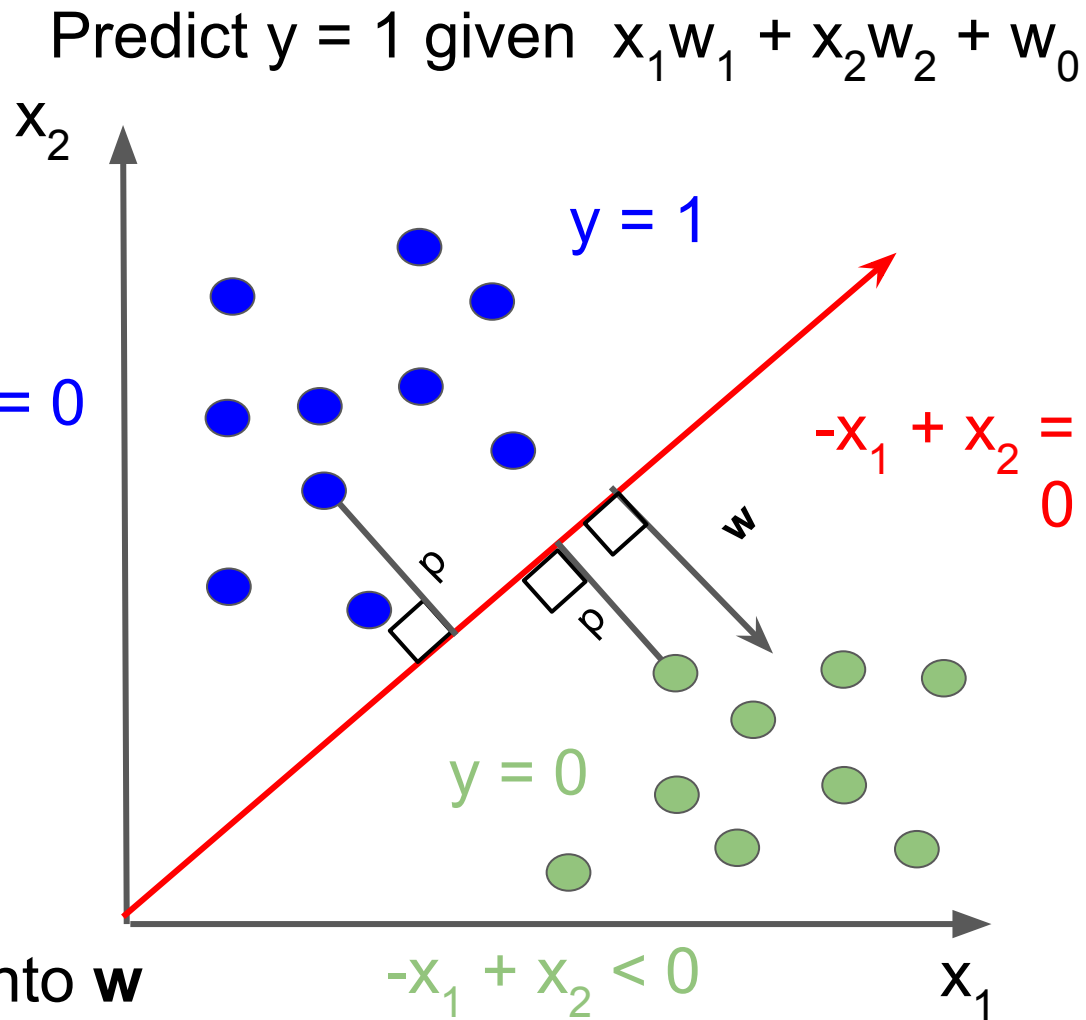
$$\min_{\mathbf{w}} \frac{1}{2} \sum_{j=1}^m \mathbf{w}_j^2 = \frac{1}{2} \|\mathbf{w}\|^2$$

$-x_1 + x_2 \geq 0$

$$\mathbf{p} \|\mathbf{w}\| \geq 1 \quad \text{if } y = 1$$

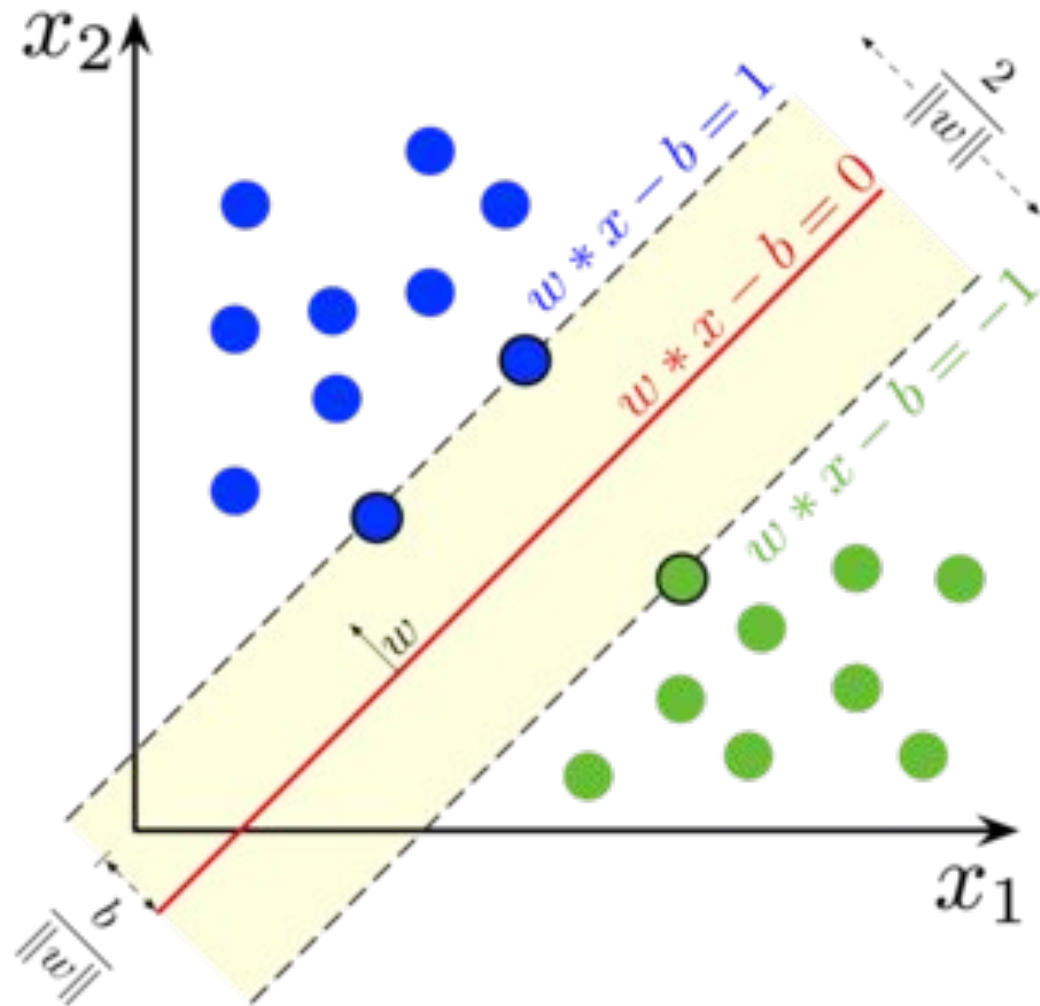
$$\mathbf{p} \|\mathbf{w}\| \leq -1 \quad \text{if } y = 0$$

Where \mathbf{p} is projection of \mathbf{x} onto \mathbf{w}



SVM Classification

Wikipedia



SVM Classification

Kernels will not be on the midterm!

