Métodos de Analítica II
Support Vector Machines

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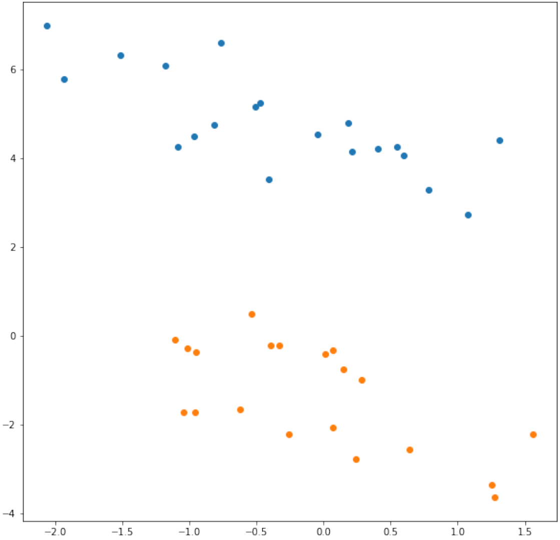
Section 1

1 Fronteras de Decisión

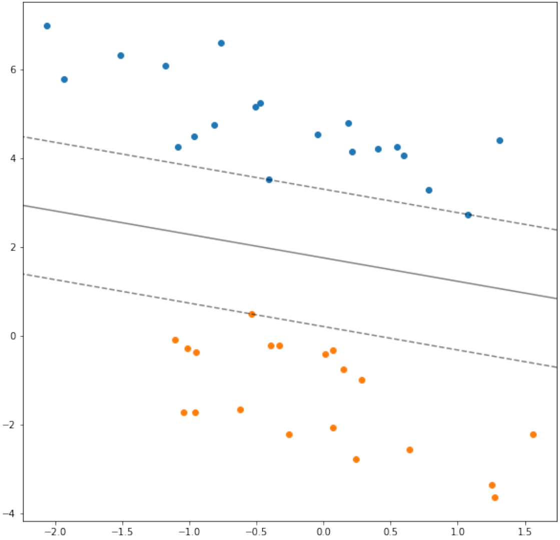
2 La vida real...

3 Kernels Comunes

Fronteras de Decisión



Separación Máxima



Section 2

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Datos No Separables

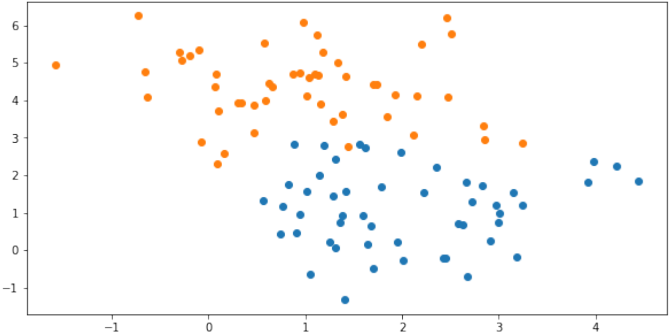


Figure: No todos los datos son linealmente separables.

Datos No Separables Linealmente

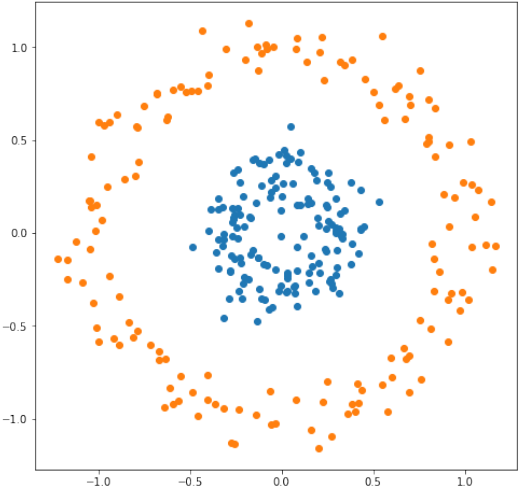
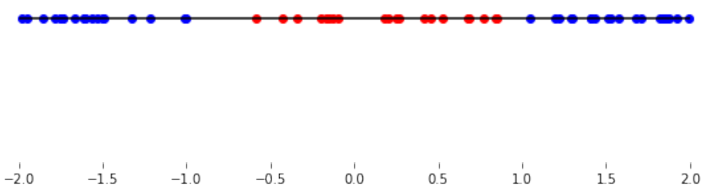
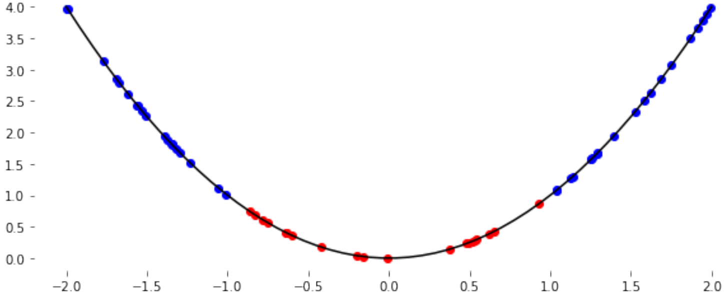


Figure: No todos los datos son linealmente separables.

