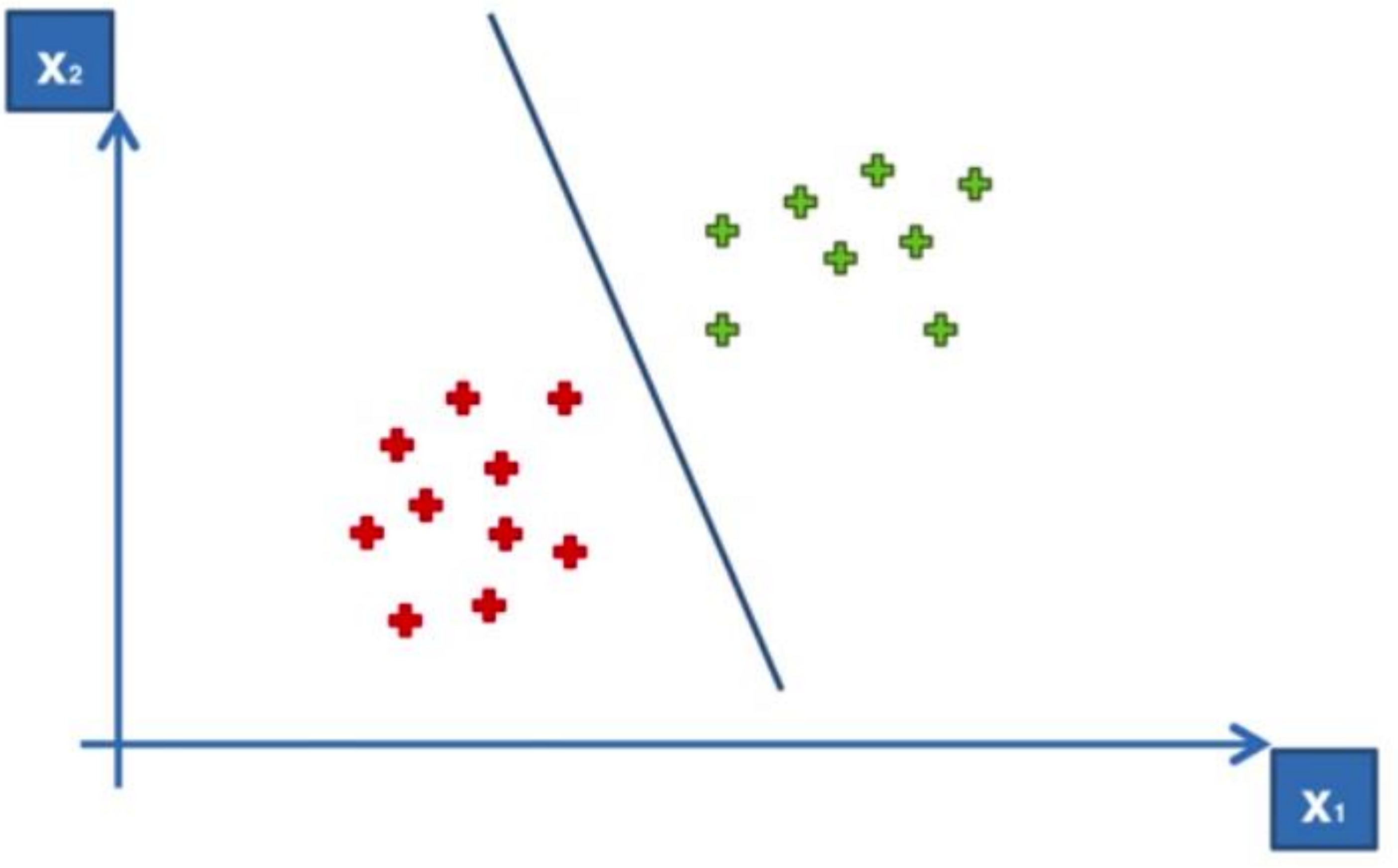
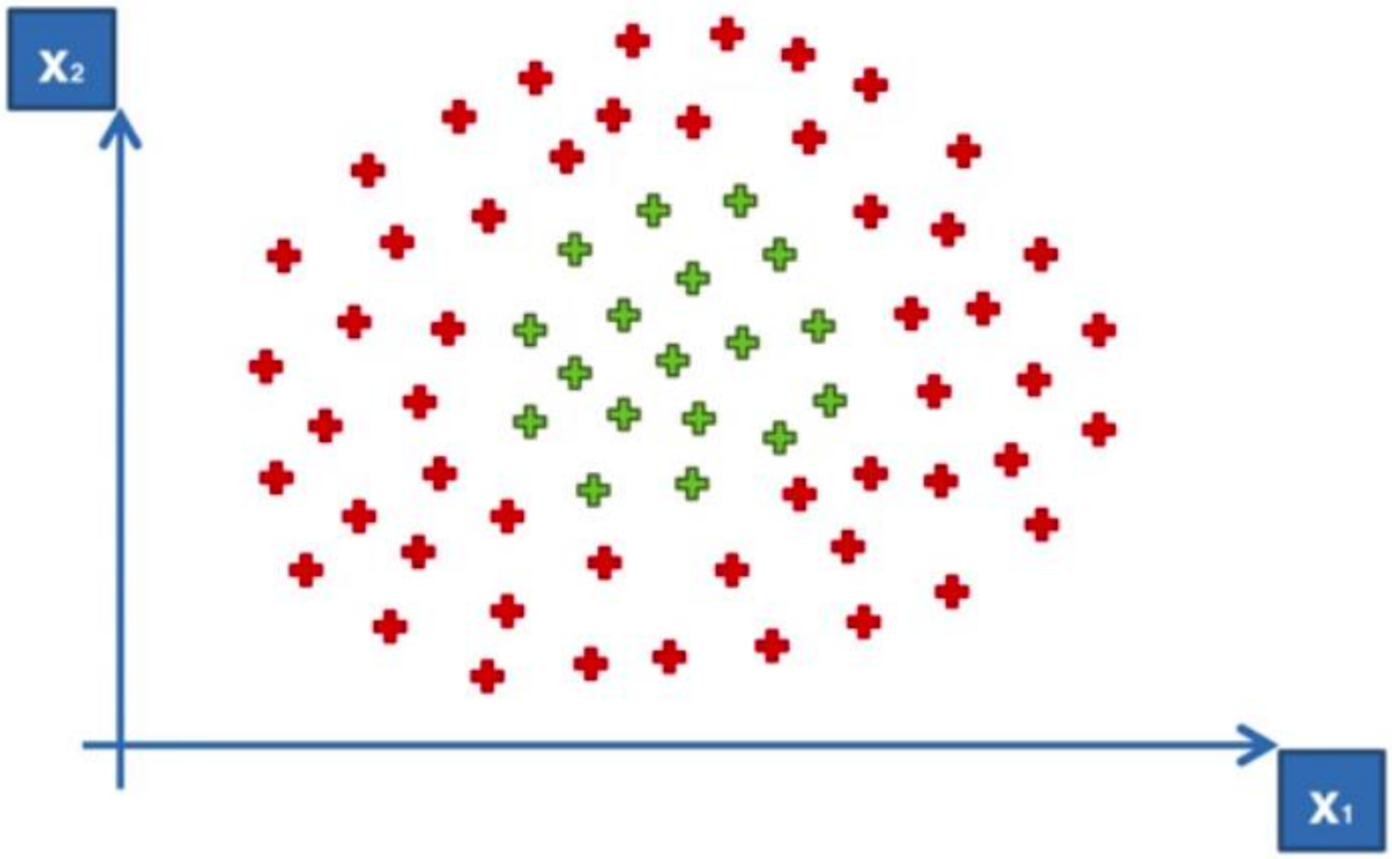
機器學習
Kernel SVM

授課老師：林彥廷

SVM separates well these points



What about these points?



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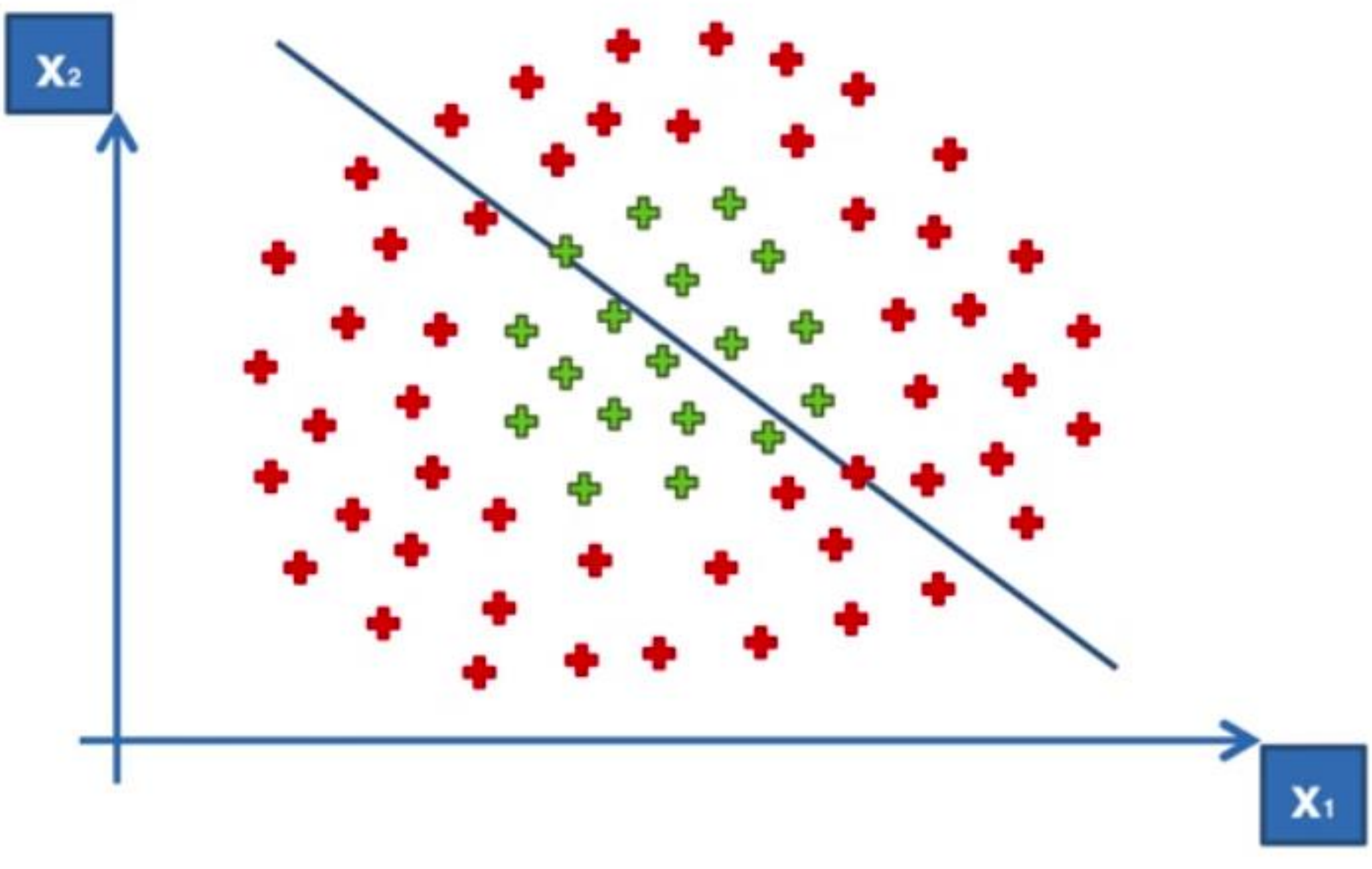

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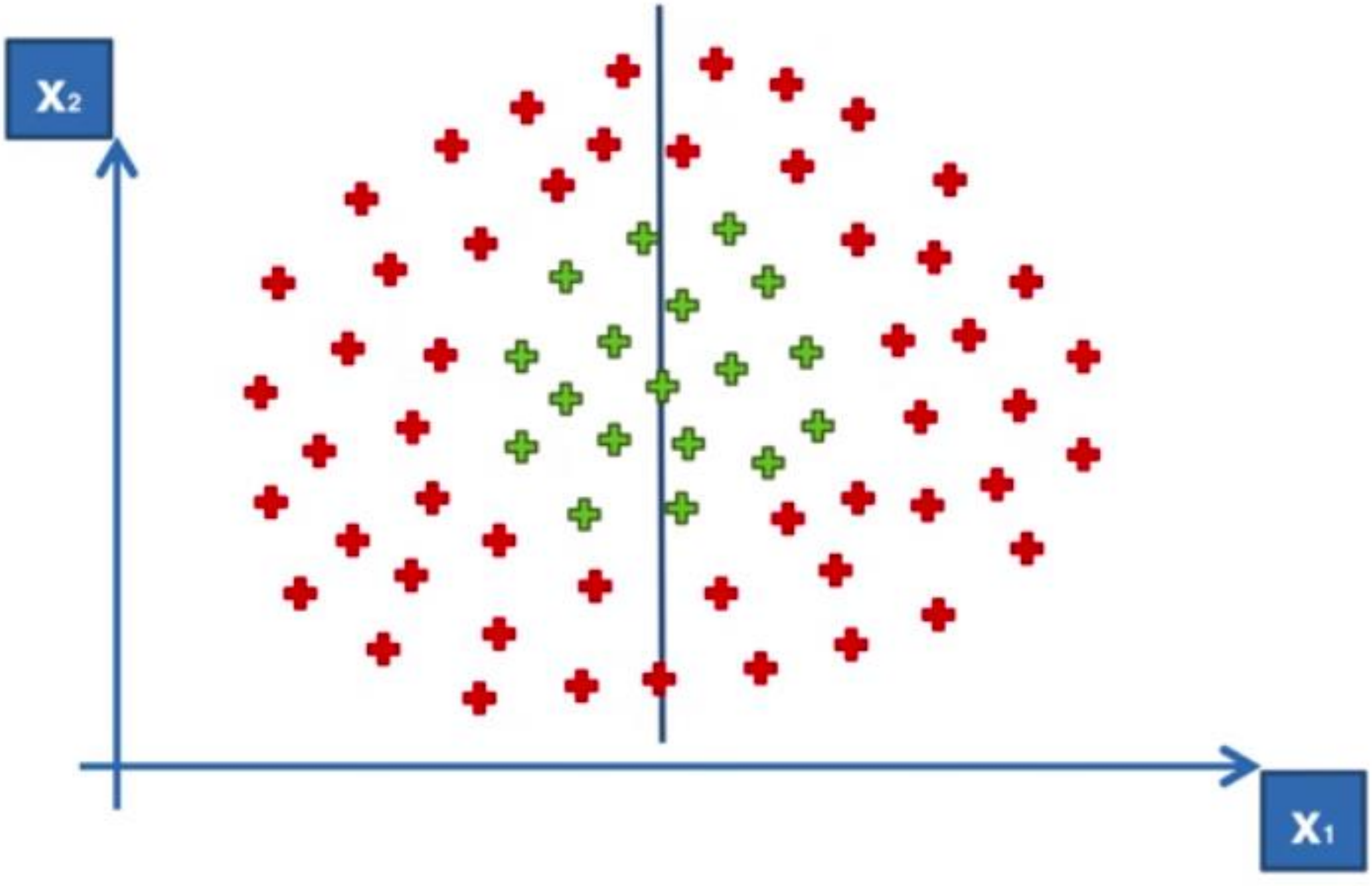

