

DATA ANALYTICS- UNIT 2

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Support Vector Machine

- Support Vector Machines (SVMs) are a type of supervised machine learning algorithm used for **classification and regression analysis**.
- The **main idea** behind SVMs is to find a hyperplane that separates the data into different classes with the maximum margin, which is the distance between the closest data points from either class and the hyperplane.
- The **margin is the distance** between the hyperplane and the closest data points from each class.

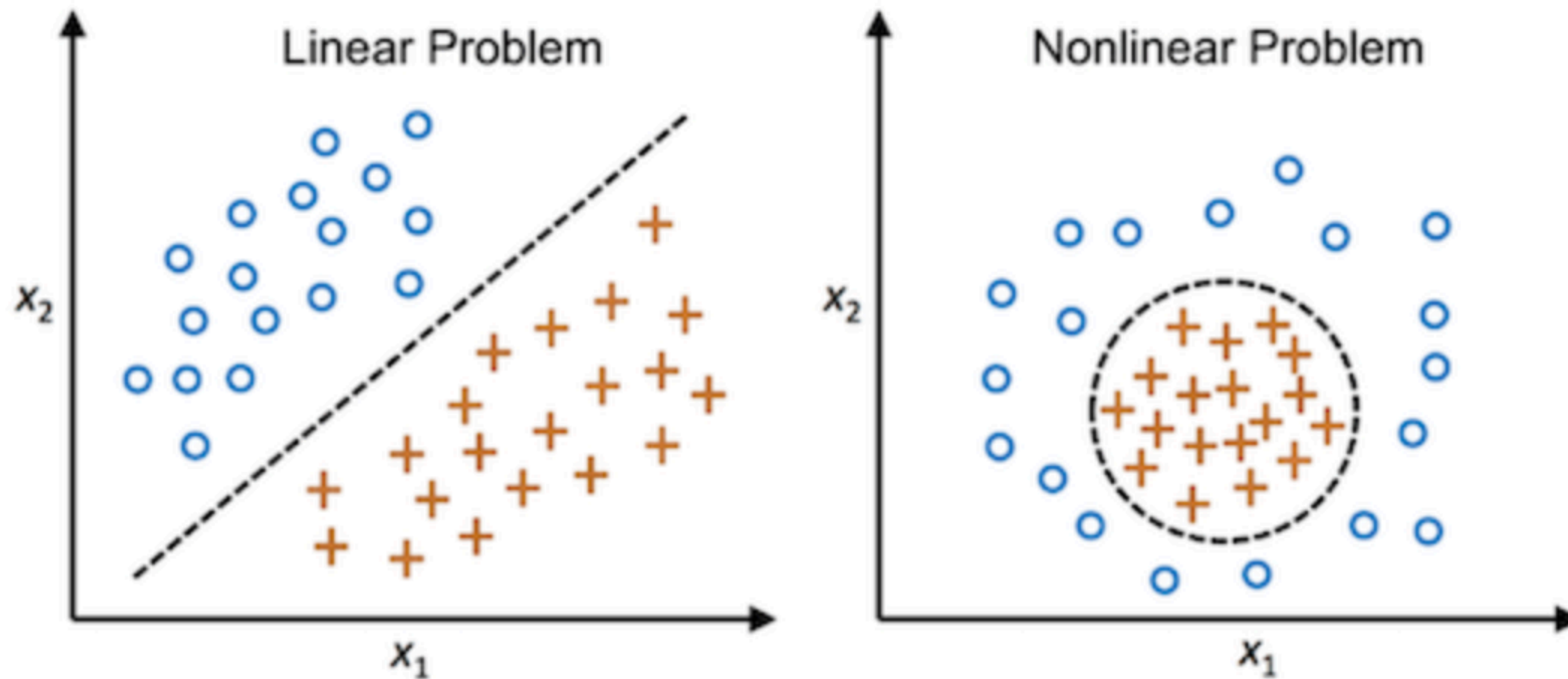
Support Vector Machine

There are two main types of support vector machine (SVM) models:

- Linear SVM
- Non-Linear SVM

The **hard-margin** and **soft-margin** support vector machine (SVM) models are two variations of linear SVM models.

