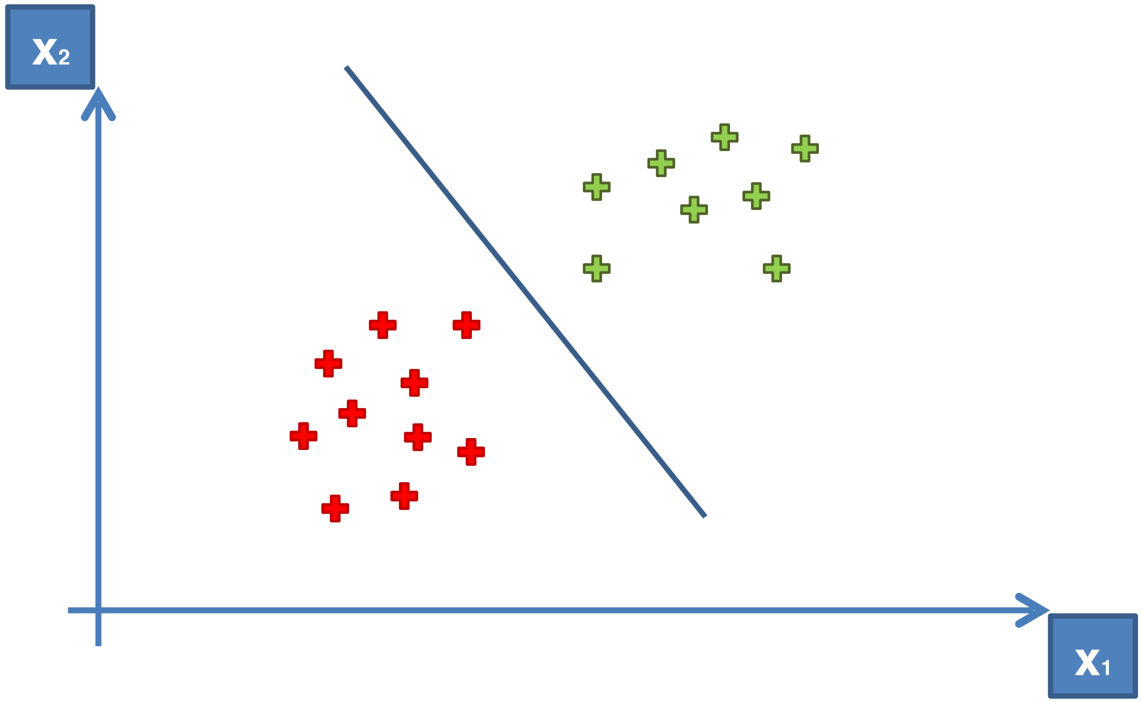
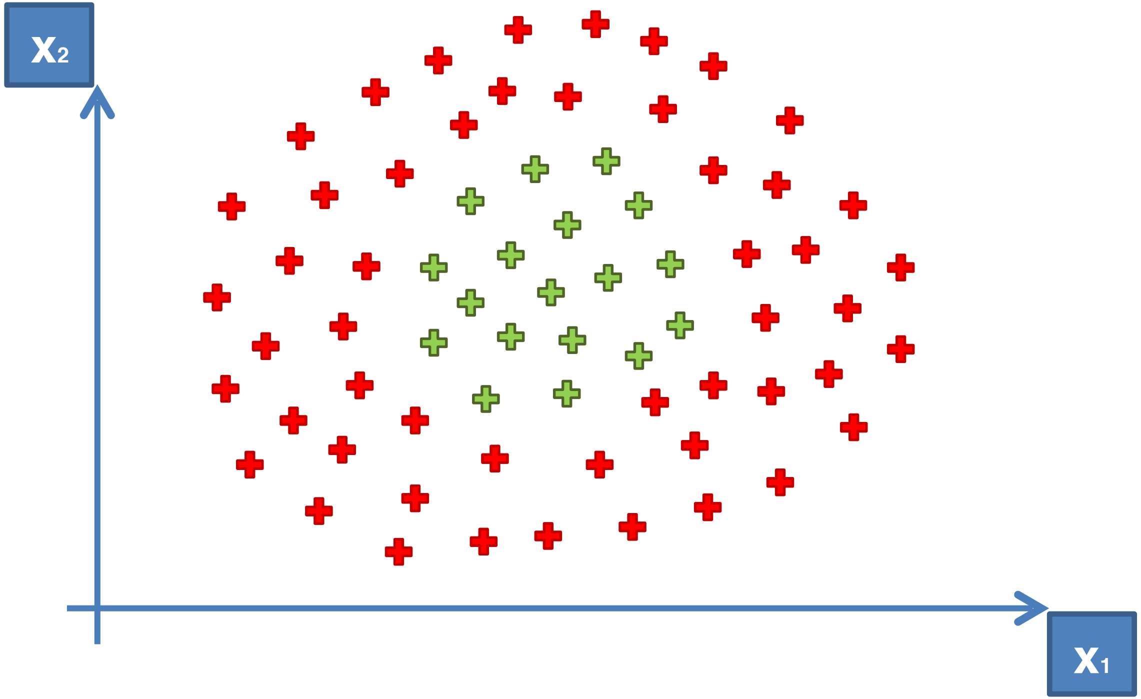
Idea del Kernel SVM

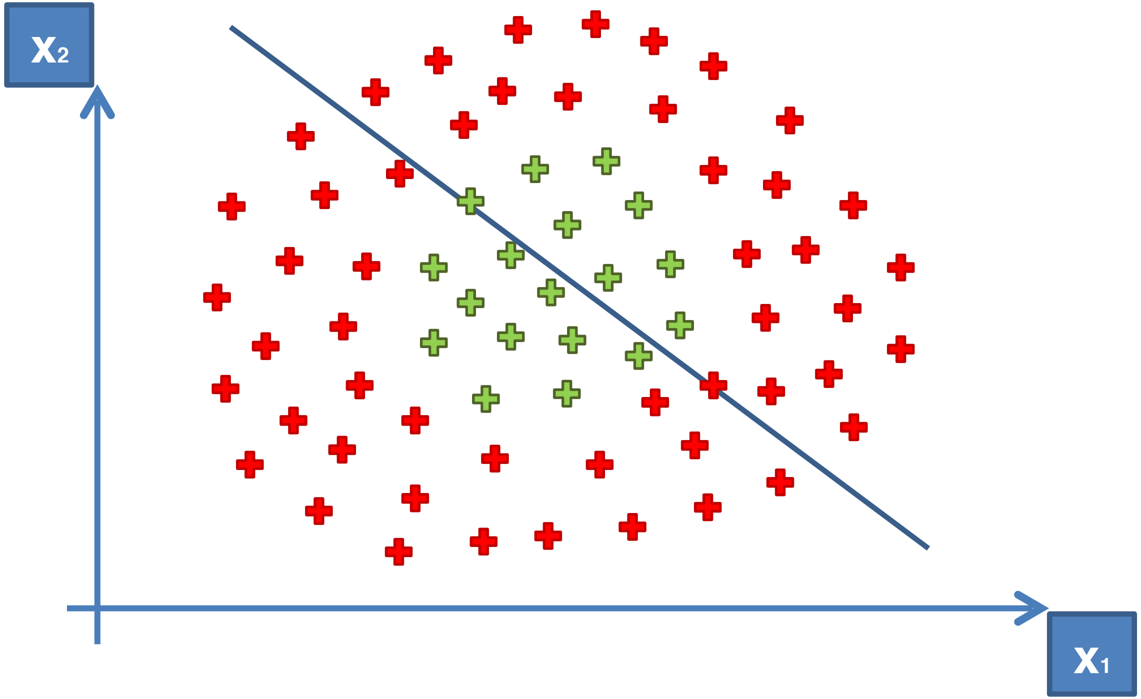
SVM separa bien estos puntos



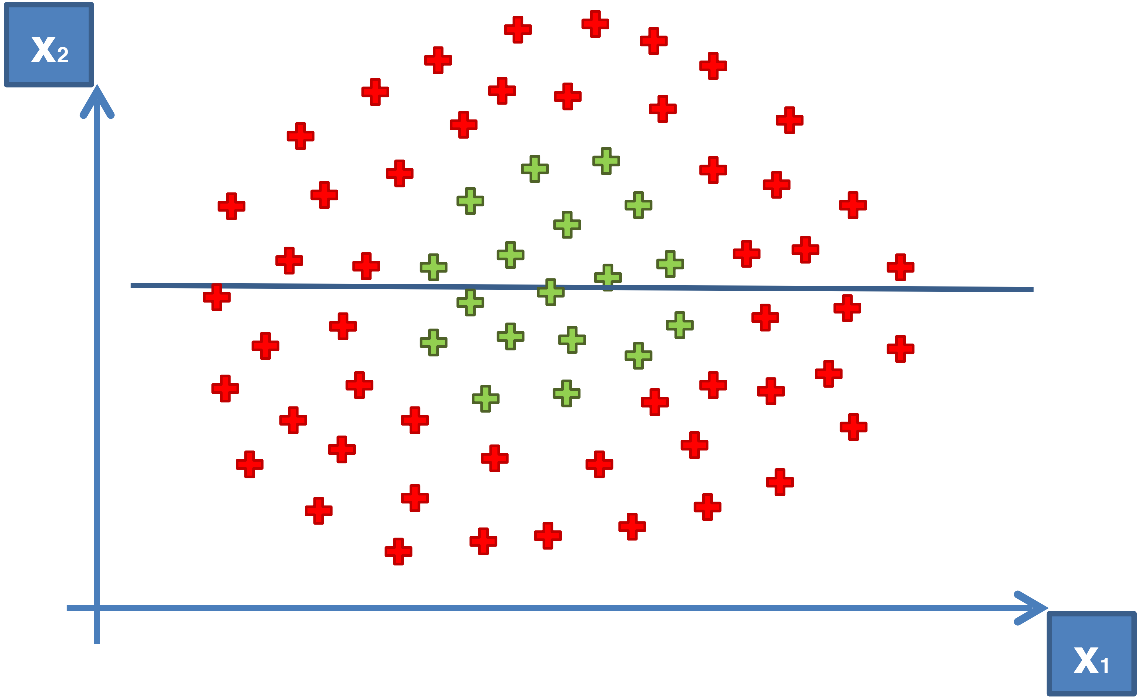
¿Y estos puntos?