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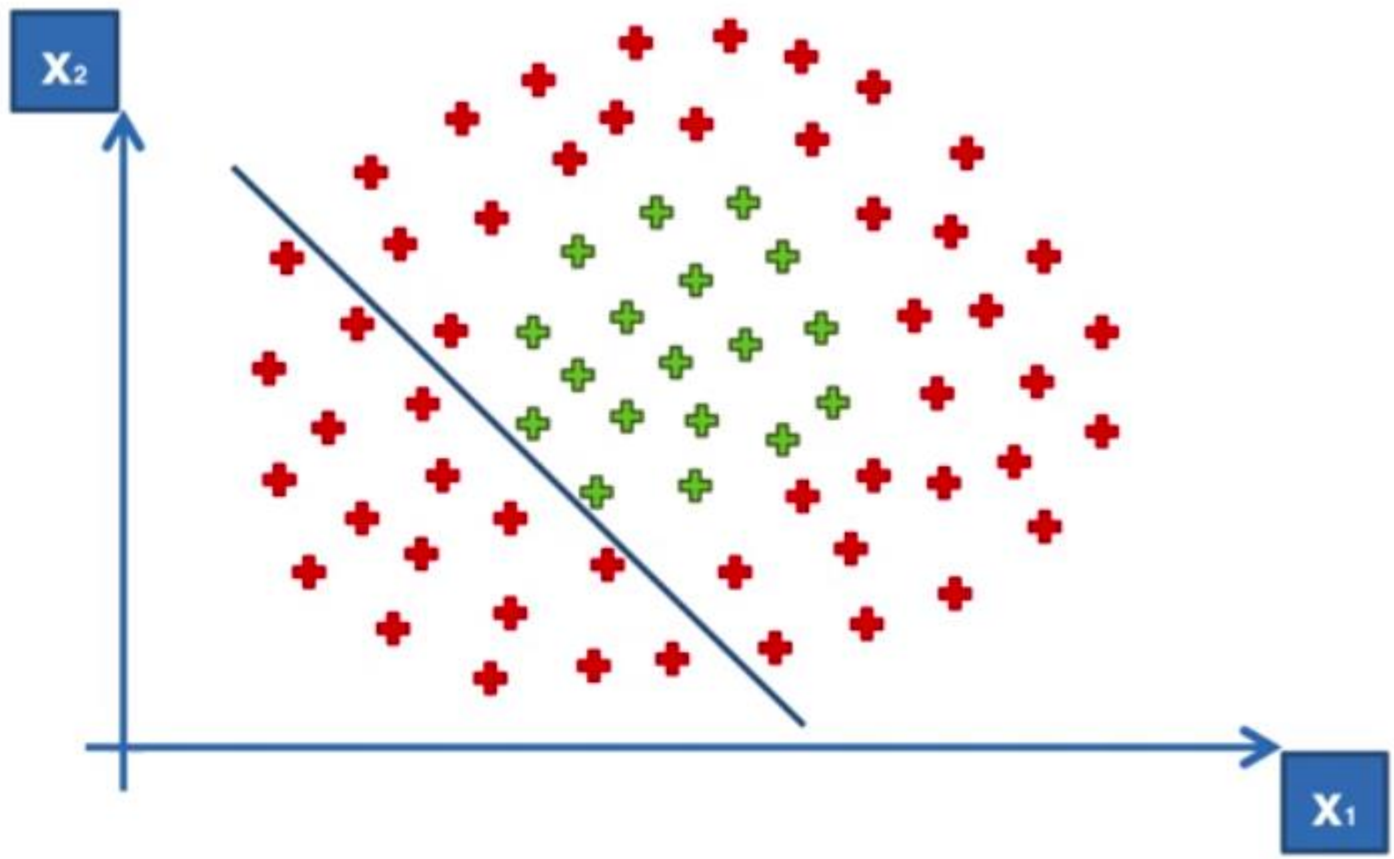

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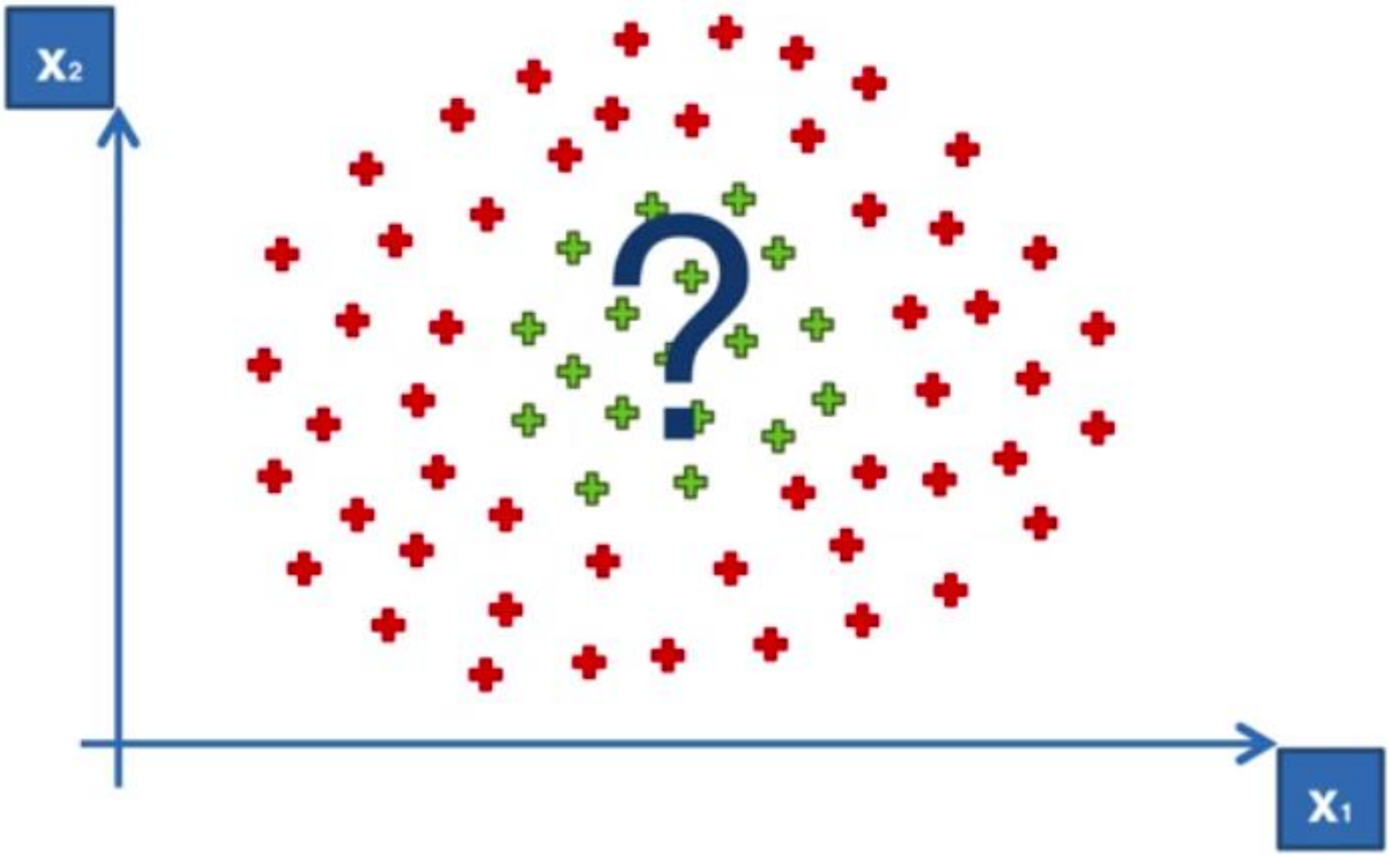
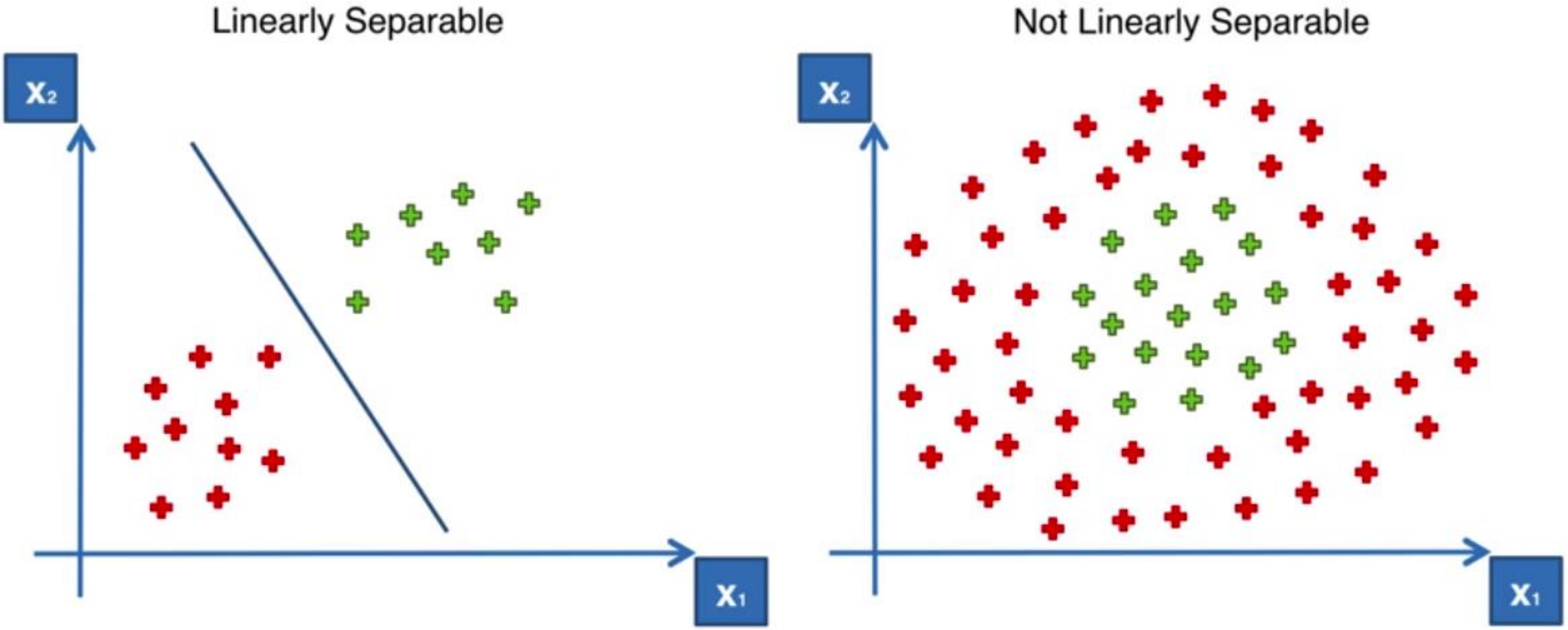


Why?