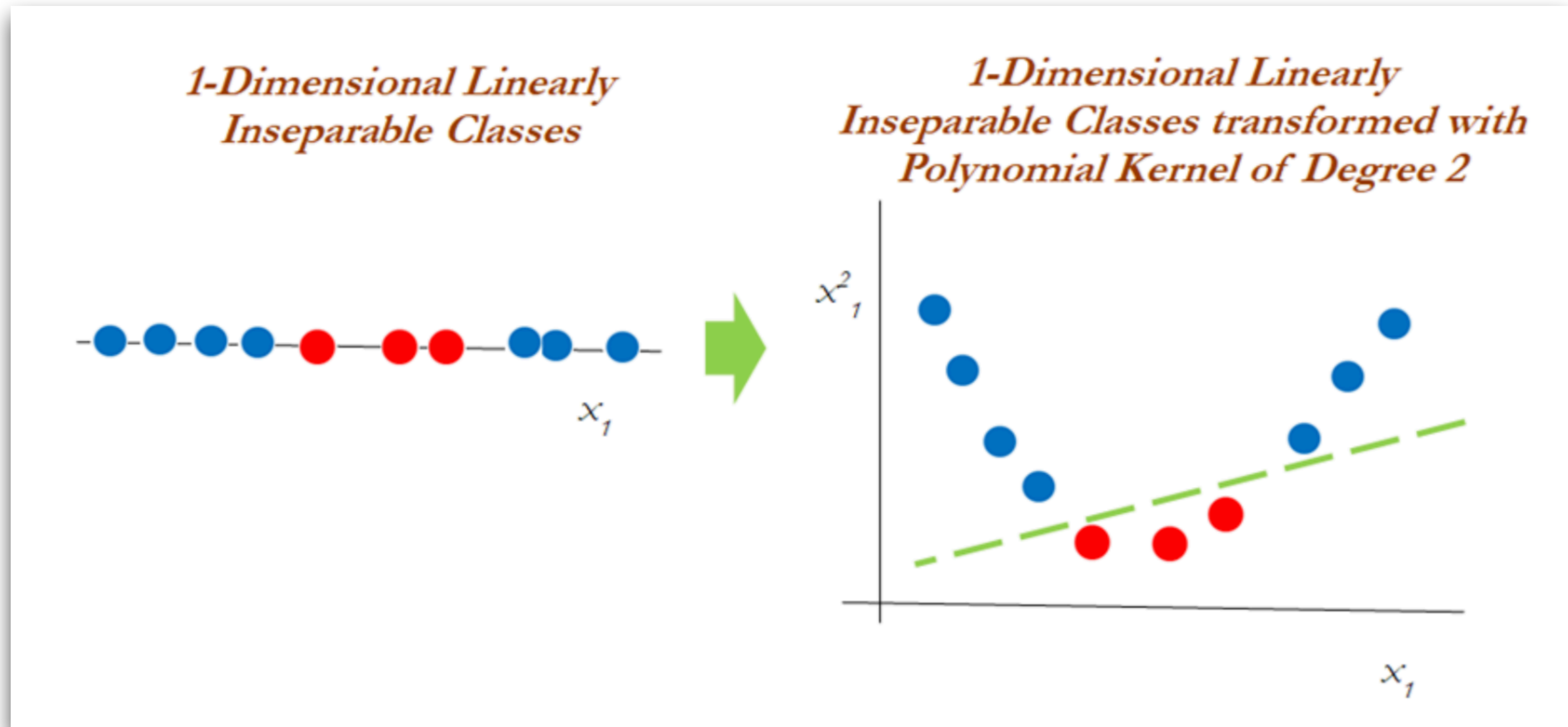
Linear vs Non Linear



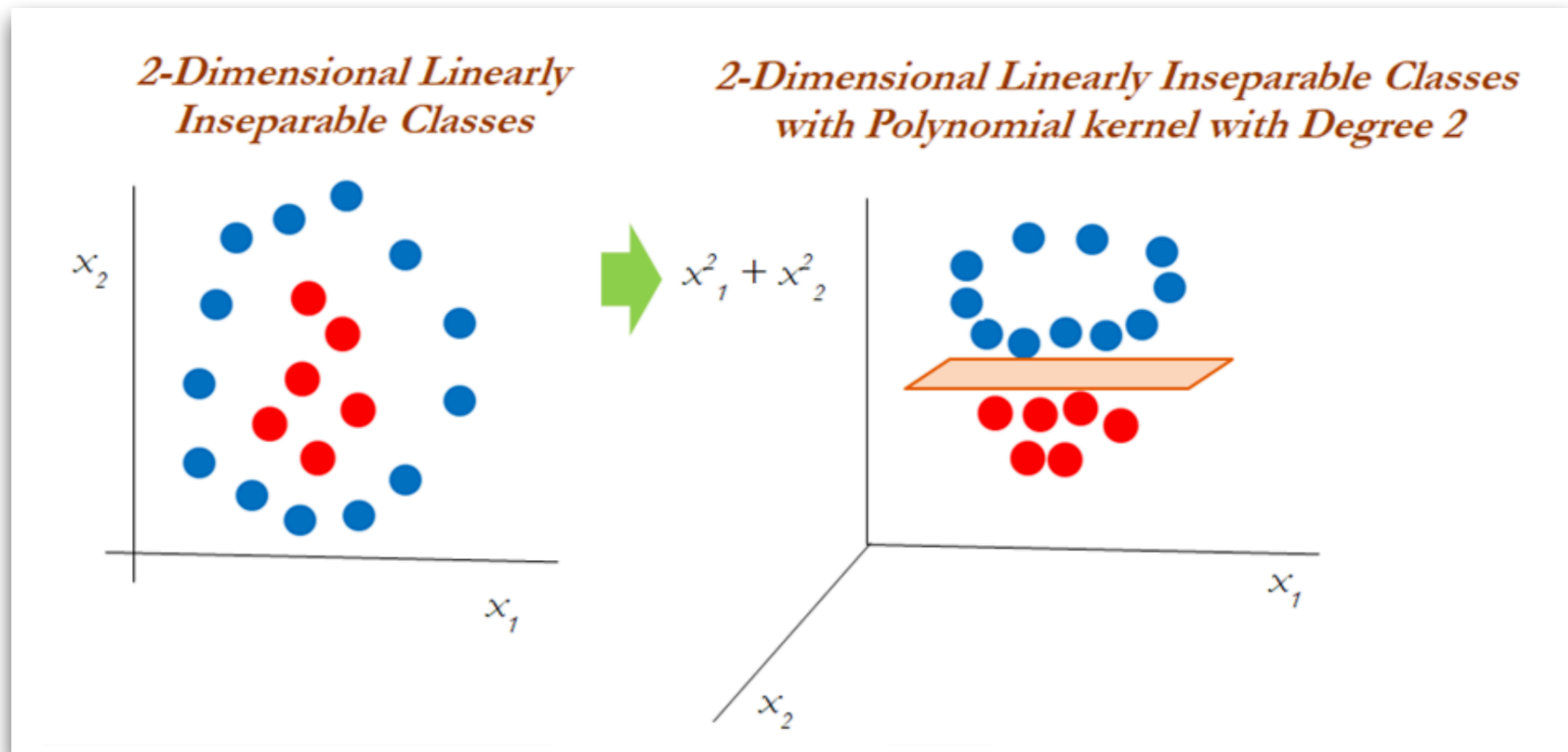
Kernel

Kernel is a function that is used to map the input data into a higher-dimensional space where the data is easier to classify using a linear boundary.