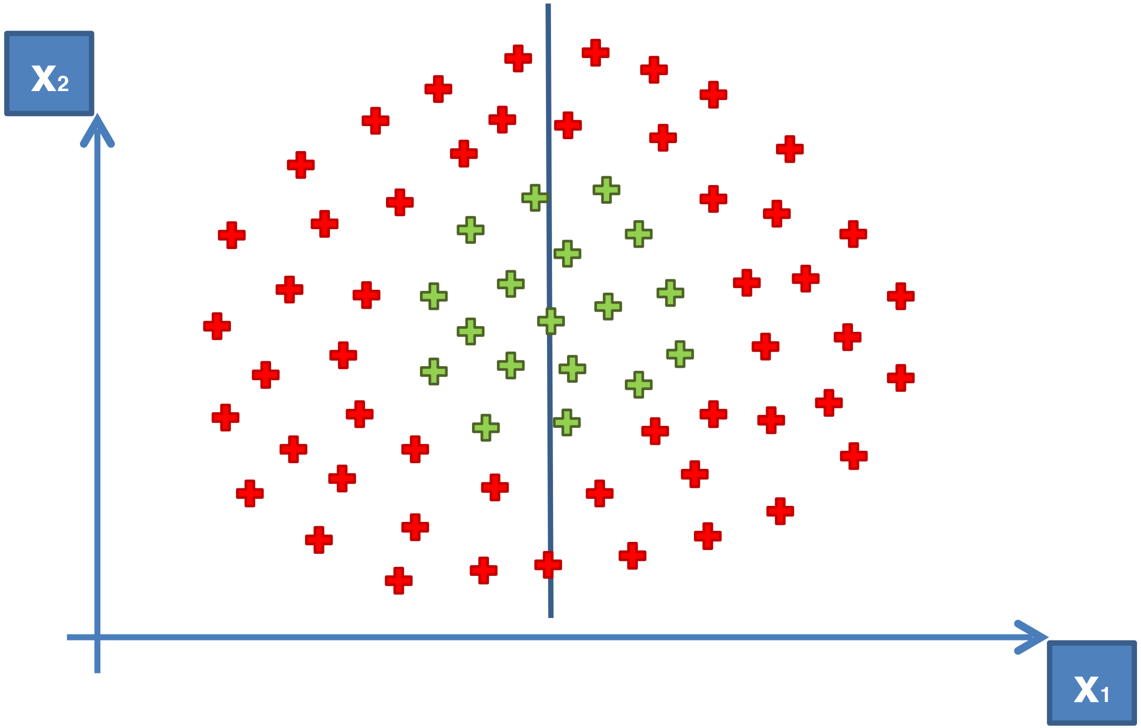
¿Y estos puntos?



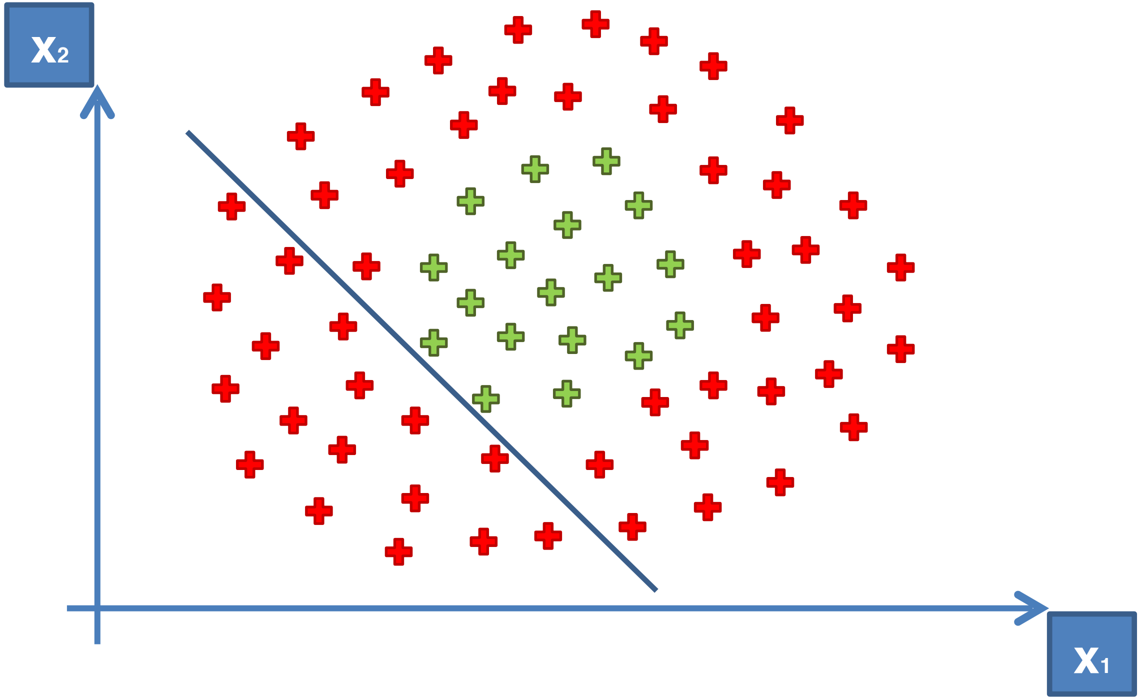
¿Y estos puntos?



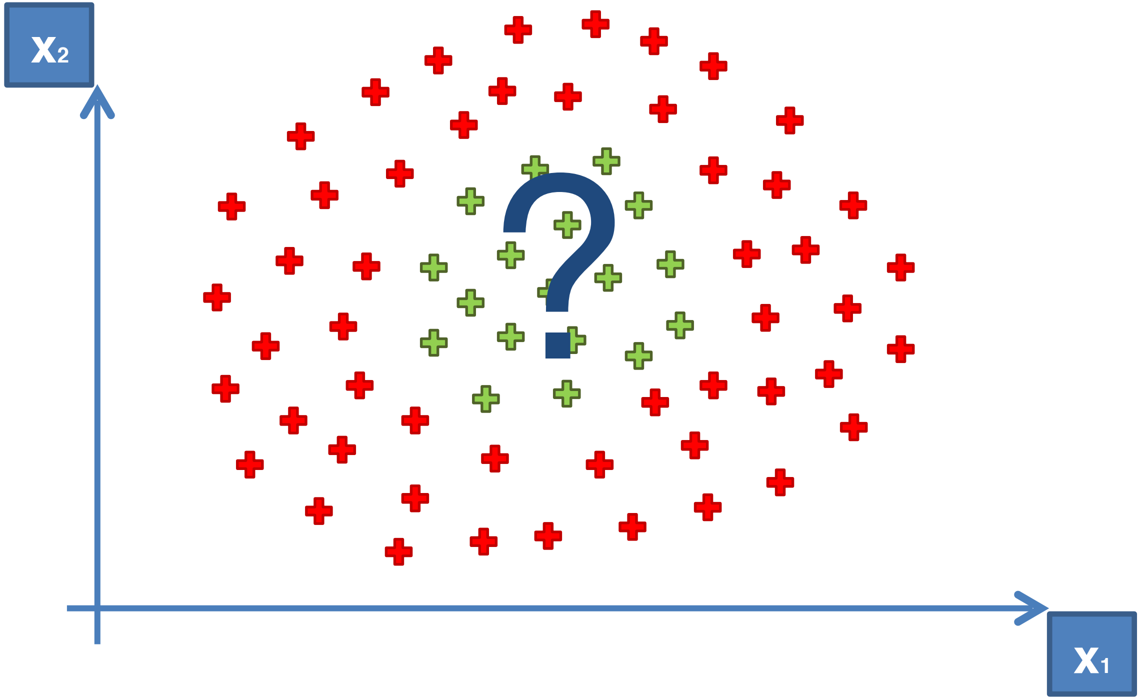
¿Y estos puntos?



¿Y estos puntos?