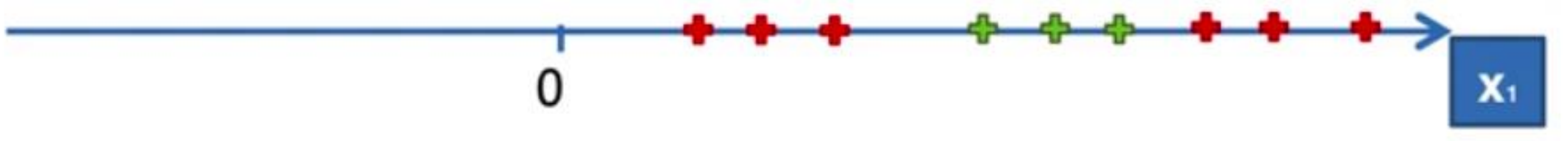
Because the data points are not
LINEARLY SEPARABLE

Linear Separability



A Higher-Dimensional Space

Mapping to a Higher Dimension



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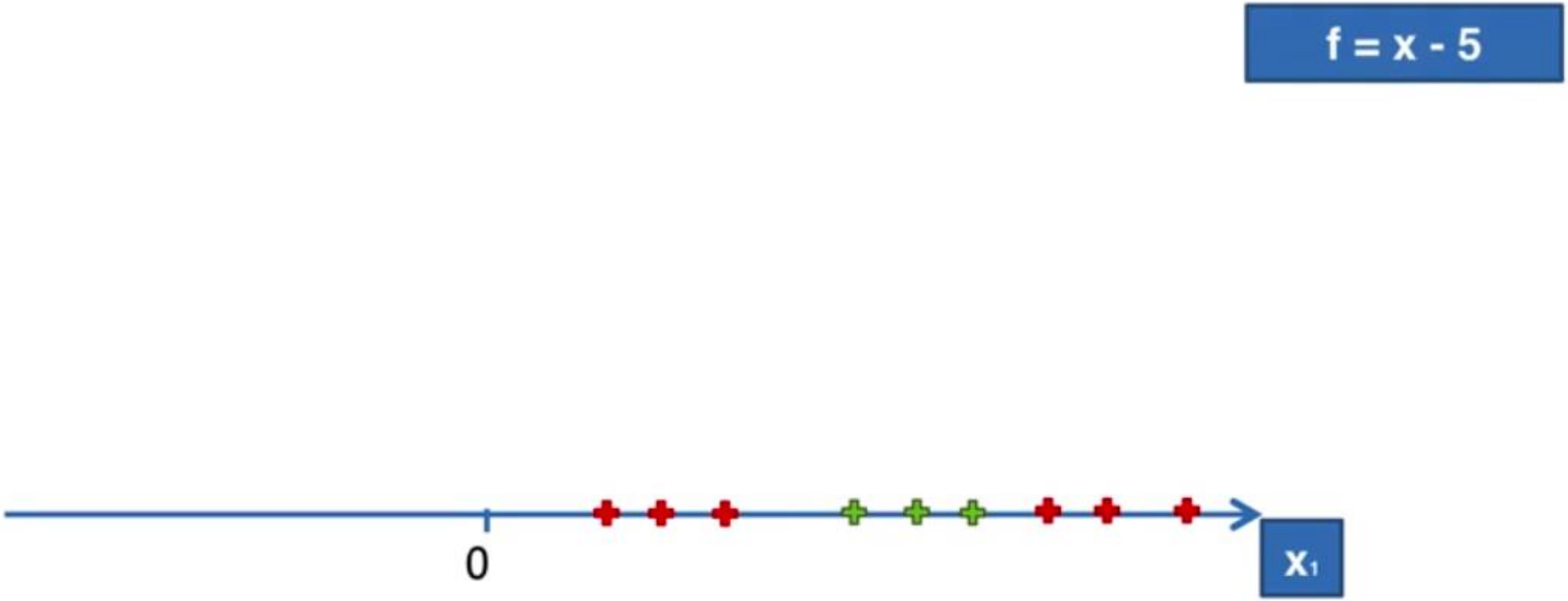

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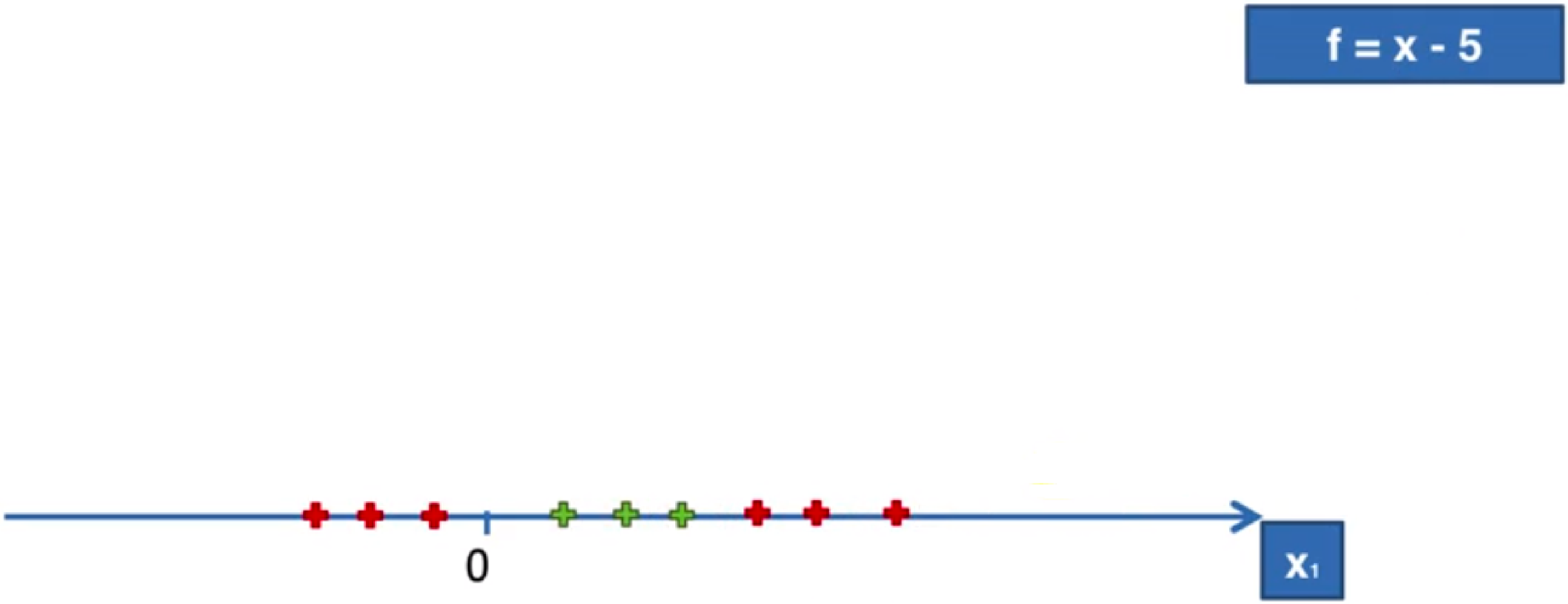

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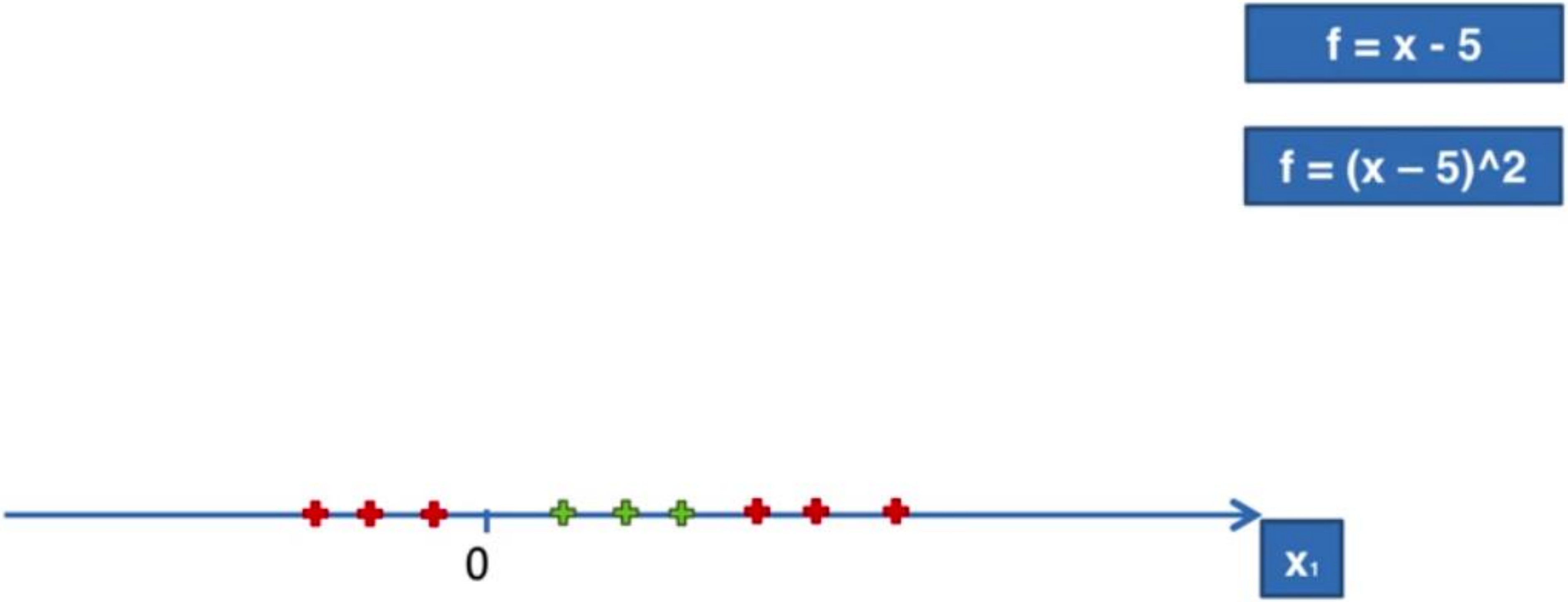

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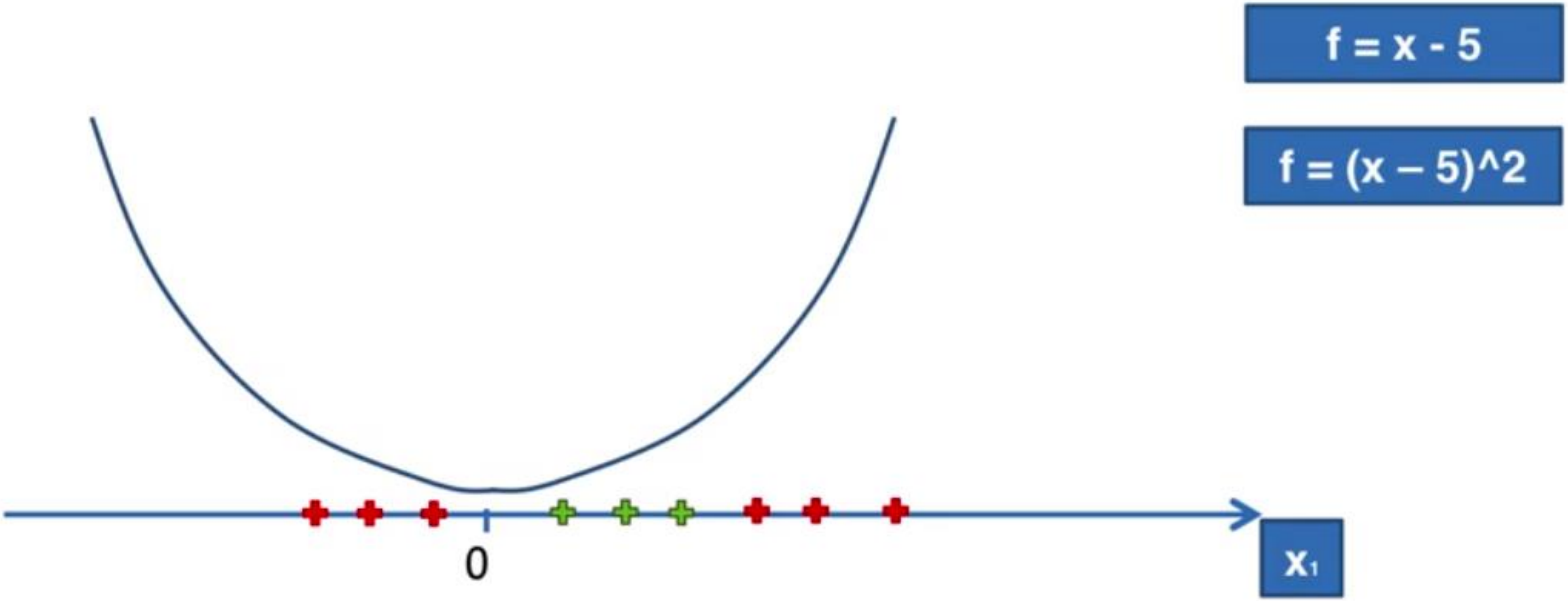

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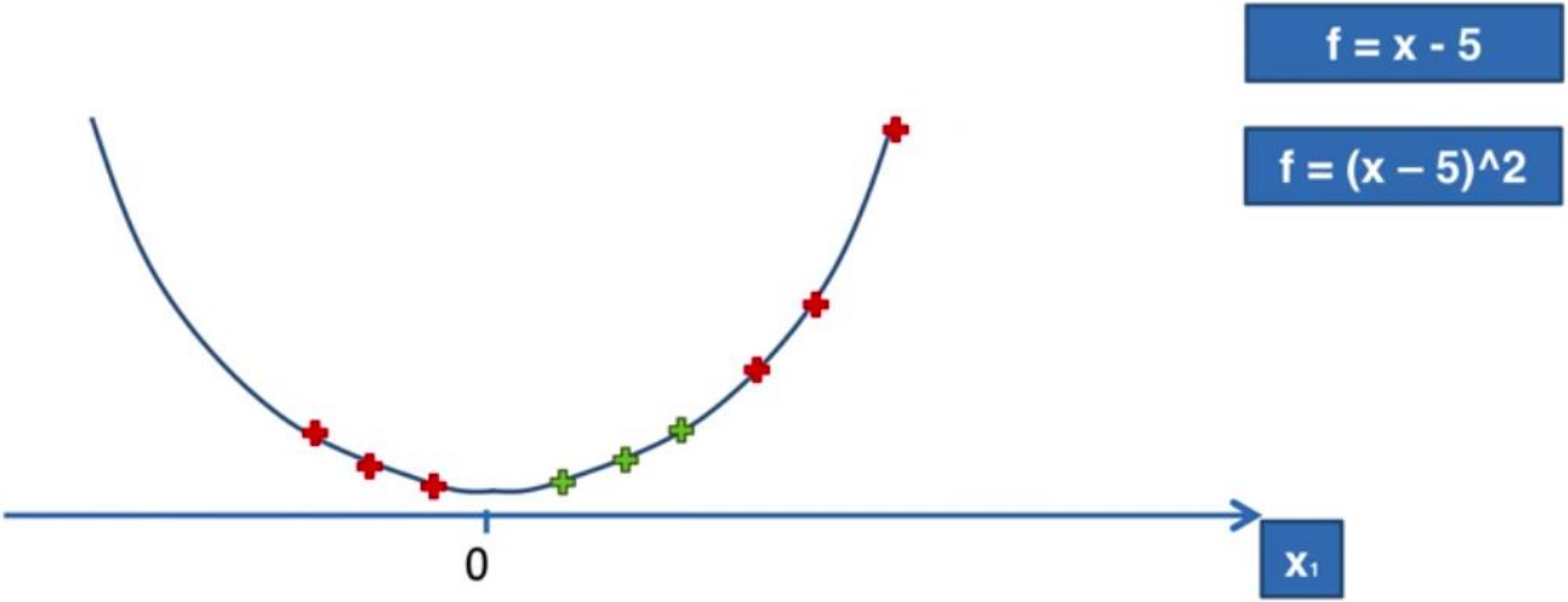