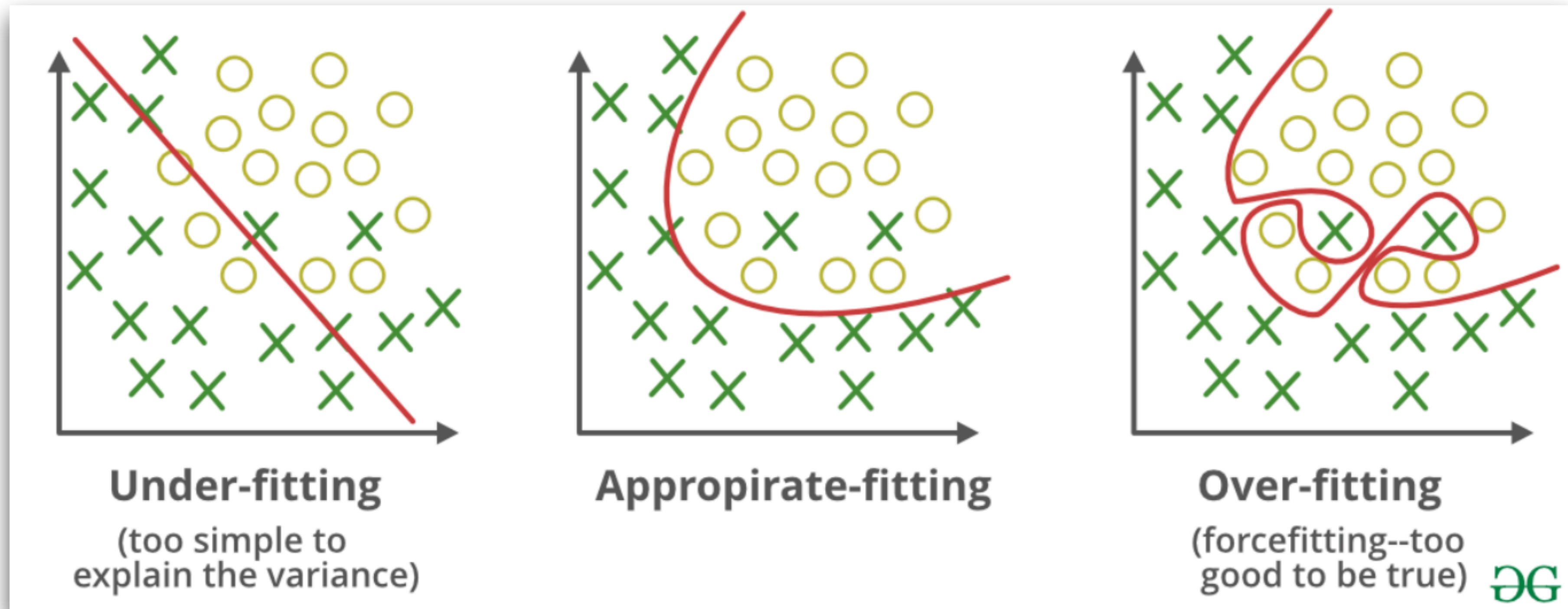
Inseparable to Separable



Inseparable to Separable

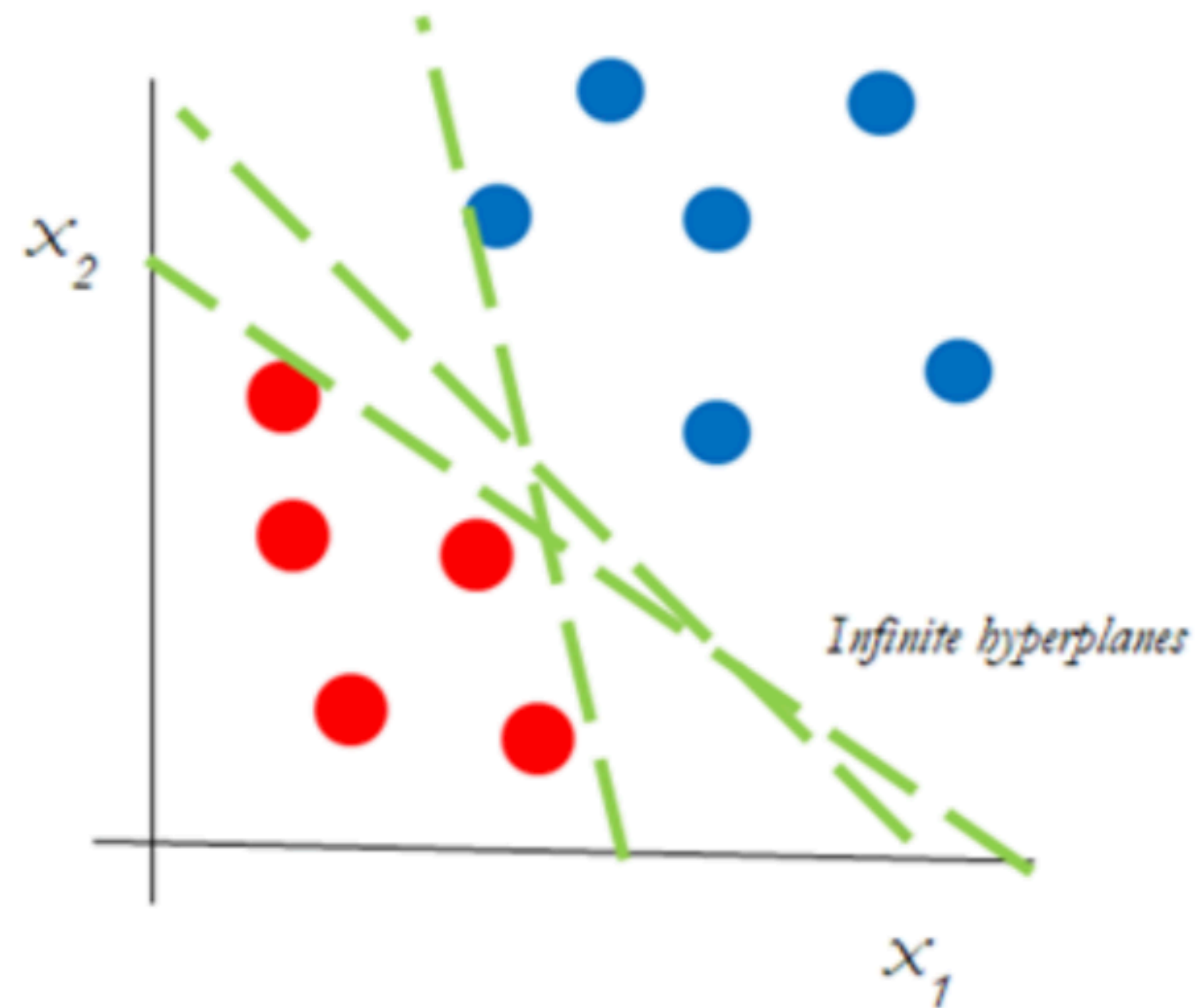


Model Fitting