Datos No Separables Linealmente



Datos No Separables Linealmente



Datos No Separables Linealmente

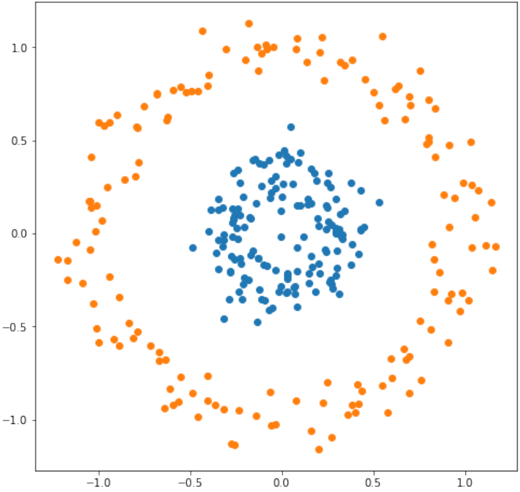


Figure: No todos los datos son linealmente separables.

¡Ahora son separables!

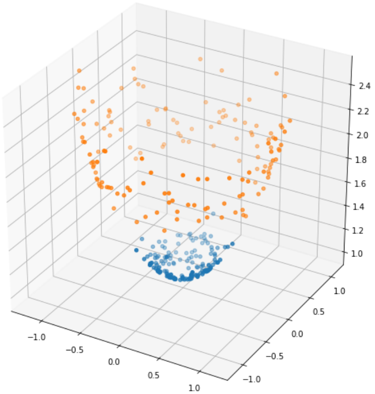


Figure: Volvimos nuestros datos linealmente separables en una dimensión más alta

¡Ahora son separables!

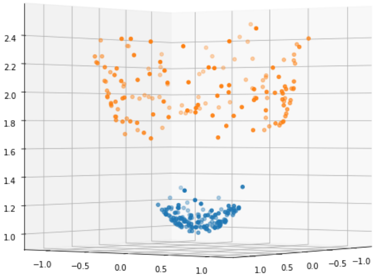


Figure: Volvimos nuestros datos linealmente separables en una dimensión más alta

Section 3

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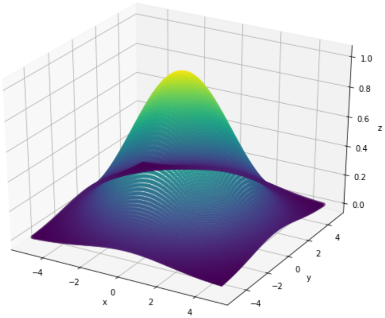
Kernel Gaussiano - RBF

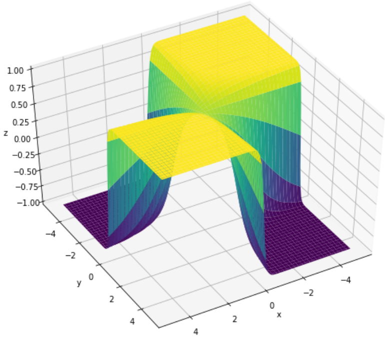
$$\kappa(X, X') = e^{-gamma||X-X'||^2}$$

$$\kappa(X, X') = e^{-\frac{||X-X'||^2}{2\sigma^2}}$$



Kernel Sigmoide

$$\kappa(X, X') = \tanh(\gamma < X, X' > +)$$



Kernel Polinomial

$$\kappa_d(X, X') = (1 + < X, X' >)^d$$

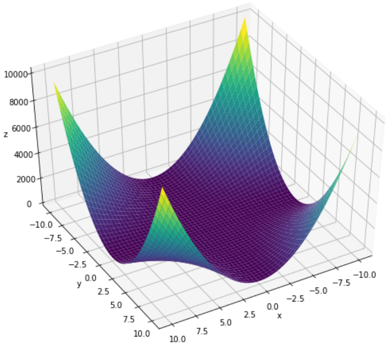


Figure: d = 2

Kernel Polinomial

$$\kappa_d(X, X') = (1+ < X, X'>)^d$$

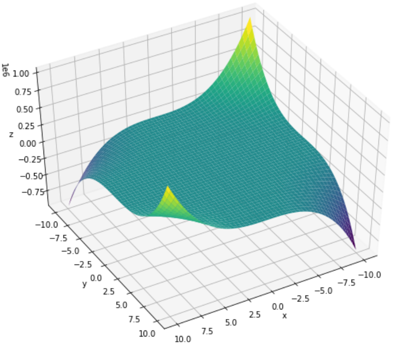


Figure: d = 3