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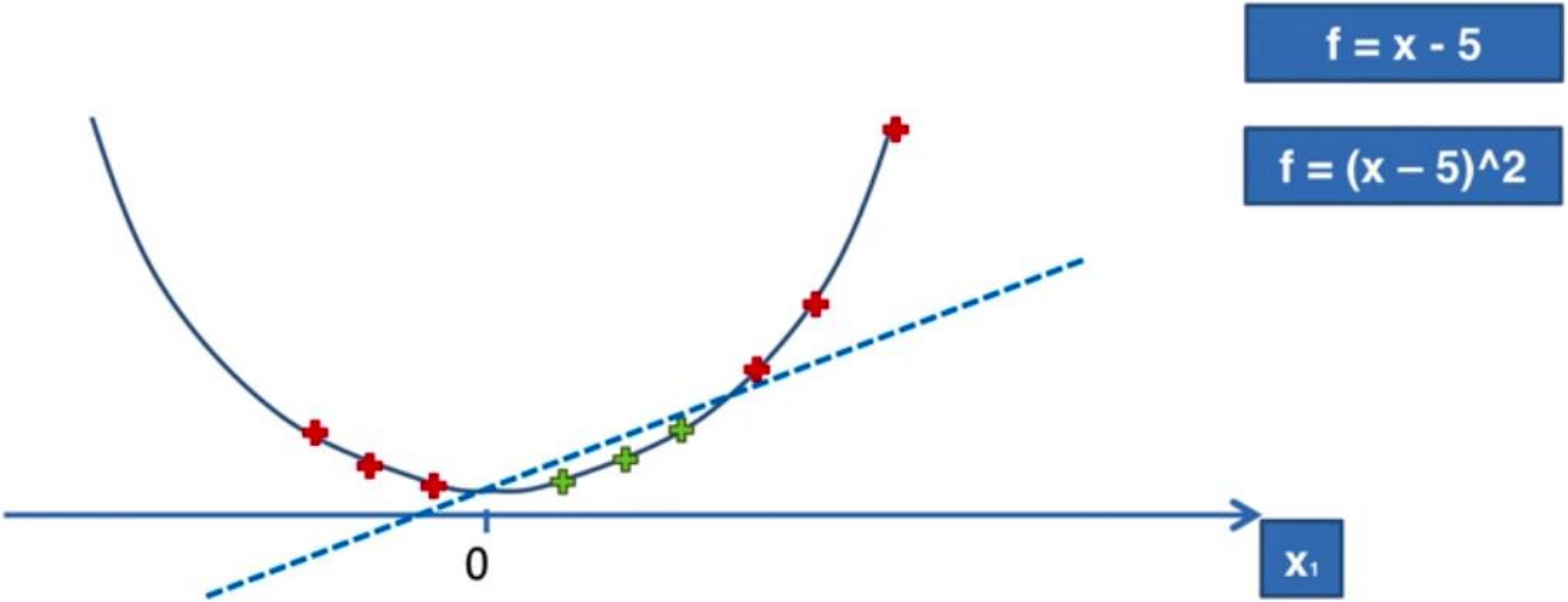

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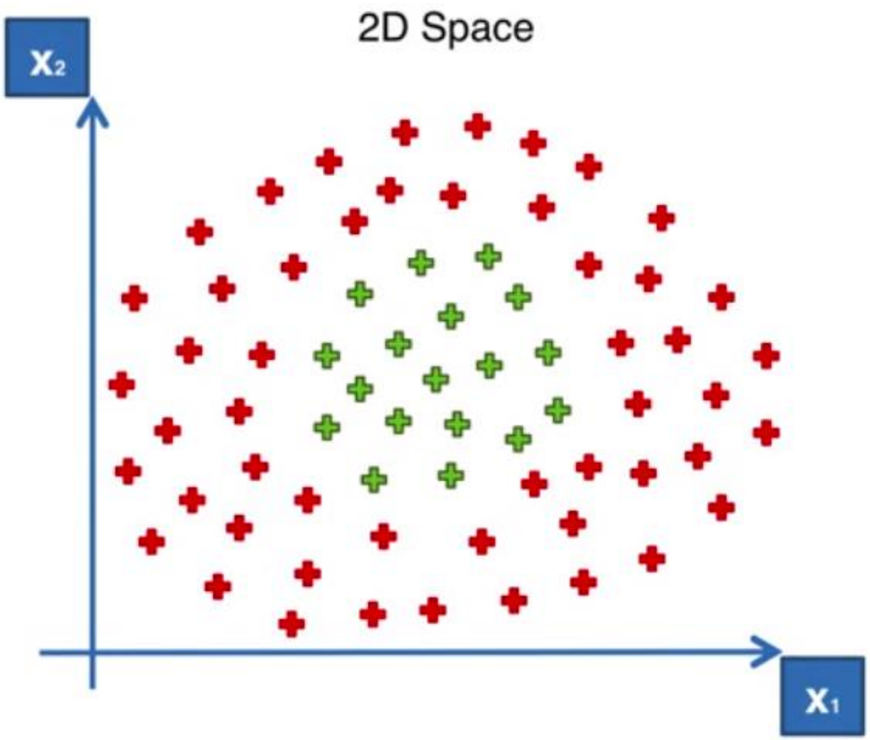

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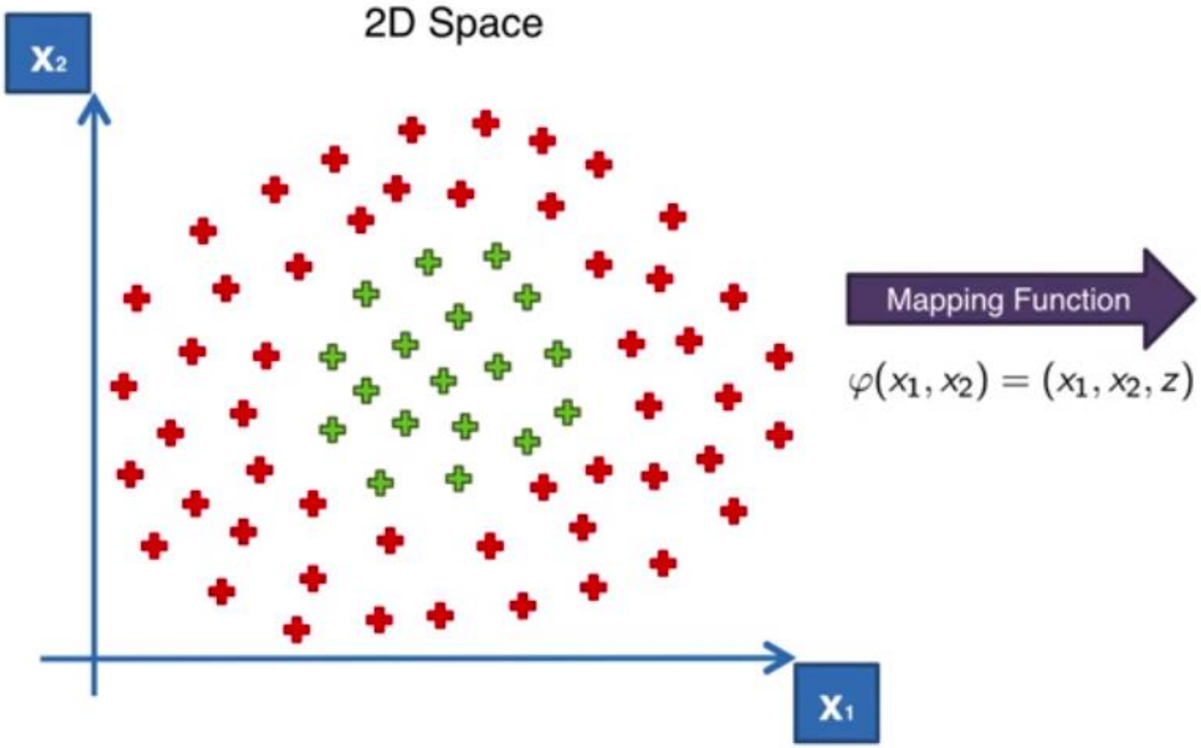
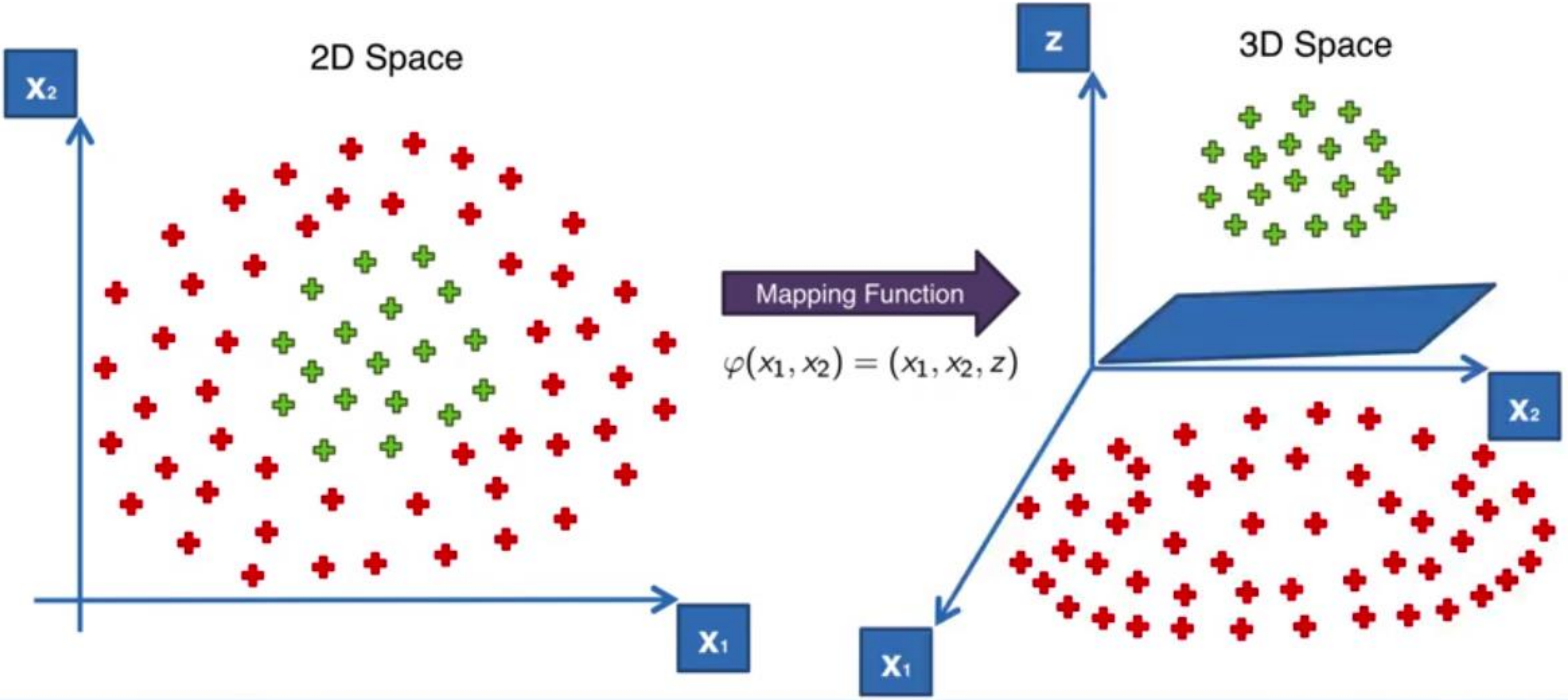
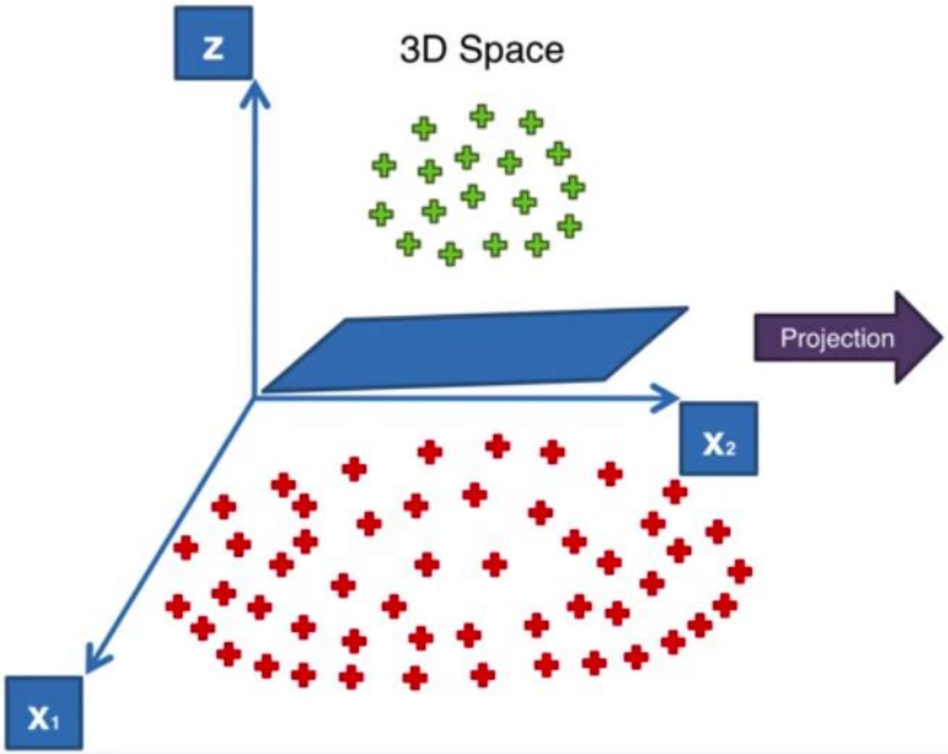