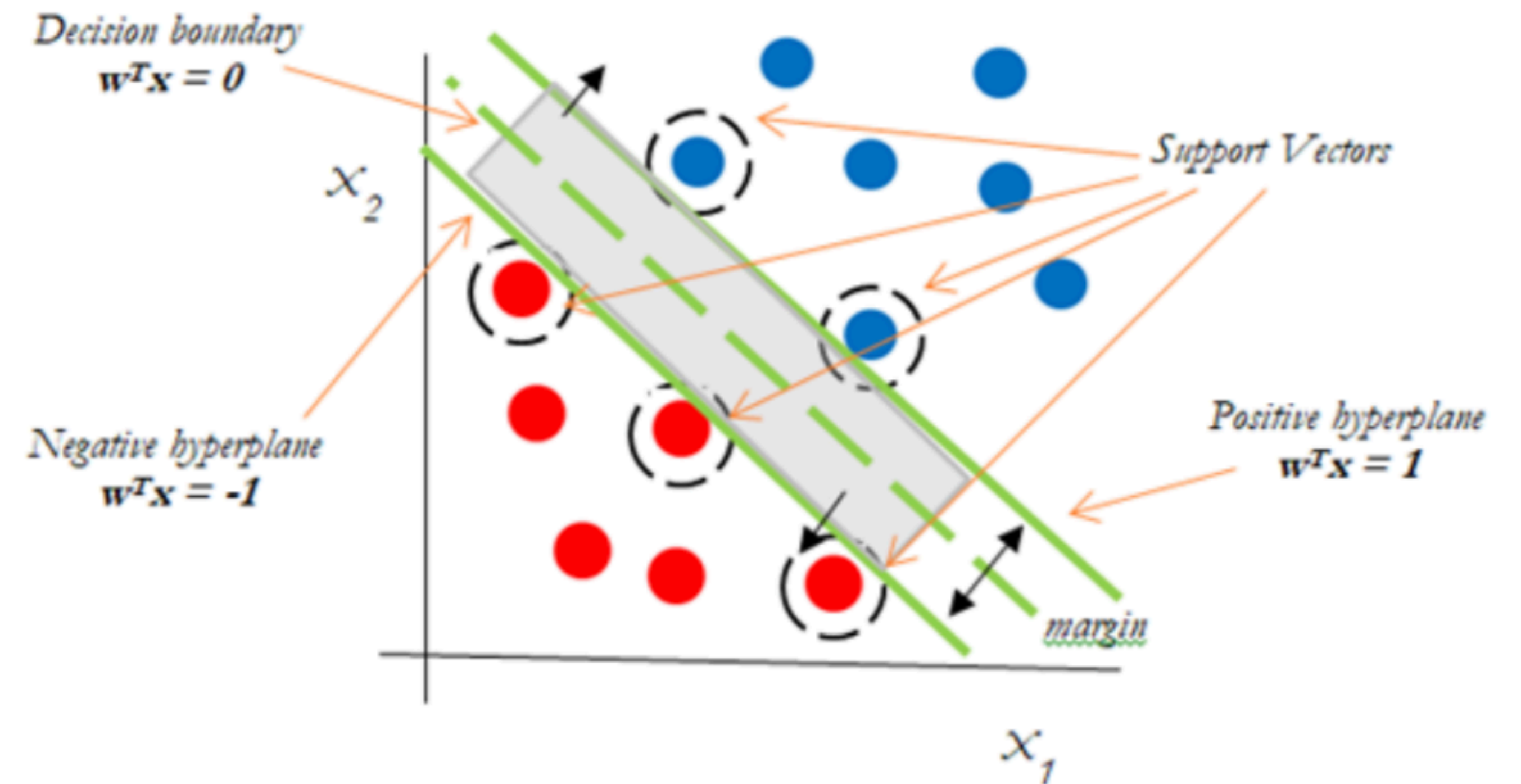


Hyperplanes

Infinite Hyperplanes



Maximum Margin Classifier



Dual Formulation