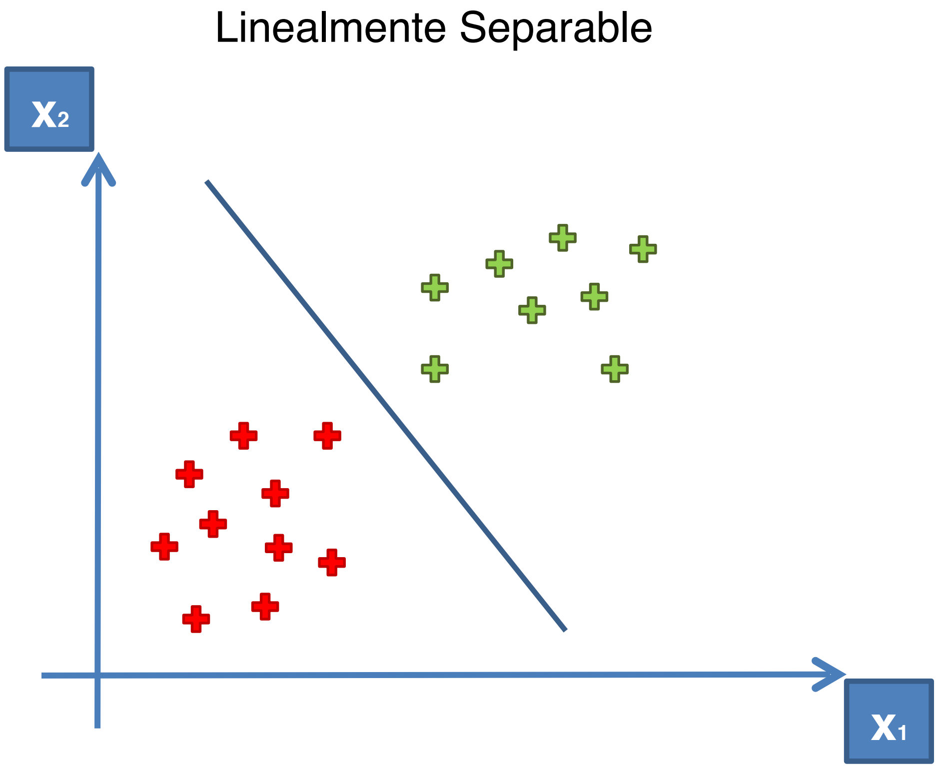
¿Y estos puntos?

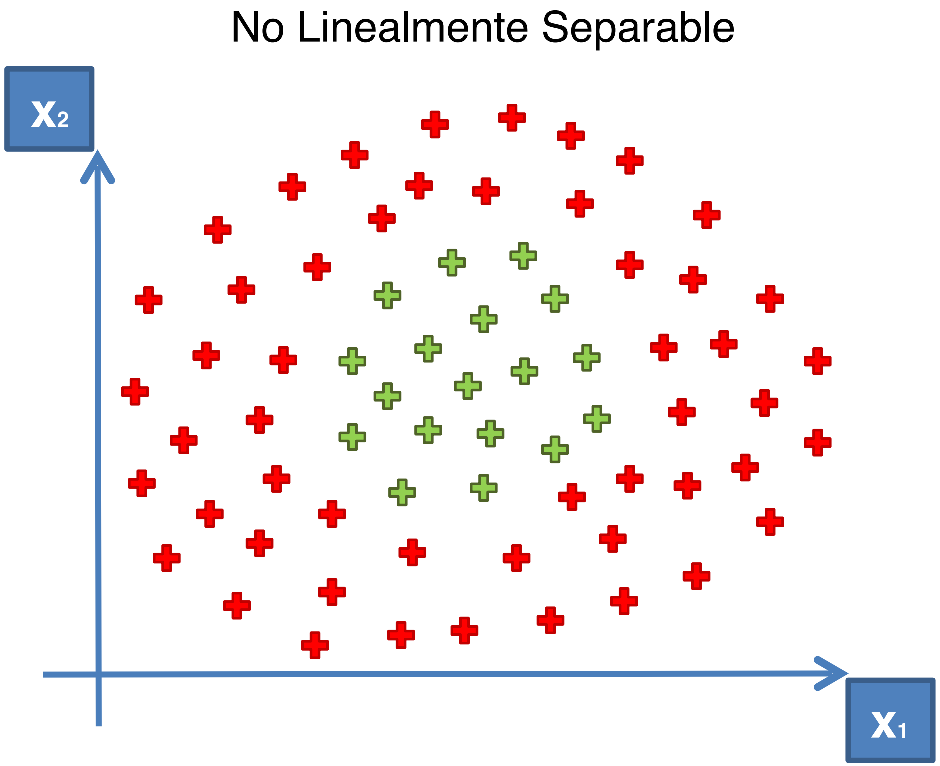


¿Por qué no funciona?