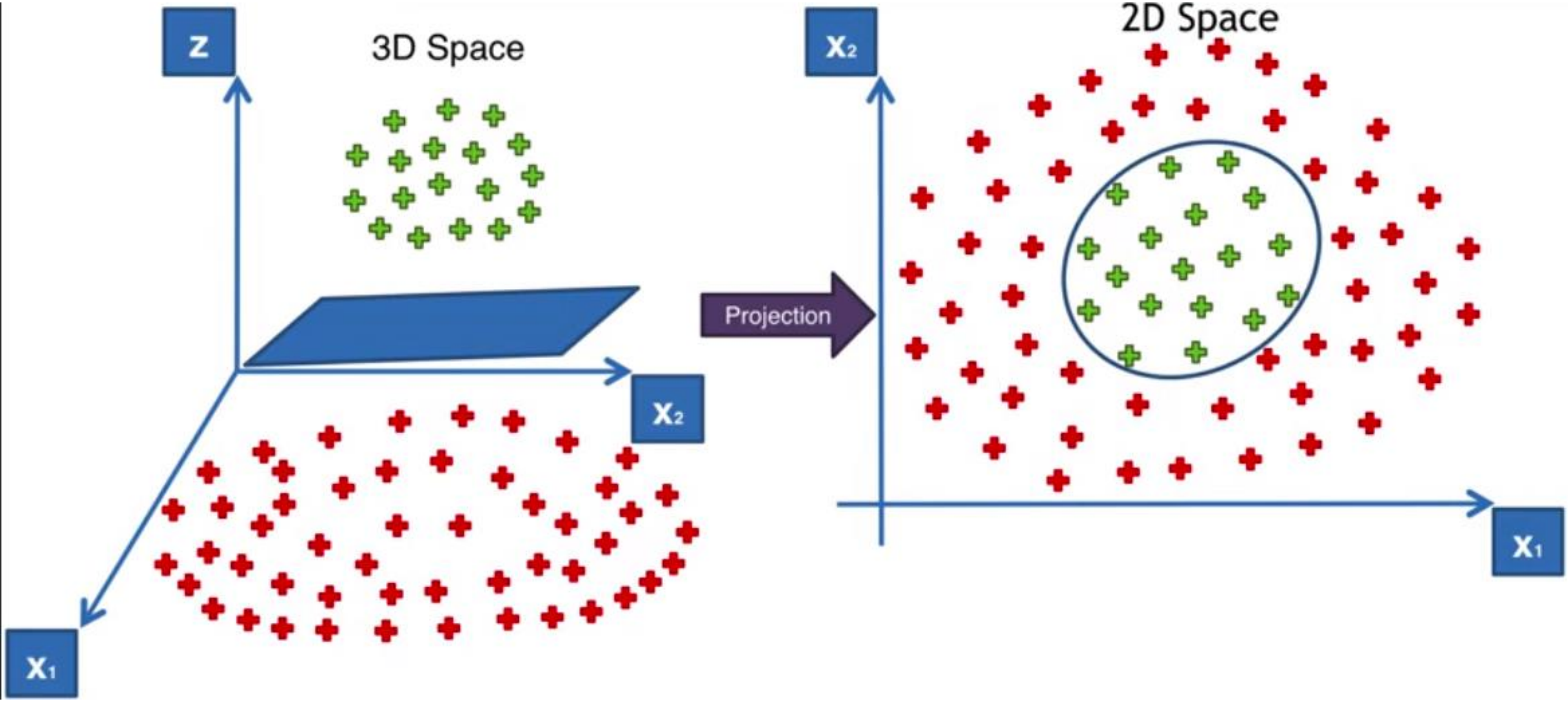
Mapping to a Higher Dimension



Projecting back to 2D Space



Projecting back to 2D Space



But there is a catch…

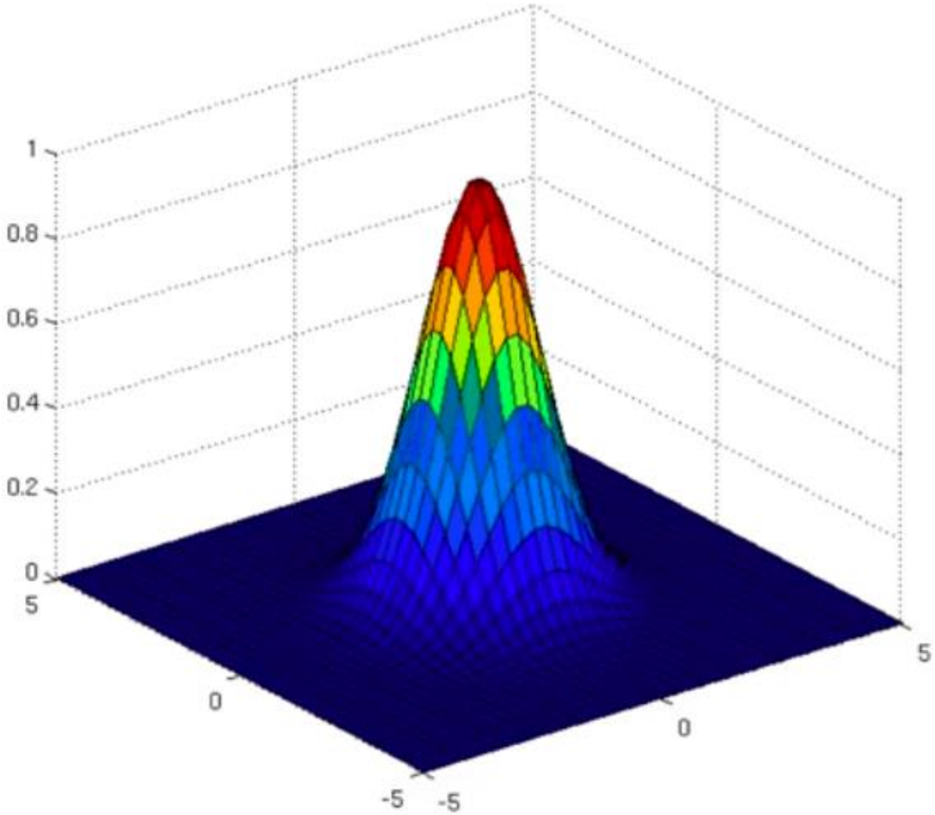
Mapping to a Higher Dimensional Space
can be highly compute-intensive

The Kernel Trick

The Gaussian RBF kernel

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

The Gaussian RBF kernel



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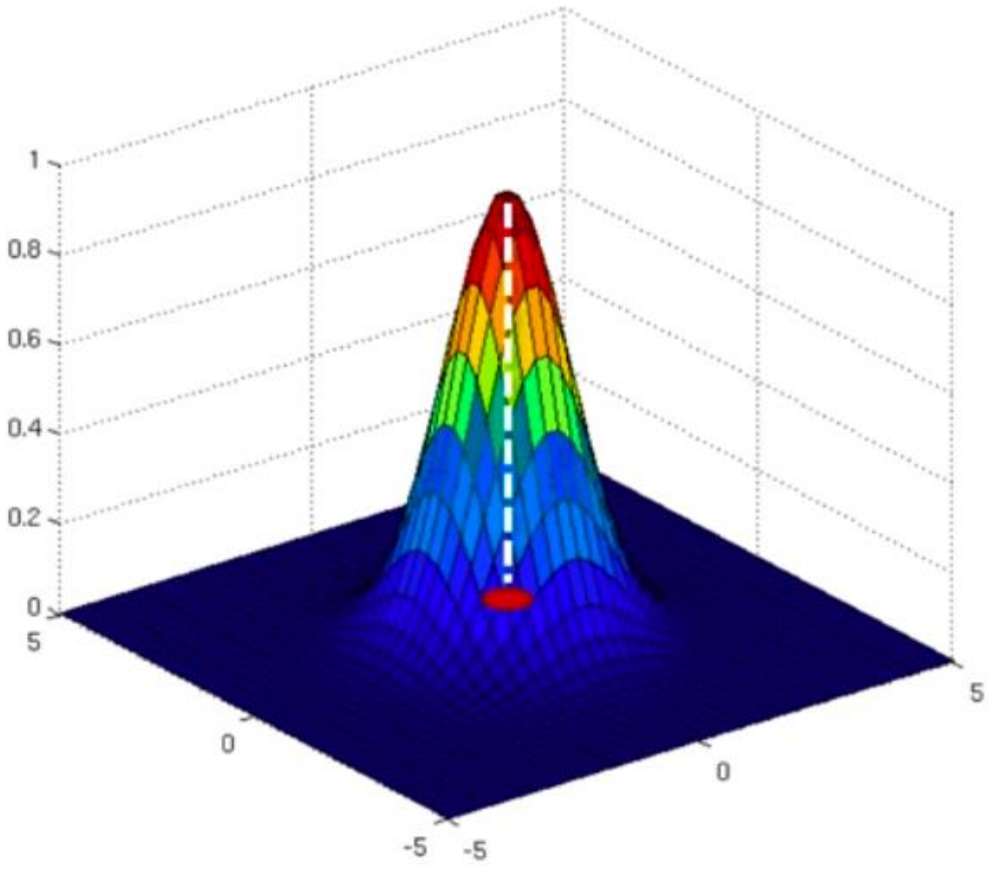

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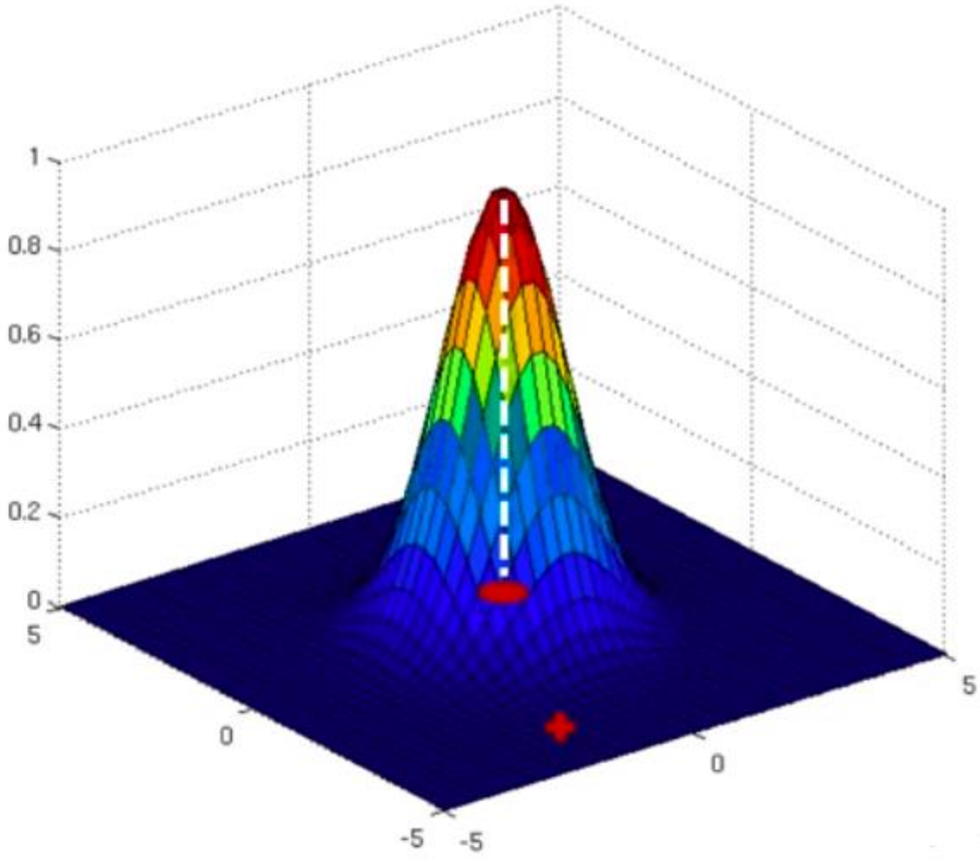

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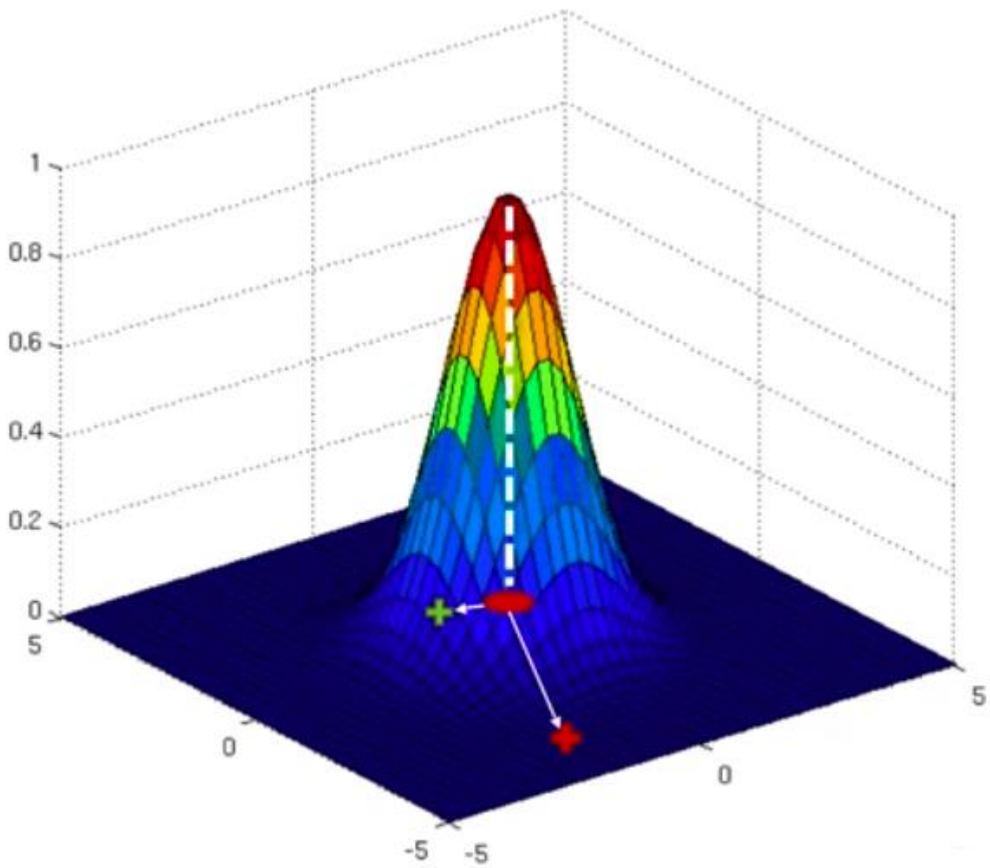