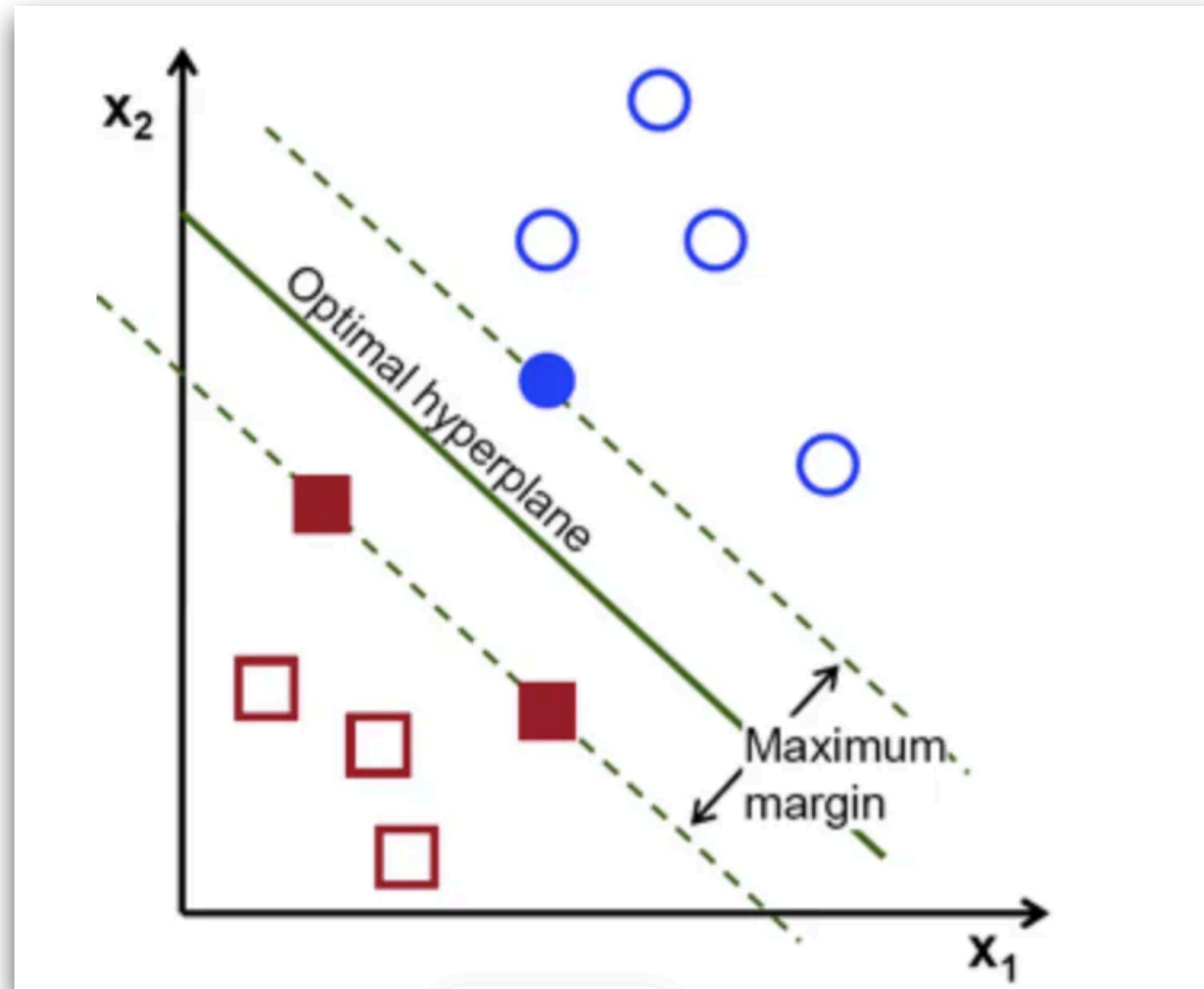


Image Credit: <https://medium.com/@sathvikchiramana/svm-dual-formulation-7535caa84f17>

Why Optimal Hyperplane