Porque esta nube de puntos no es LINEALMENTE SEPARABLE

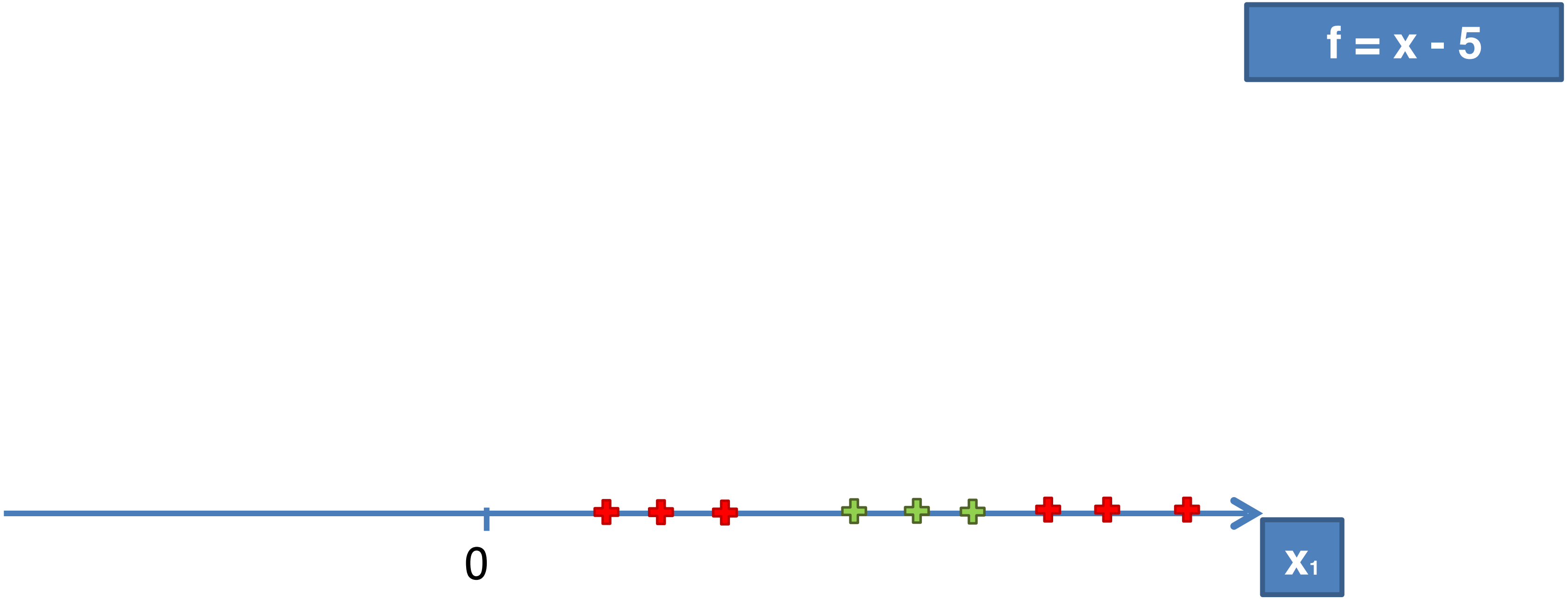
Linealmente Separable





Espacios de Dimensión Superior

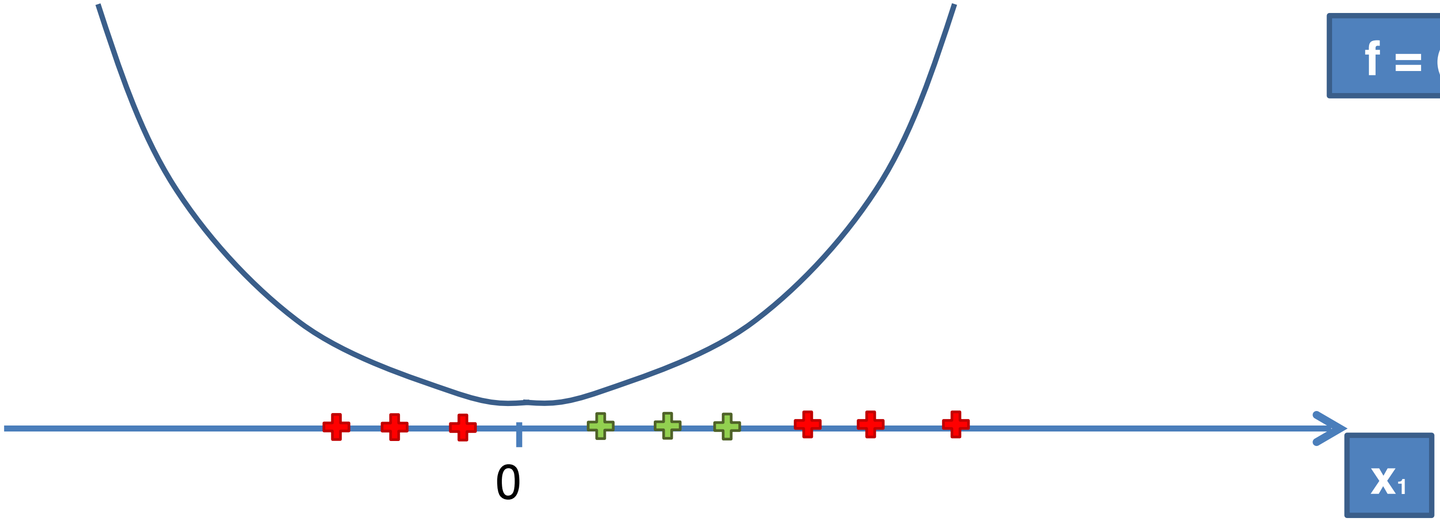
Transformando a una Dimensión Superior



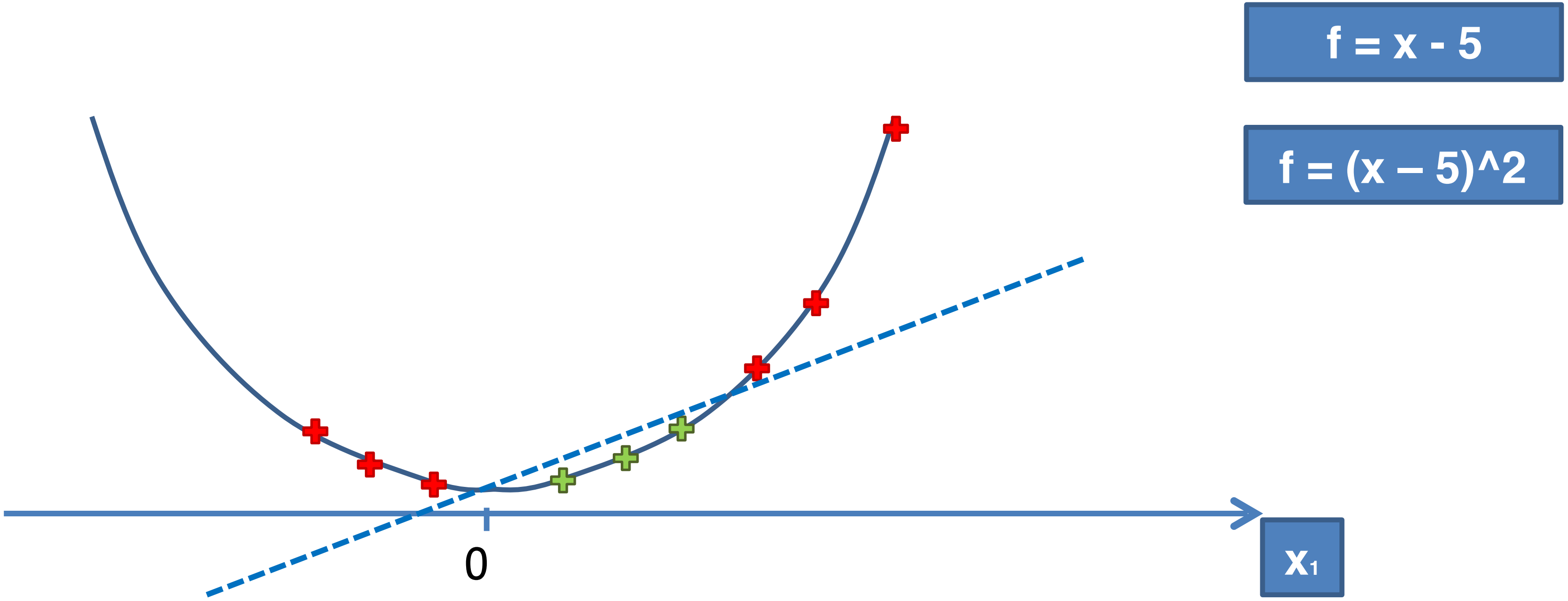
Transformando a una Dimensión Superior

$f = x - 5$

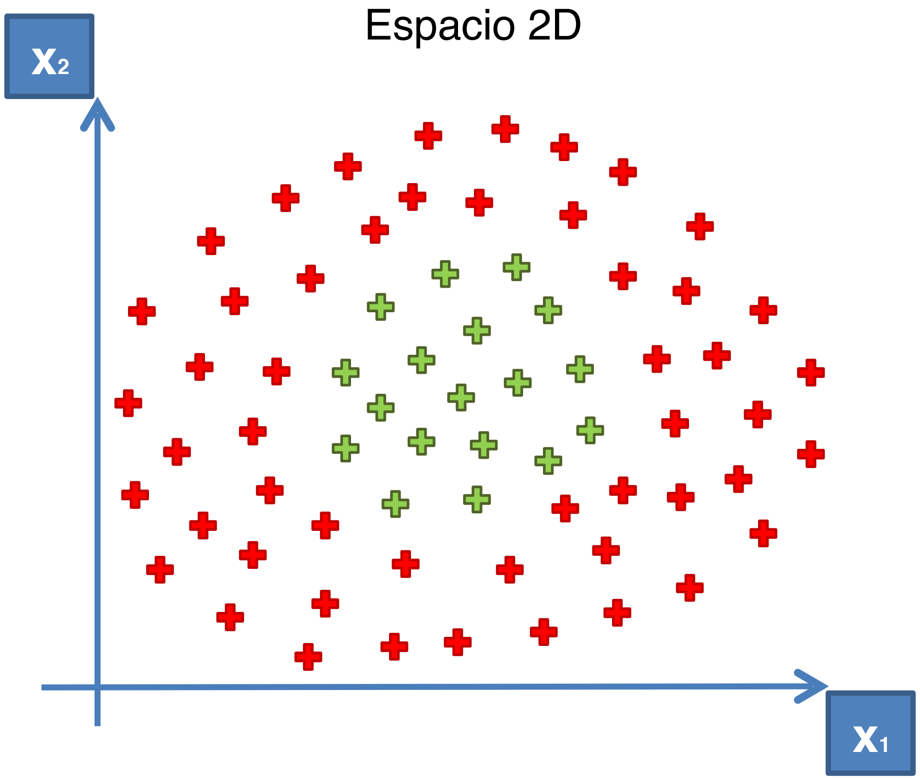
$f = (x - 5)^2$



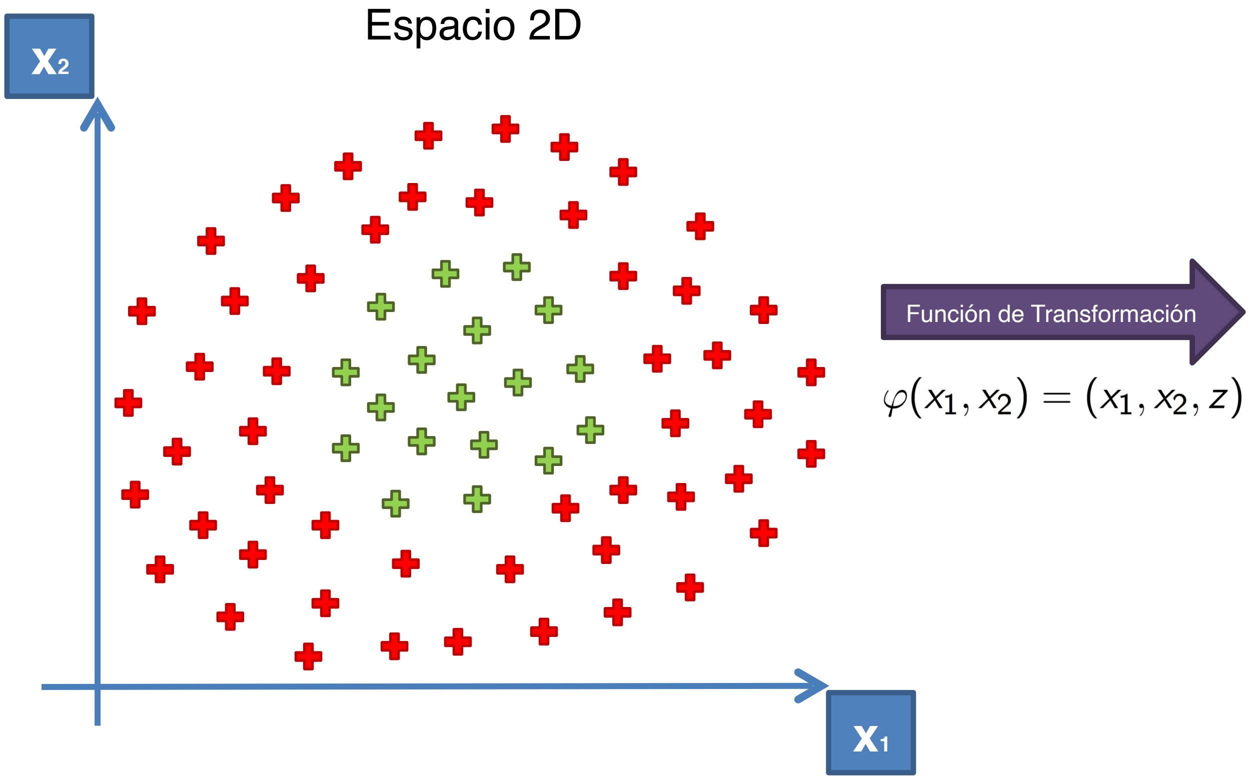
Transformando a una Dimensión Superior