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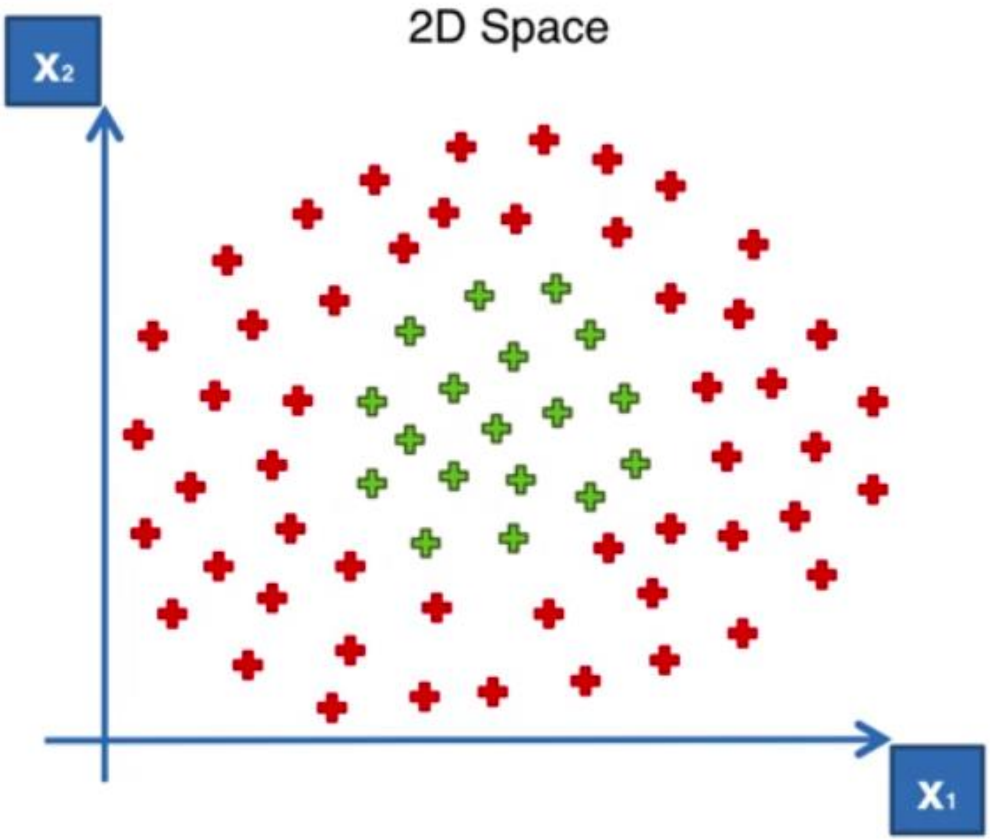

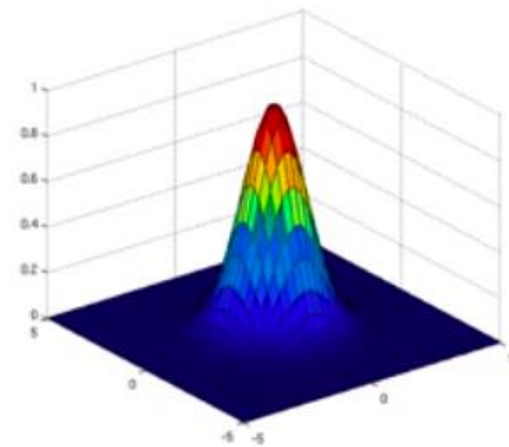

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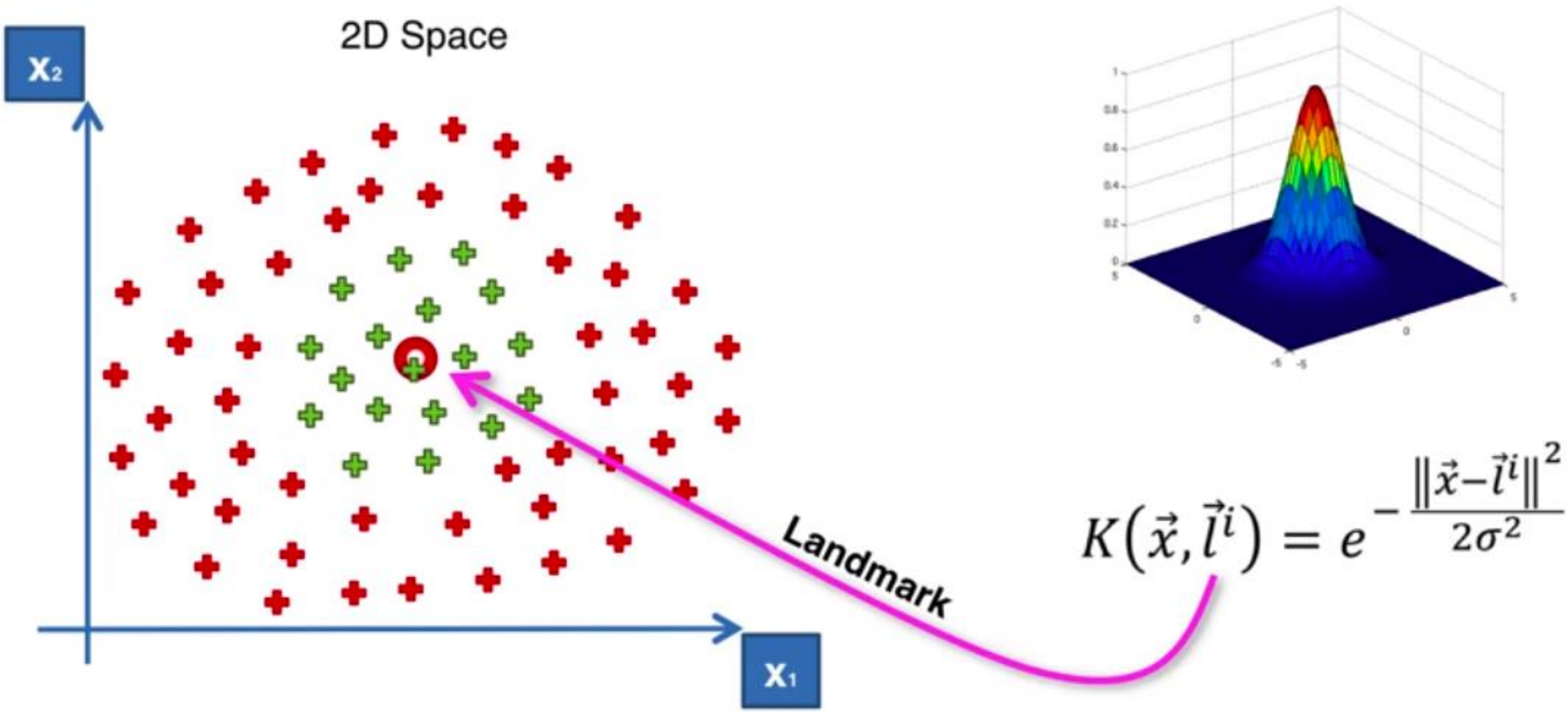

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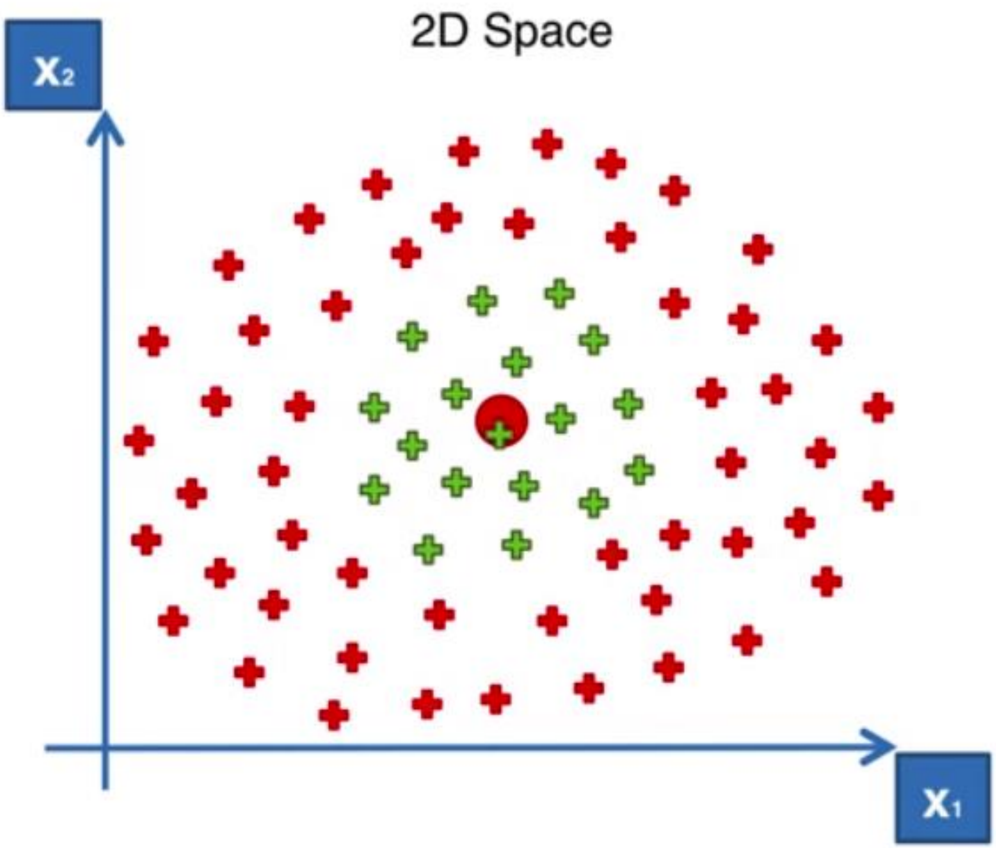