Transformando a una Dimensión Superior

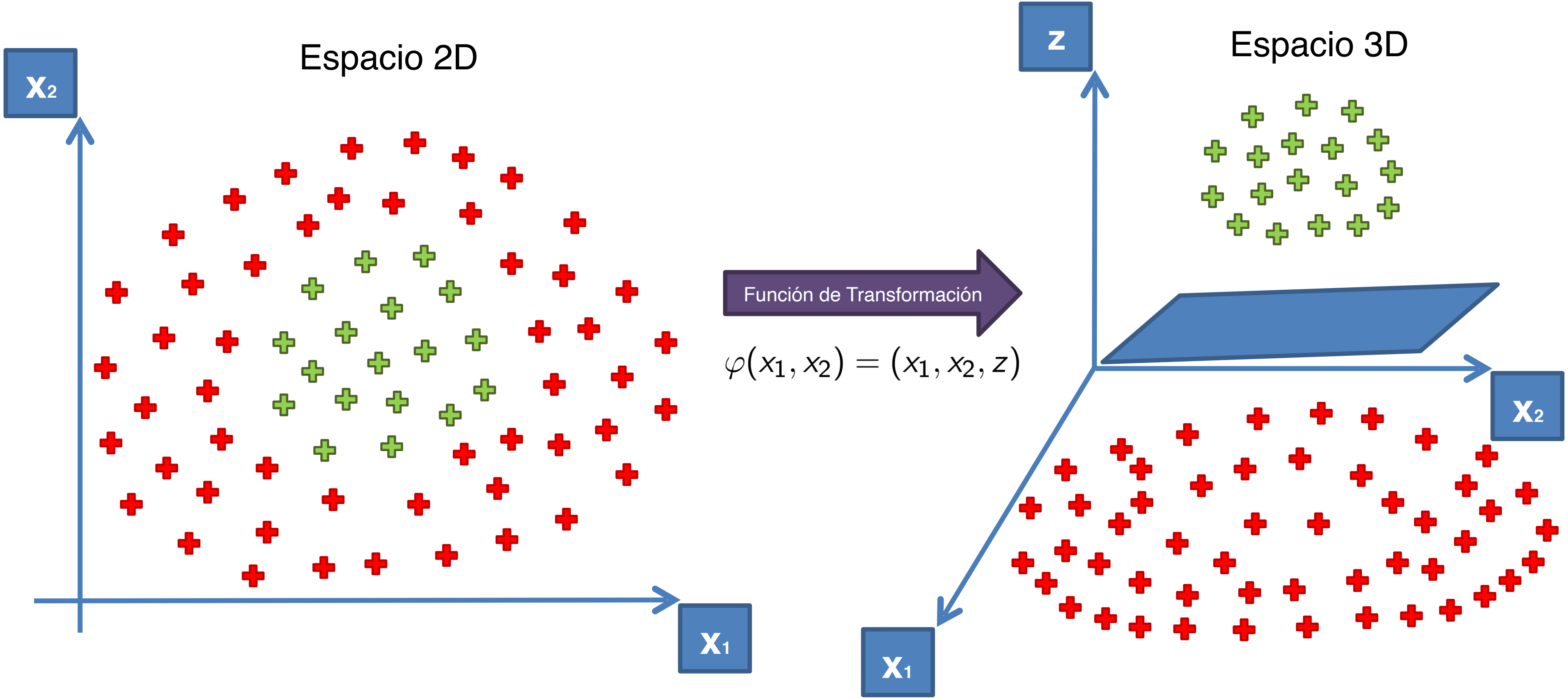


Transformando a una Dimensión Superior

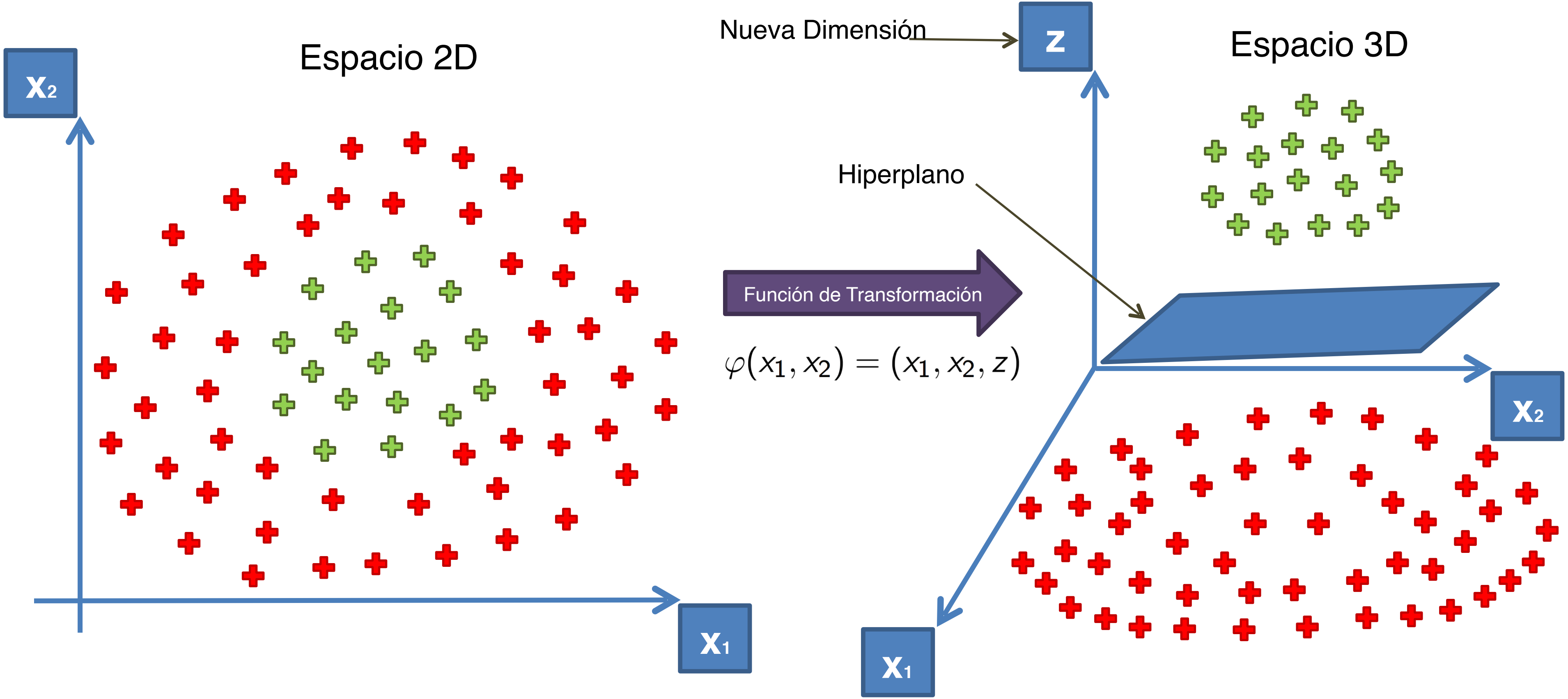


$$\varphi(x_1, x_2) = (x_1, x_2, z)$$

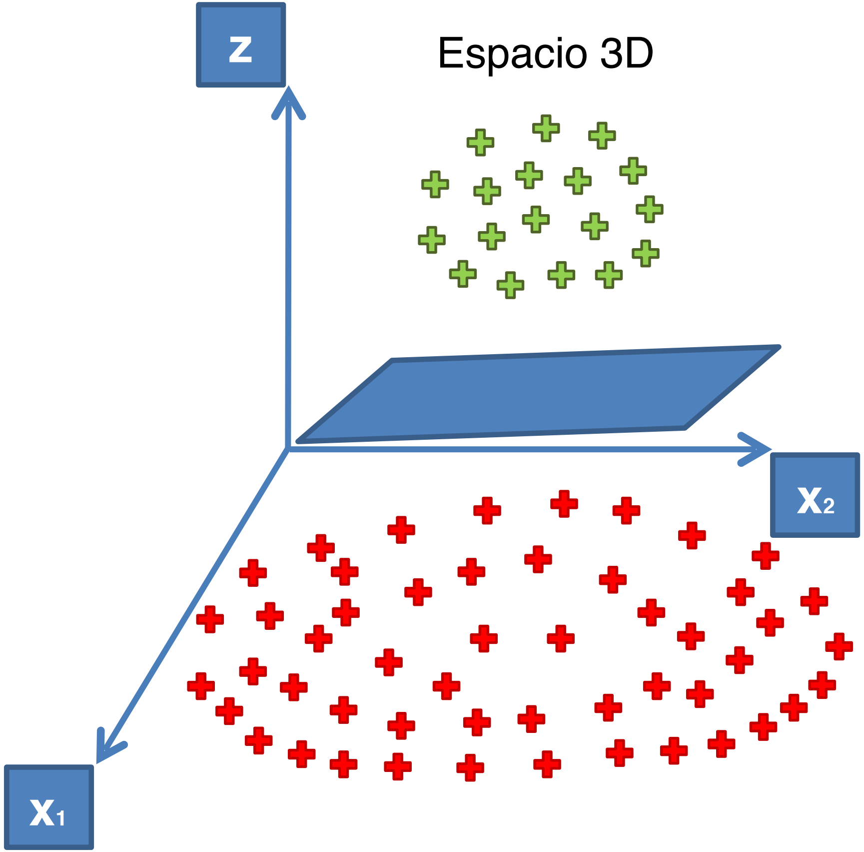
Transformando a una Dimensión Superior



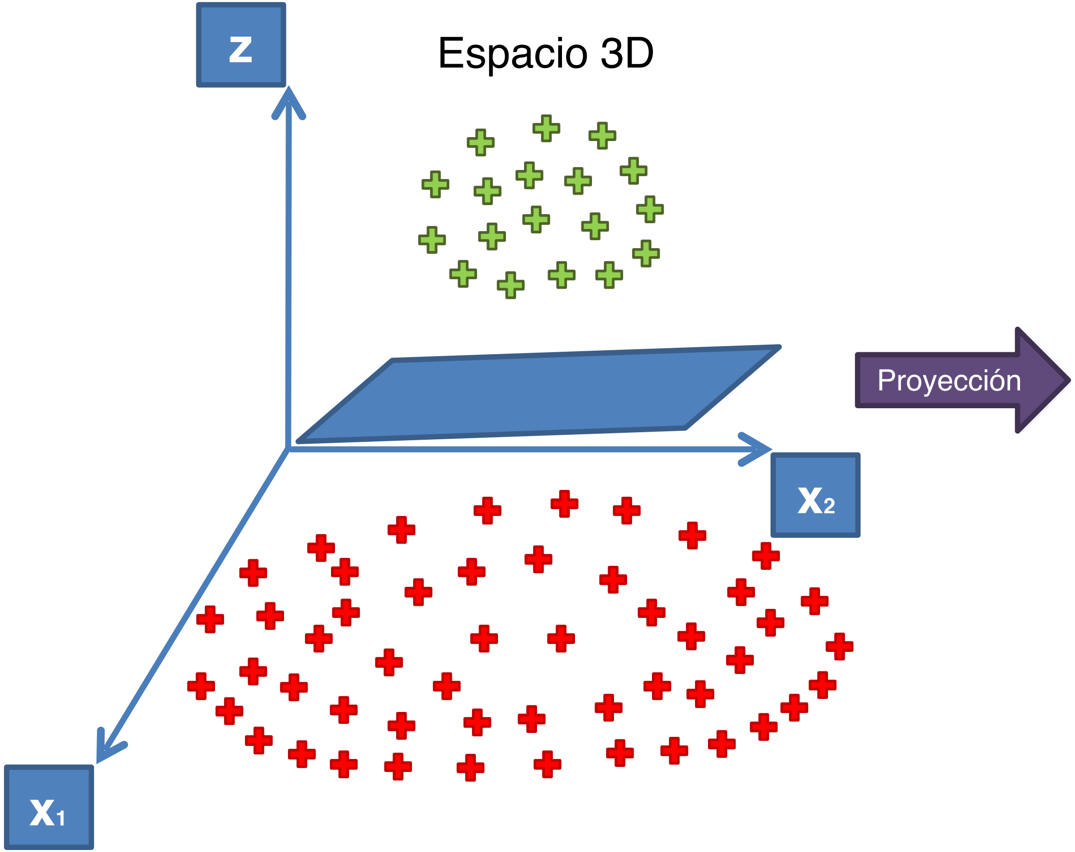
Transformando a una Dimensión Superior



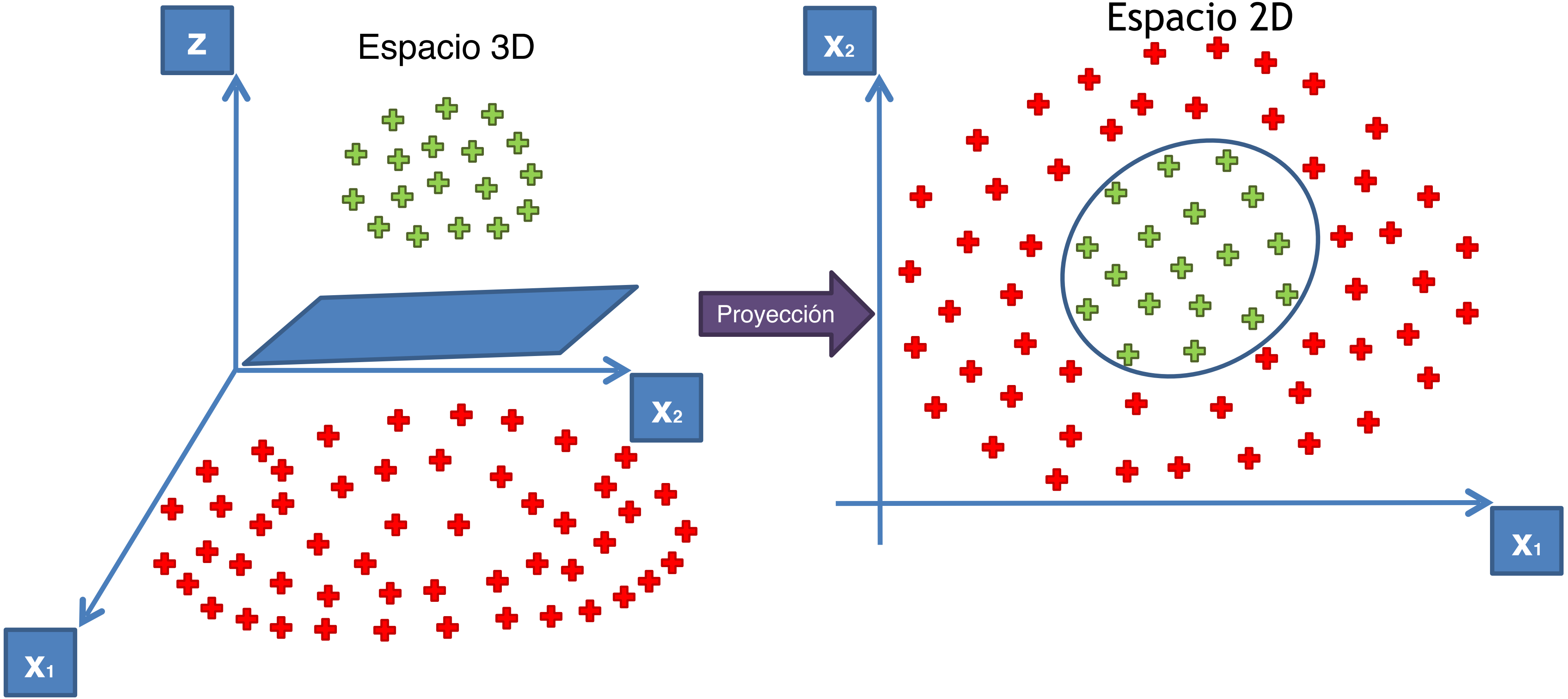
Proyectando de vuelta al espacio 2D



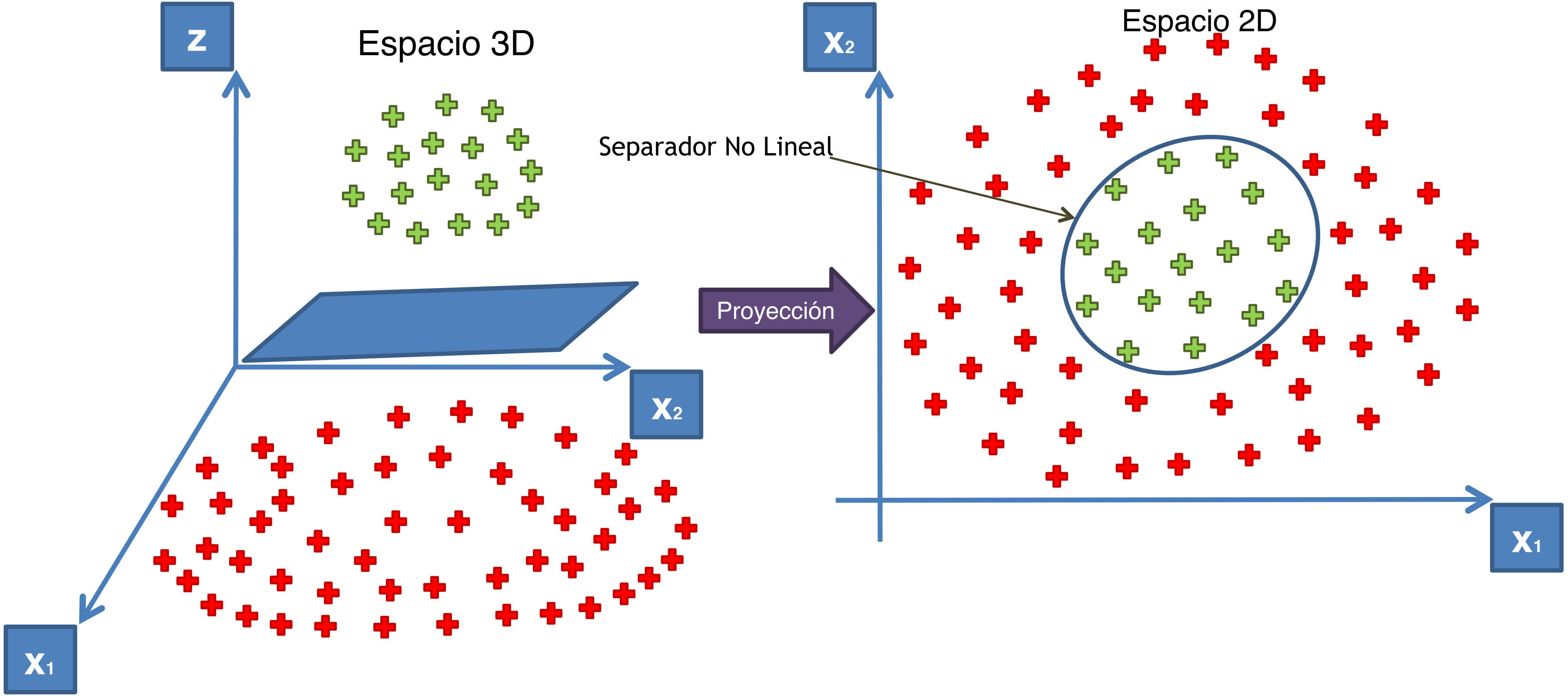