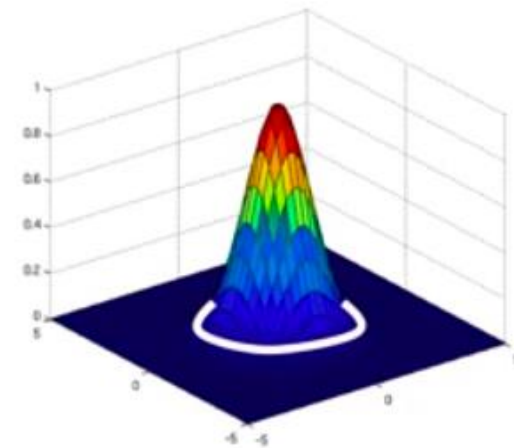

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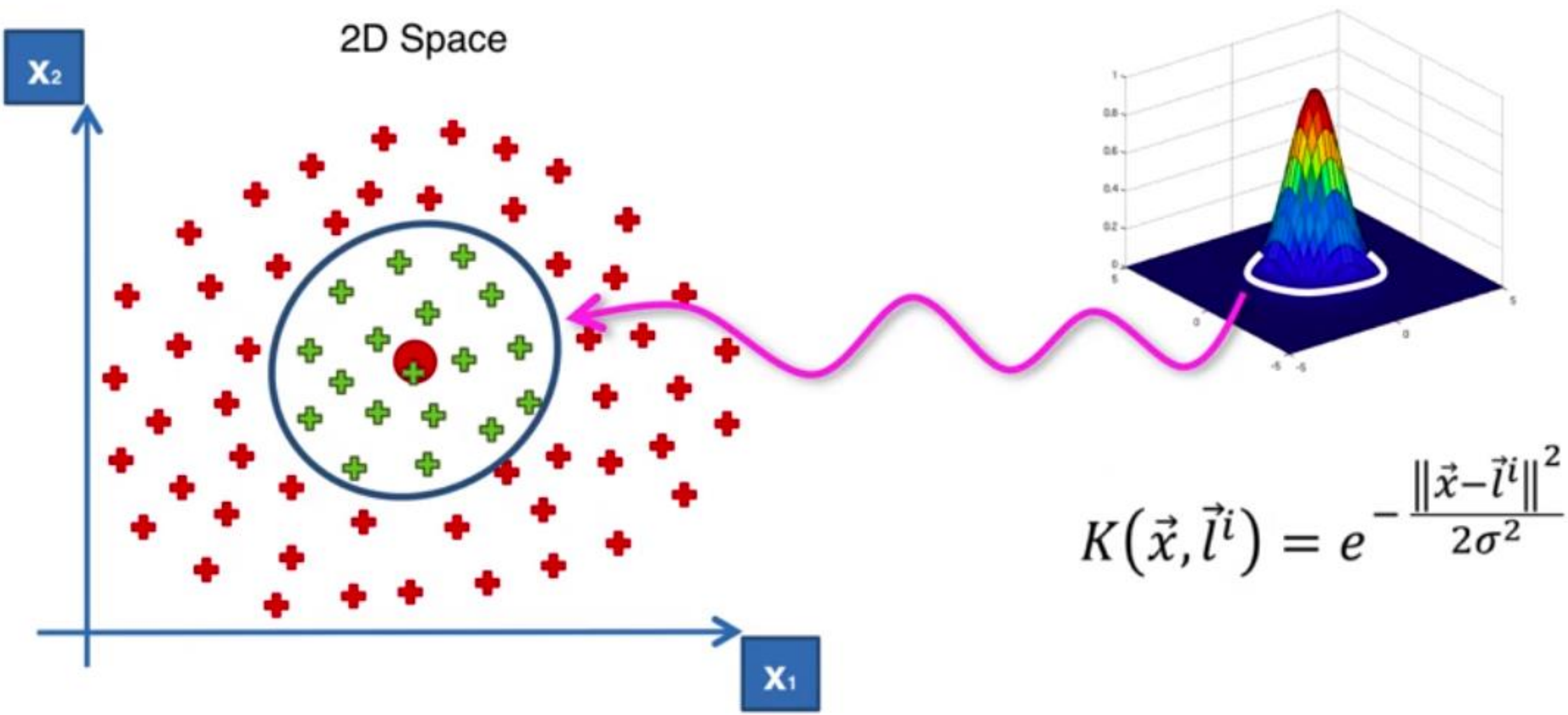
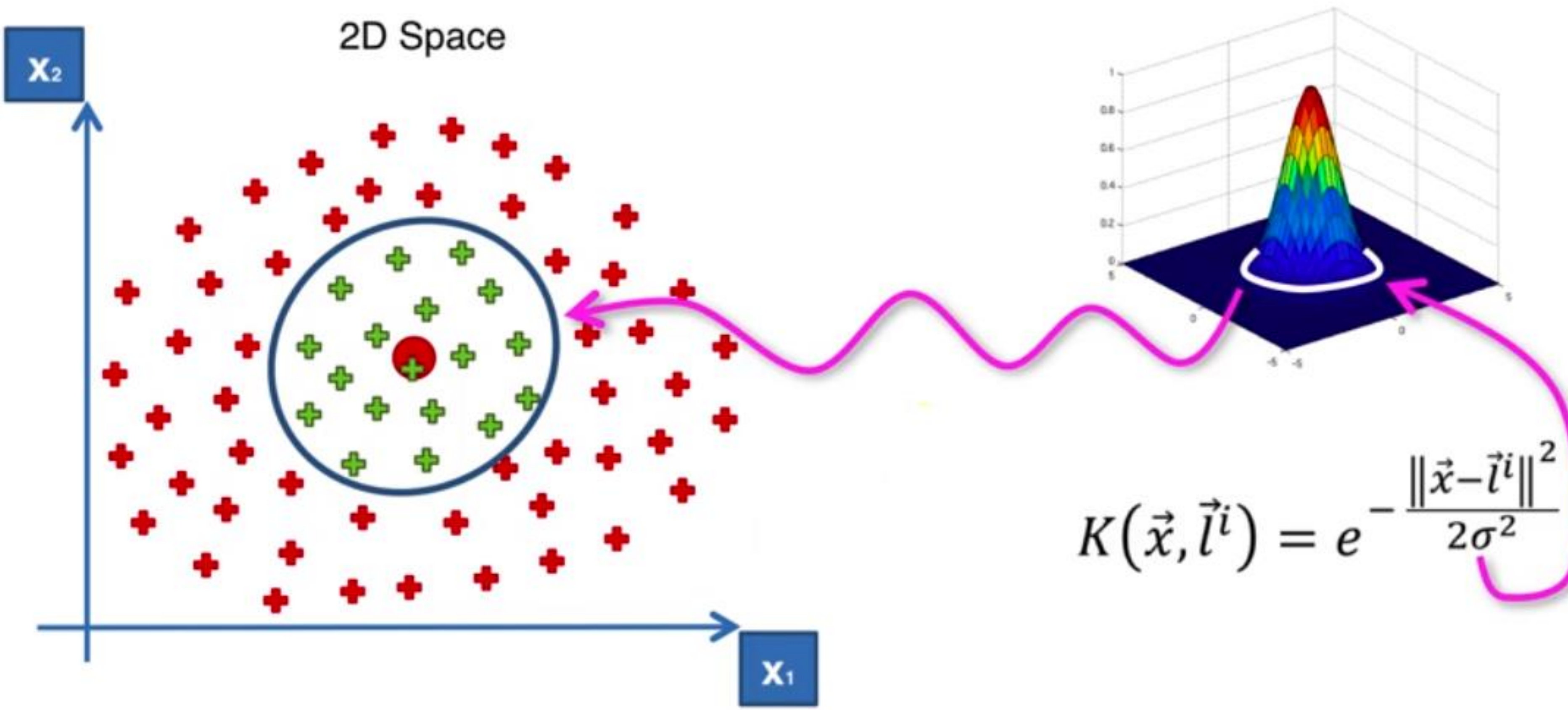


$$K(\vec{x},\vec{l}^{i}) = e^{-\frac{\left\|\vec{x}-\vec{l}^{i}\right\|^{2}}{2\sigma^{2}}}$$

The Gaussian RBF kernel



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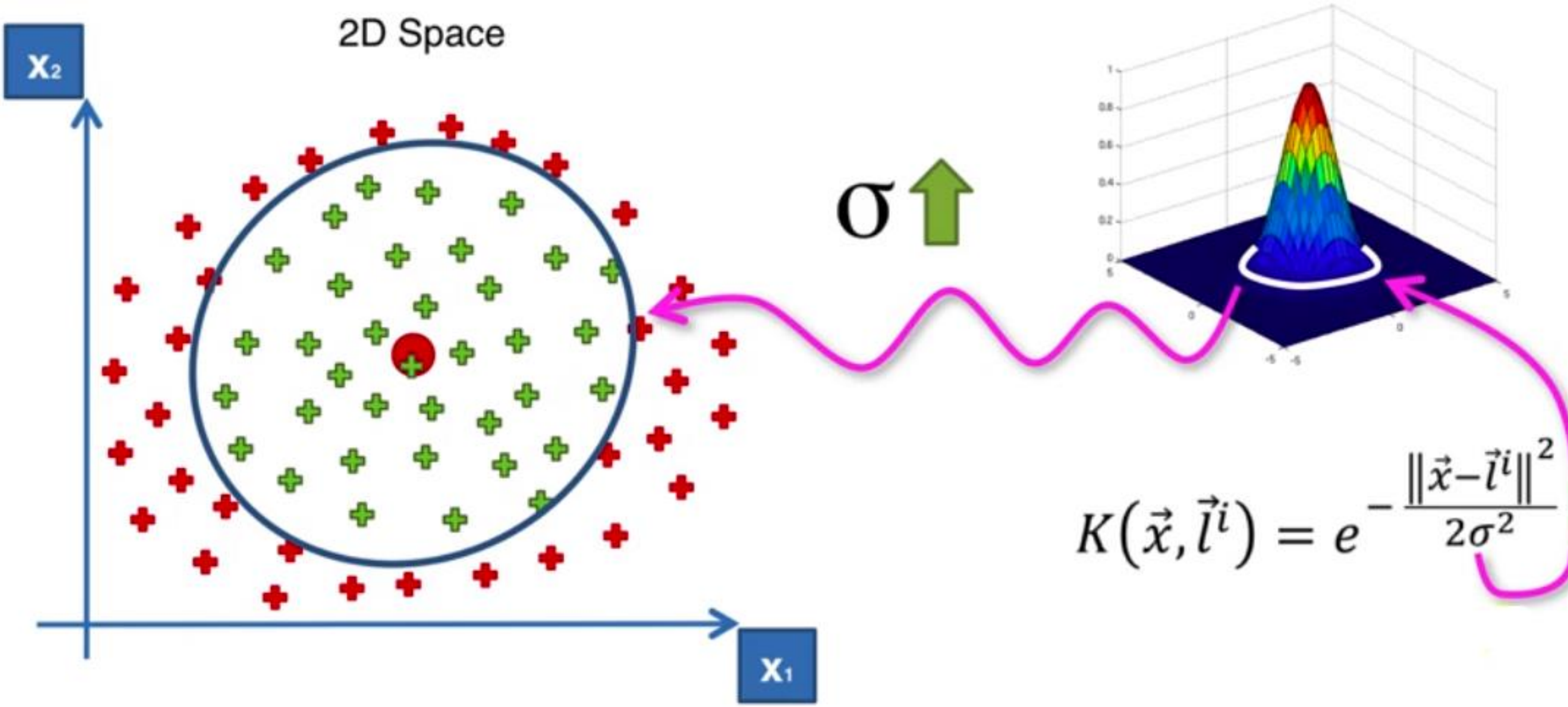

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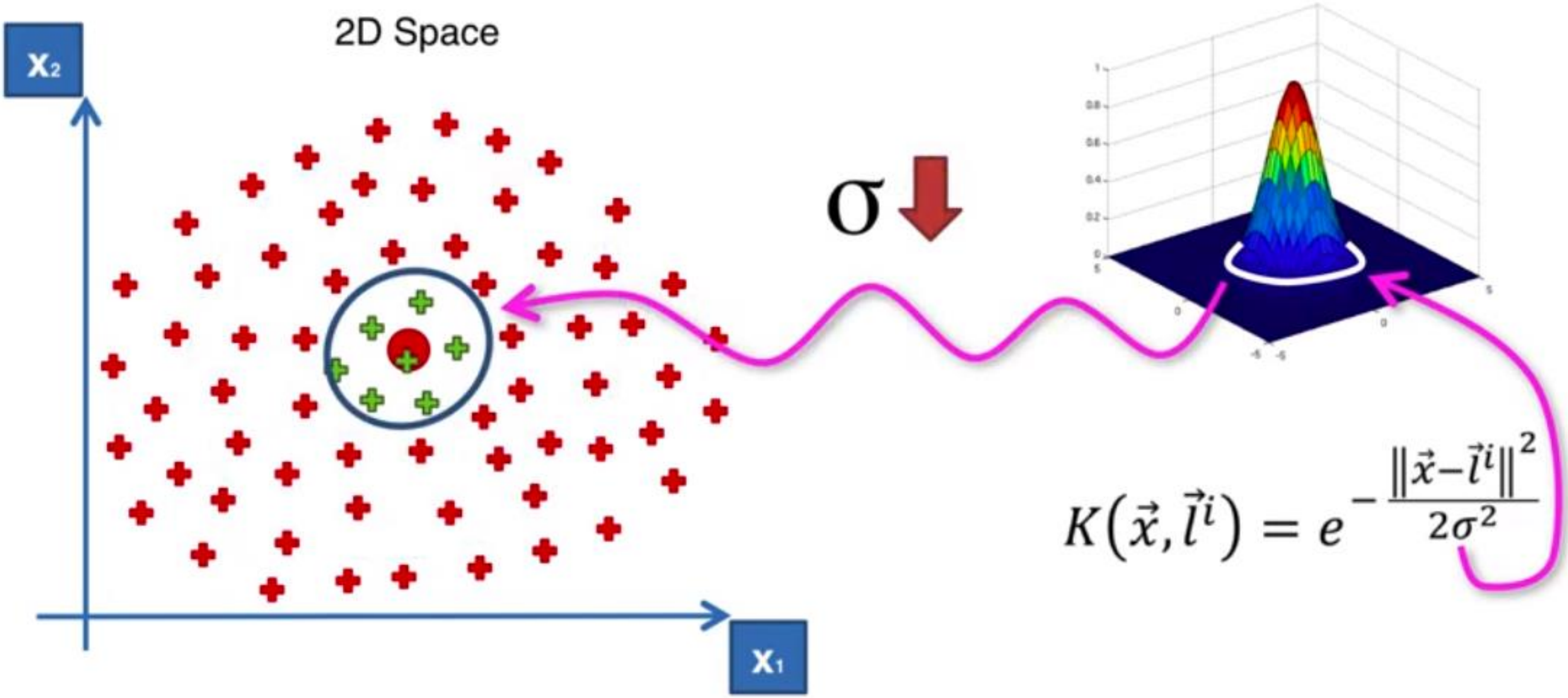

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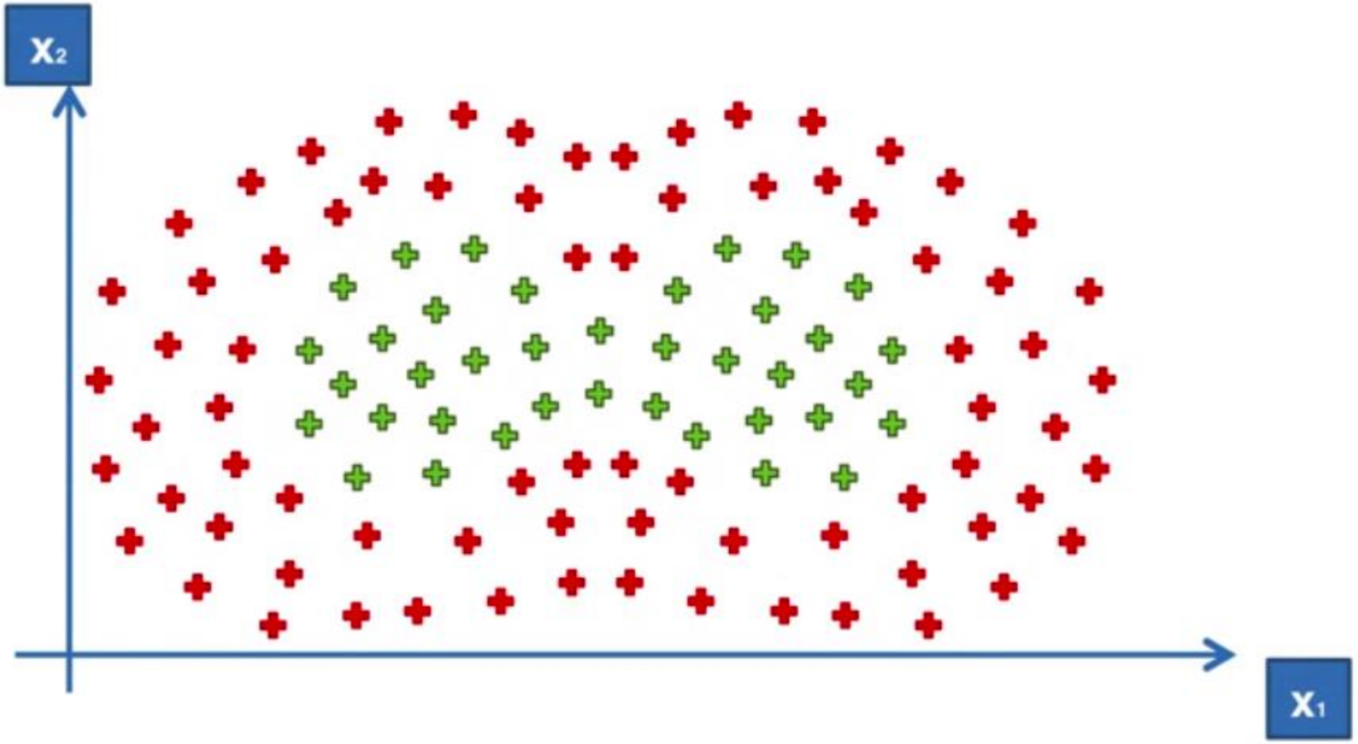

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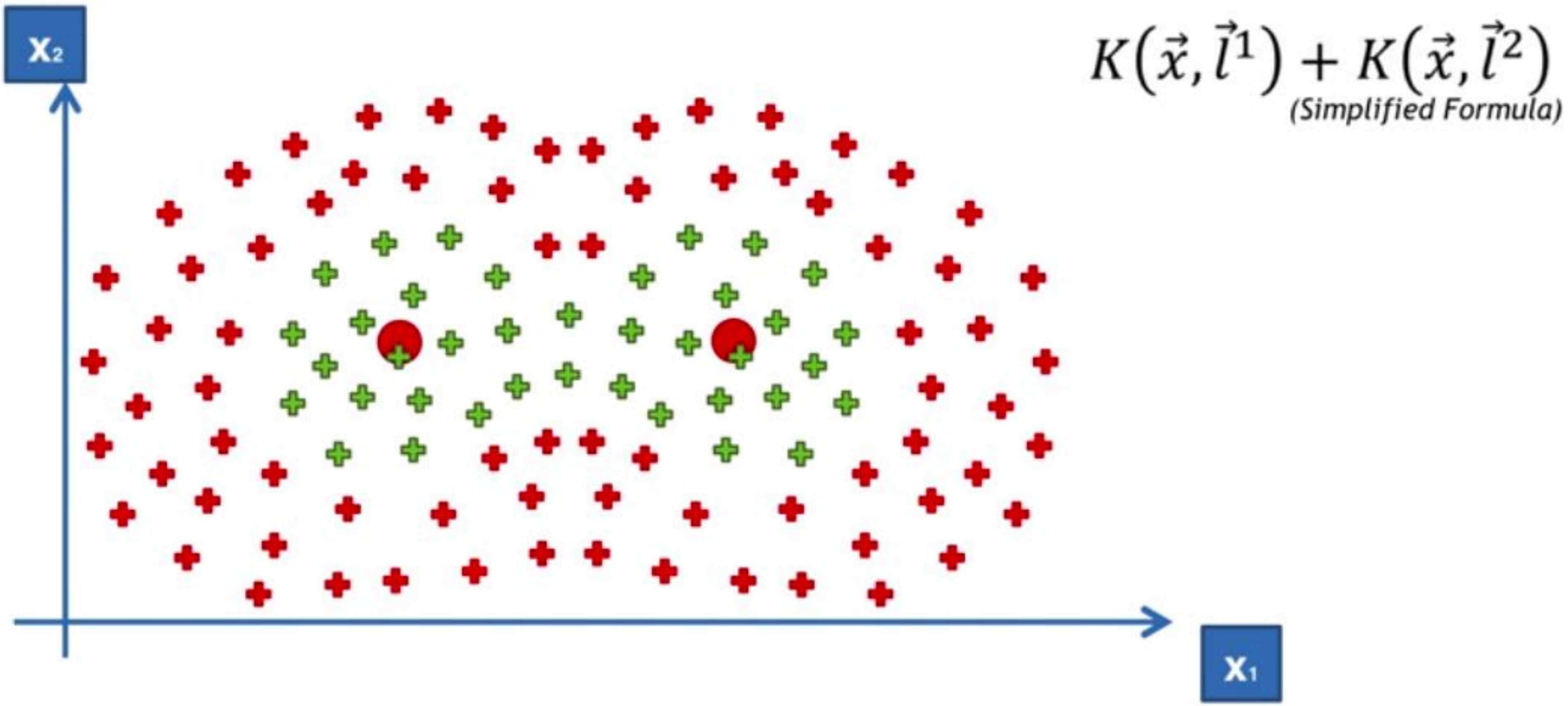

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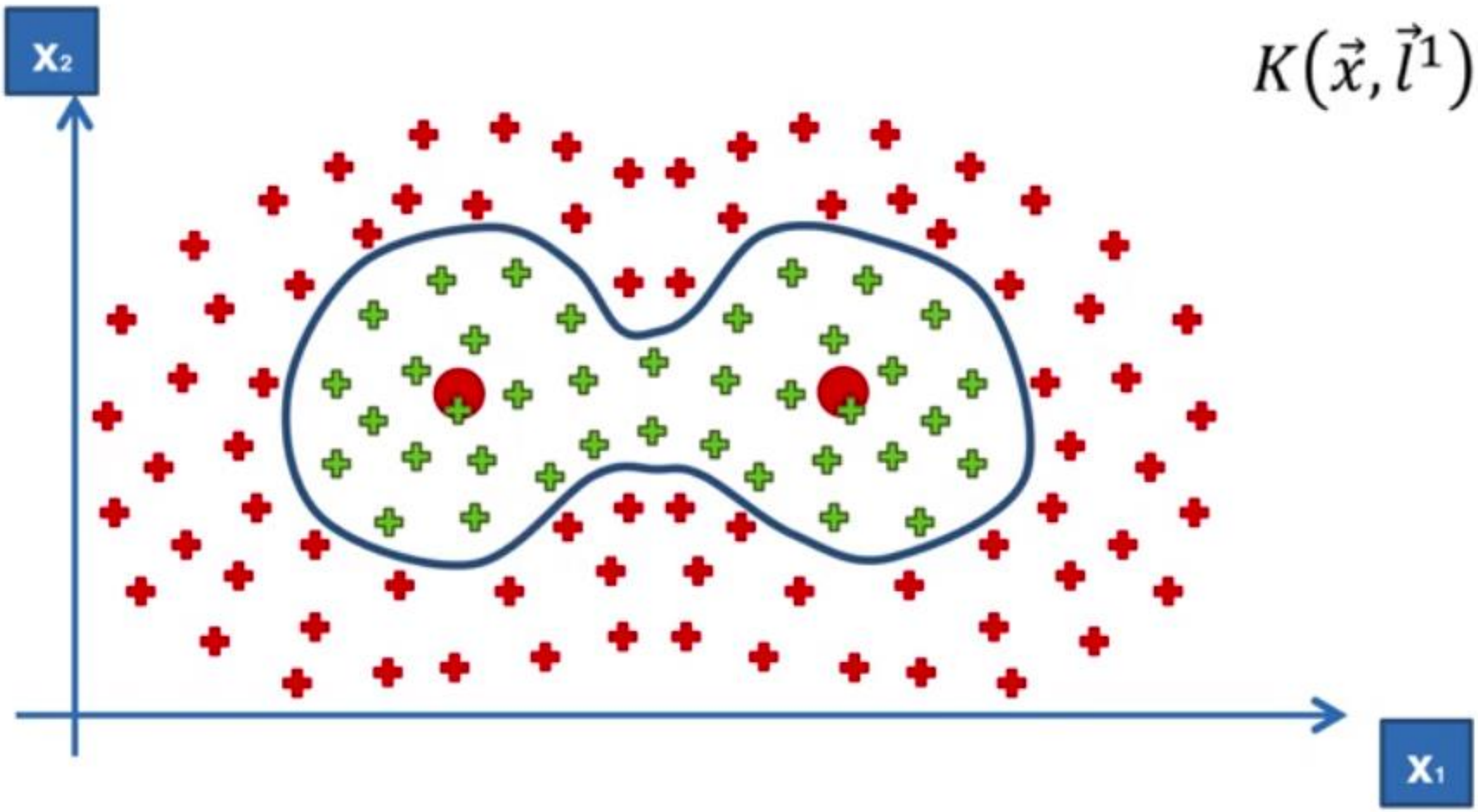
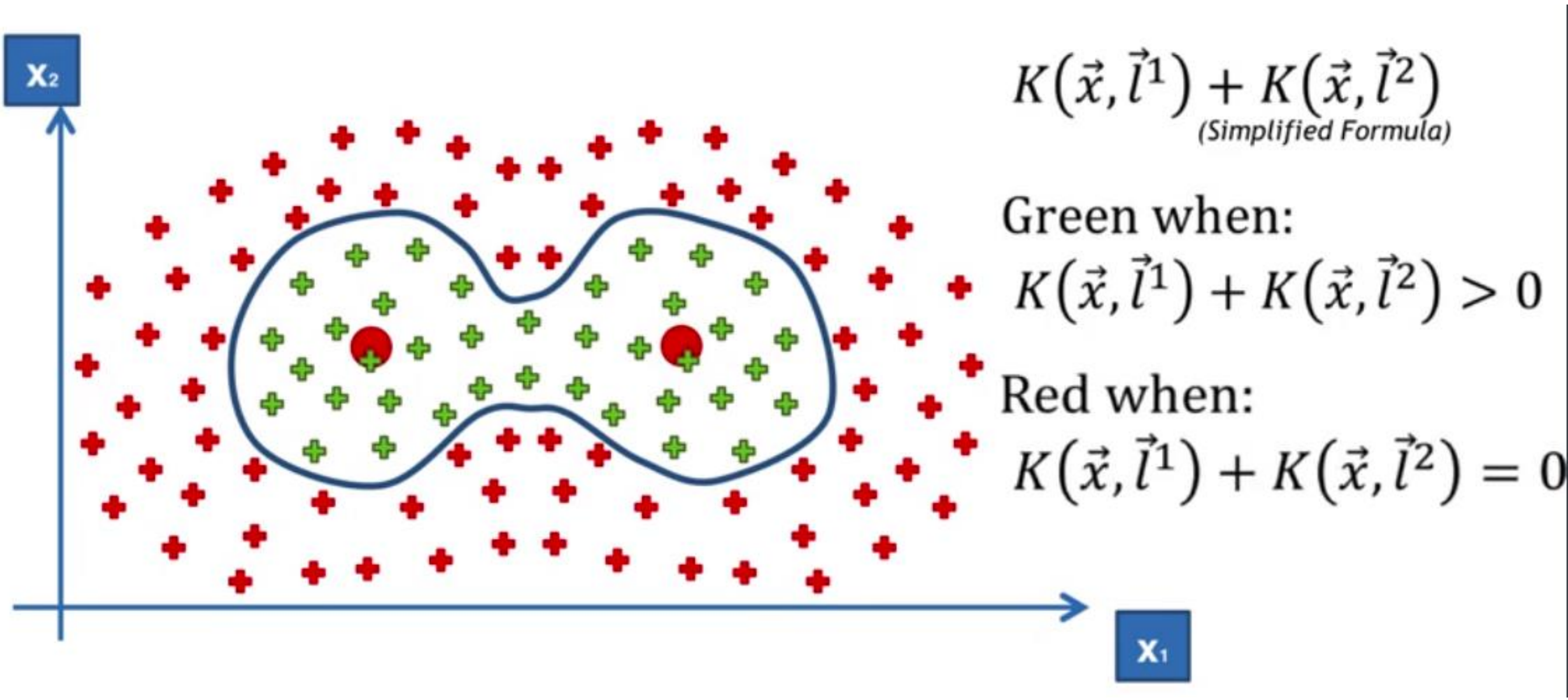


$$K(\vec{x}, \vec{l}^1) + K(\vec{x}, \vec{l}^2)$$

(Simplified Formula)

The Gaussian RBF kernel



Types of Kernel Functions

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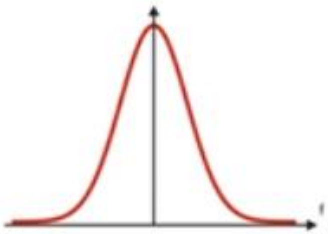
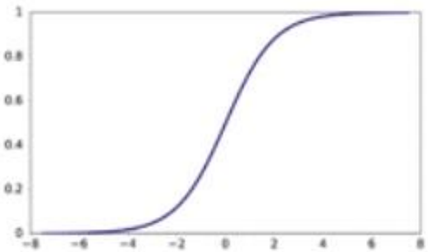


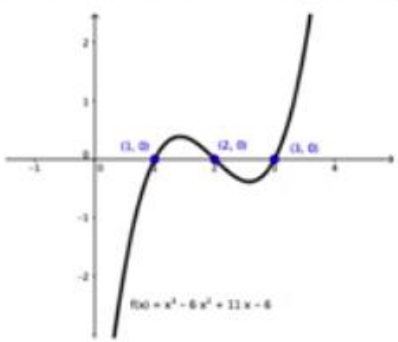
Gaussian RBF Kernel

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



Sigmoid Kernel

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



Polynomial Kernel

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

Kernel Functions for Machine Learning Applications

http://crsouza.com/2010/03/17/kernel-functions-for-machine-learning-applications/

THE END

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