Proyectando de vuelta al espacio 2D



Proyectando de vuelta al espacio 2D



Proyectando de vuelta al espacio 2D



Pero hay un precio a pagar…

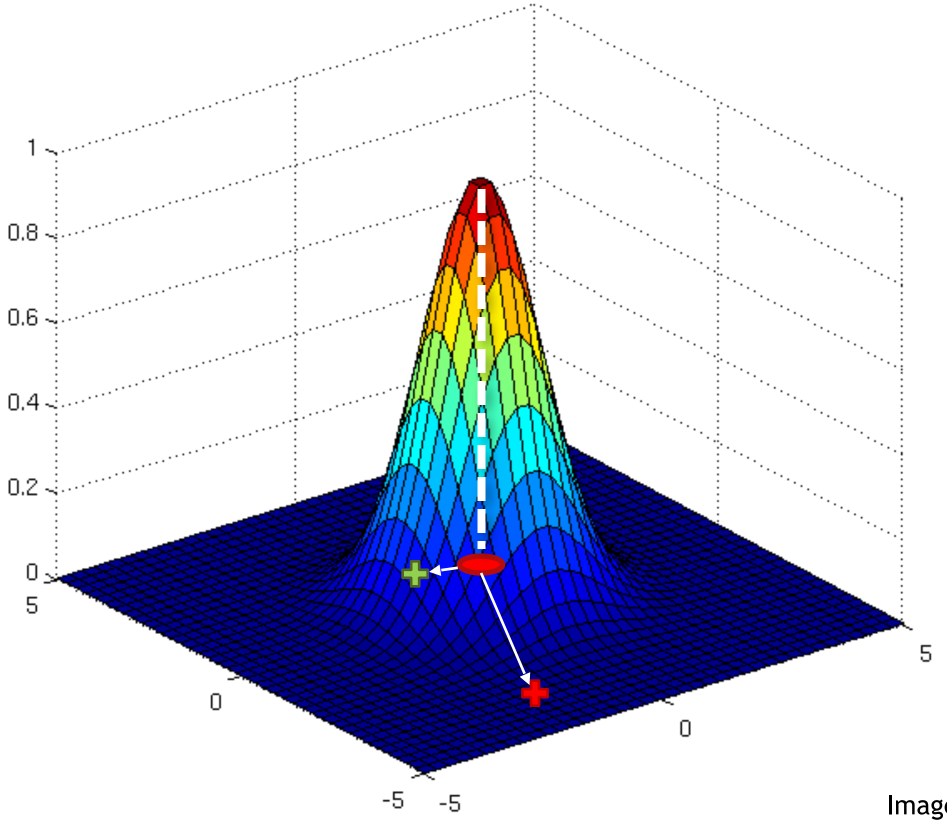
Transformar una variable a un Espacio de Dimension Superior puede ser muy costoso computacionalmente

El truco del Kernel

El Kernel Gaussiano RBF

$$K\left(\vec{x}, \vec{l}^{\,i}\right) = e^{-\frac{\left\|\vec{x} - \vec{l}^{\,i}\right\|^2}{2\sigma^2}}$$

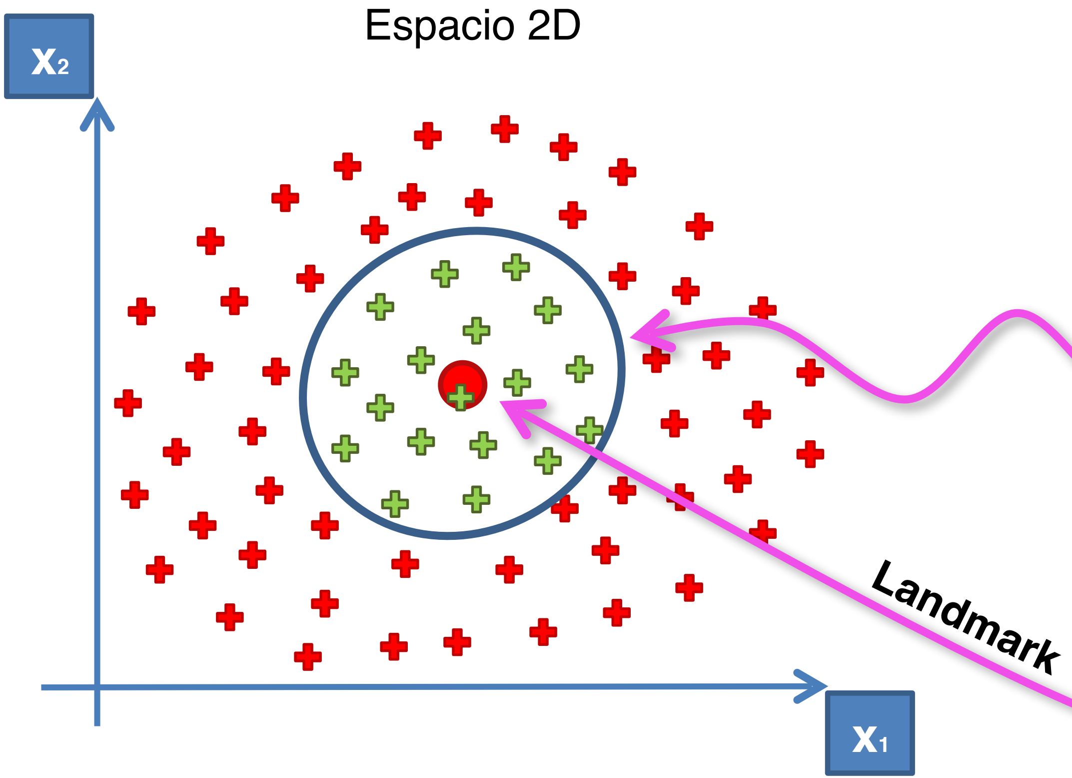
El Kernel Gaussiano RBF

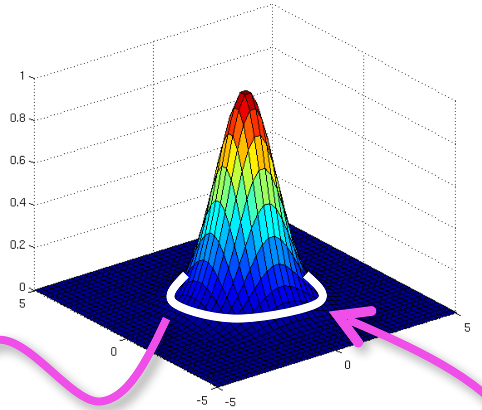


$$K\left(\vec{x}, \vec{l}^{\,i}\right) = e^{-\frac{\left\|\vec{x} - \vec{l}^{\,i}\right\|^2}{2\sigma^2}}$$

Image source: http://www.cs.toronto.edu/~duvenaud/cookbook/index.htm

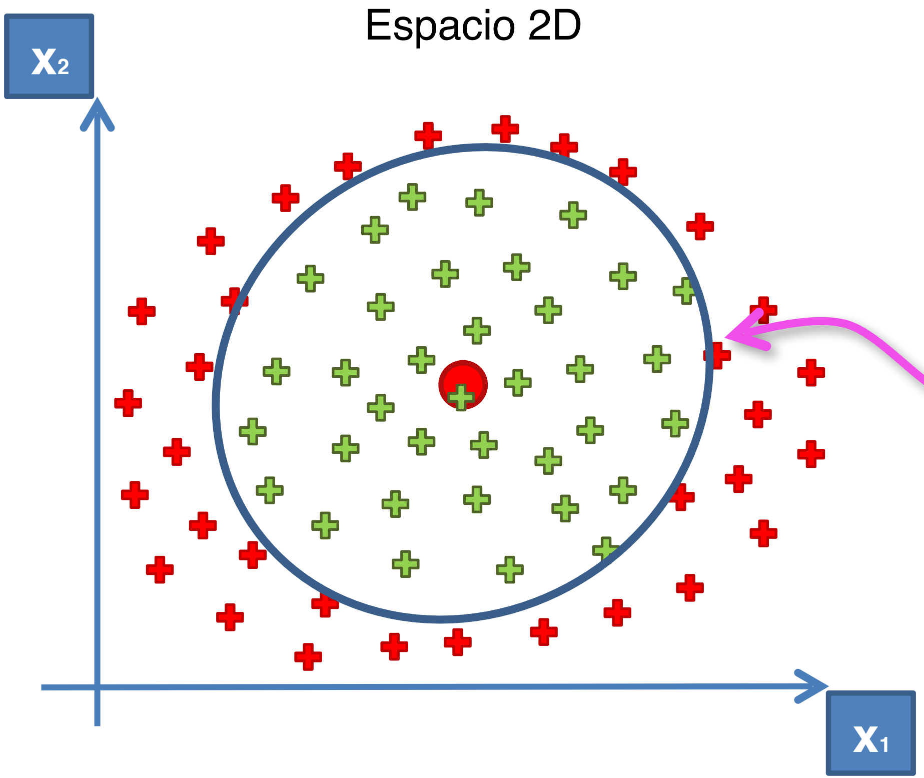
El Kernel Gaussiano RBF



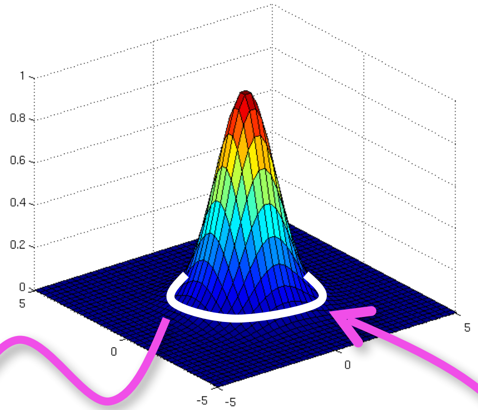


$$K\left(\vec{x}, \vec{l}^{\,i}\right) = e^{-\frac{\left\|\vec{x} - \vec{l}^{\,i}\right\|^2}{2\sigma^2}}$$

El Kernel Gaussiano RBF

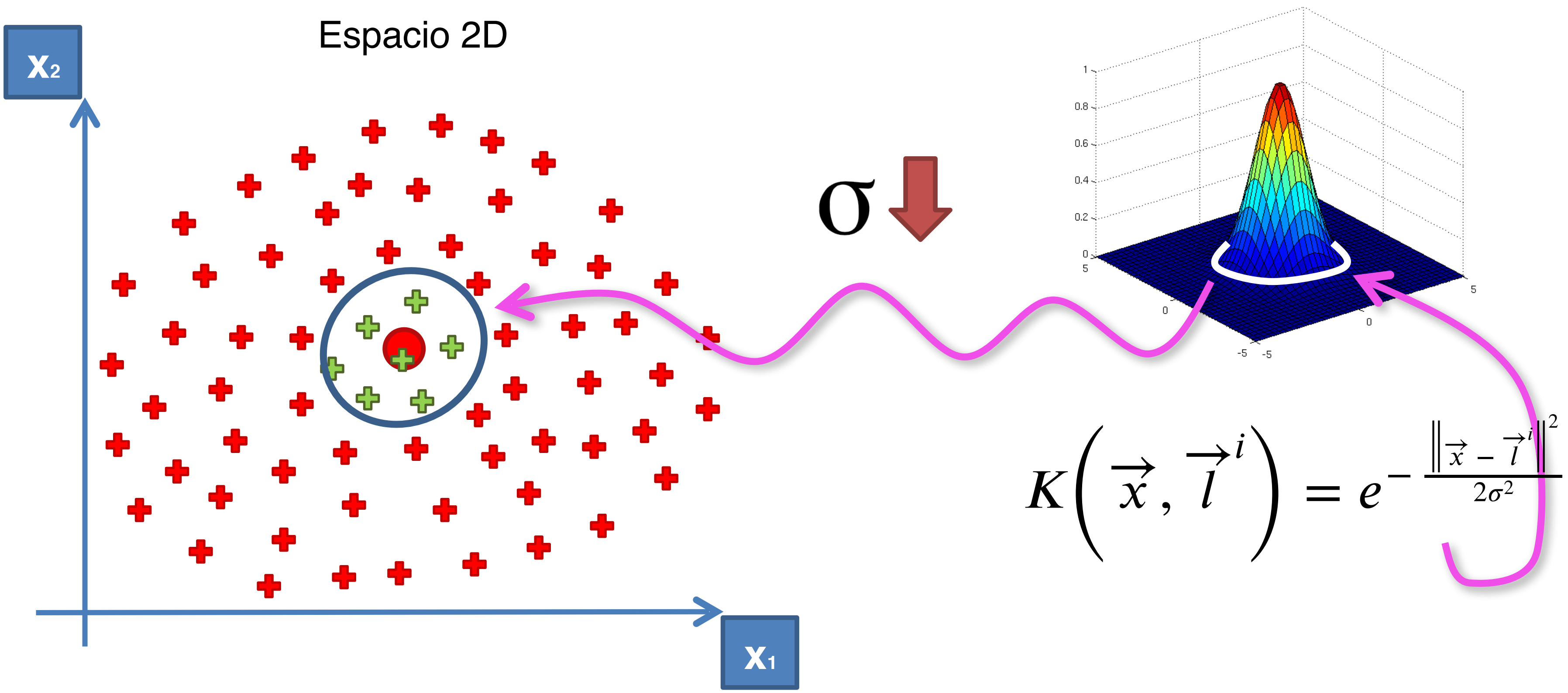


σ



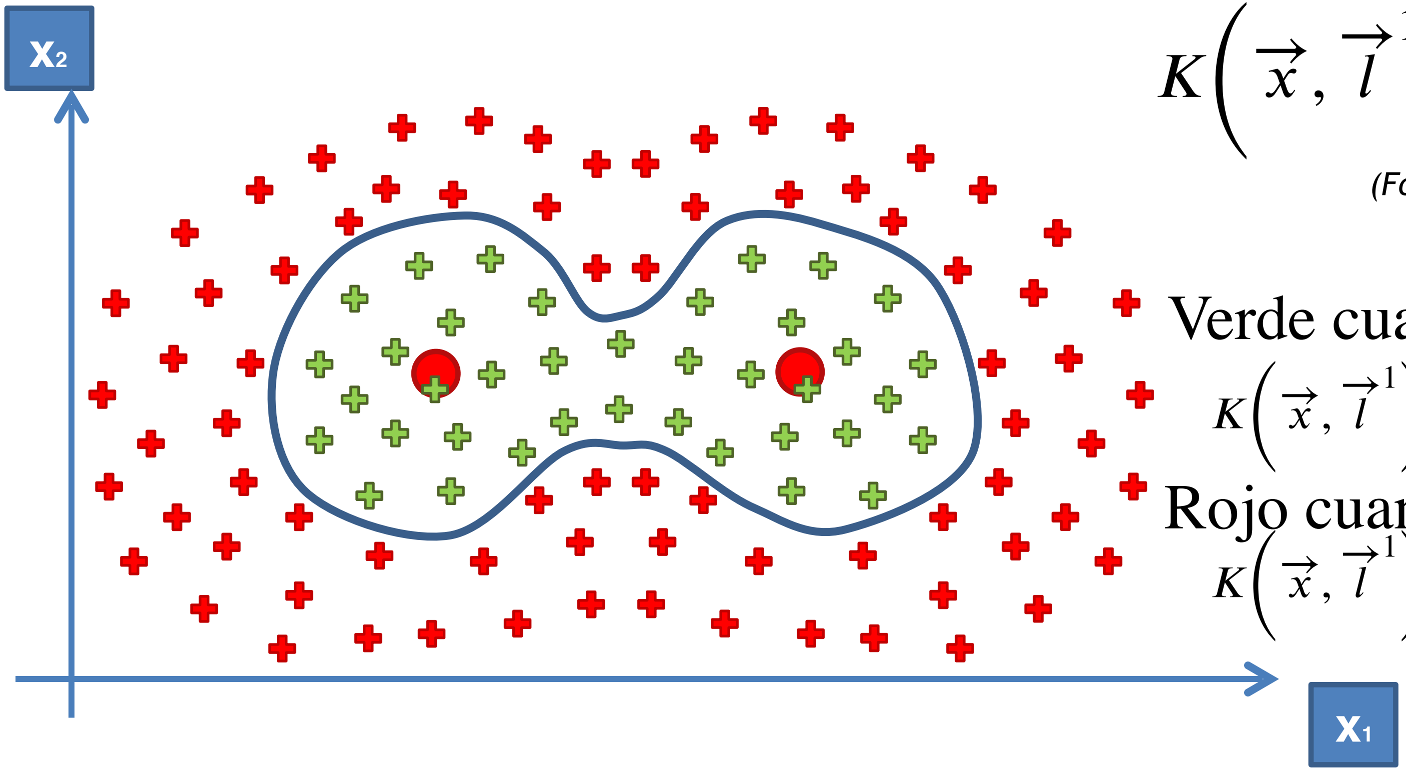
$$K\left(\vec{x}, \vec{l}^{\,i}\right) = e^{-\frac{\left\| \vec{x} - \vec{l}^{\,i} \right\|^2}{2\sigma^2}}$$

El Kernel Gaussiano RBF



$$K\left(\vec{x}, \vec{l}^{\,i}\right) = e^{-\frac{\left\|\vec{x} - \vec{l}^{\,i}\right\|^2}{2\sigma^2}}$$

El Kernel Gaussiano RBF



$$K\left(\vec{x}, \vec{l}^{\,1}\right) + K\left(\vec{x}, \vec{l}^{\,2}\right)$$

(Fórmula Simplificada)

Verde cuando:

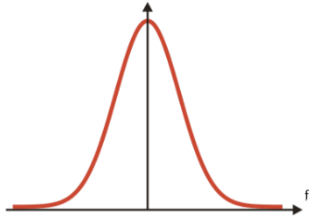
$$K\left(\vec{x}, \vec{l}^{\,1}\right) + K\left(\vec{x}, \vec{l}^{\,2}\right) > 0$$

Rojo cuando:

$$K\left(\vec{x}, \vec{l}^{\,1}\right) + K\left(\vec{x}, \vec{l}^{\,2}\right) = 0$$

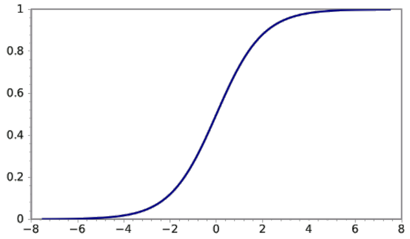
Tipos de funciones de Kernel

Tipo de Funciones de Kernel



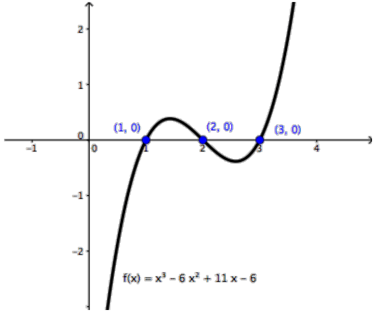
Kernel Gaussiano RBF

$$K\left(\vec{x}, \vec{l}^{\,i}\right) = e^{-\frac{\left\|\vec{x} - \vec{l}^{\,i}\right\|^2}{2\sigma^2}}$$



Kernel Sigmoide

$$K(X, Y) = \tanh\left(\gamma \cdot X^T Y + r\right)$$



Kernel Polinómico

$$K(X, Y) = \left(\gamma \cdot X^T Y + r\right)^d, \ \gamma > 0$$