- Better Generalization (By reducing overfitting)
- Improved Separation
- Robustness to Outliers

Kernel in SVM

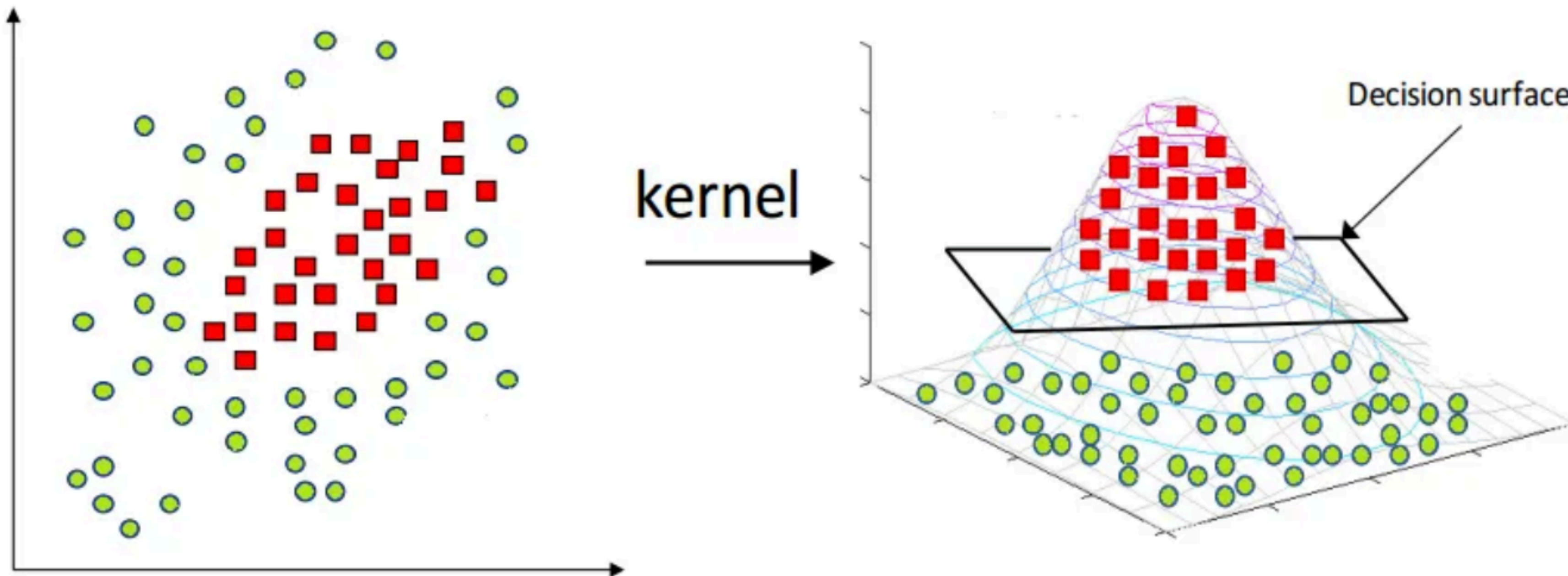
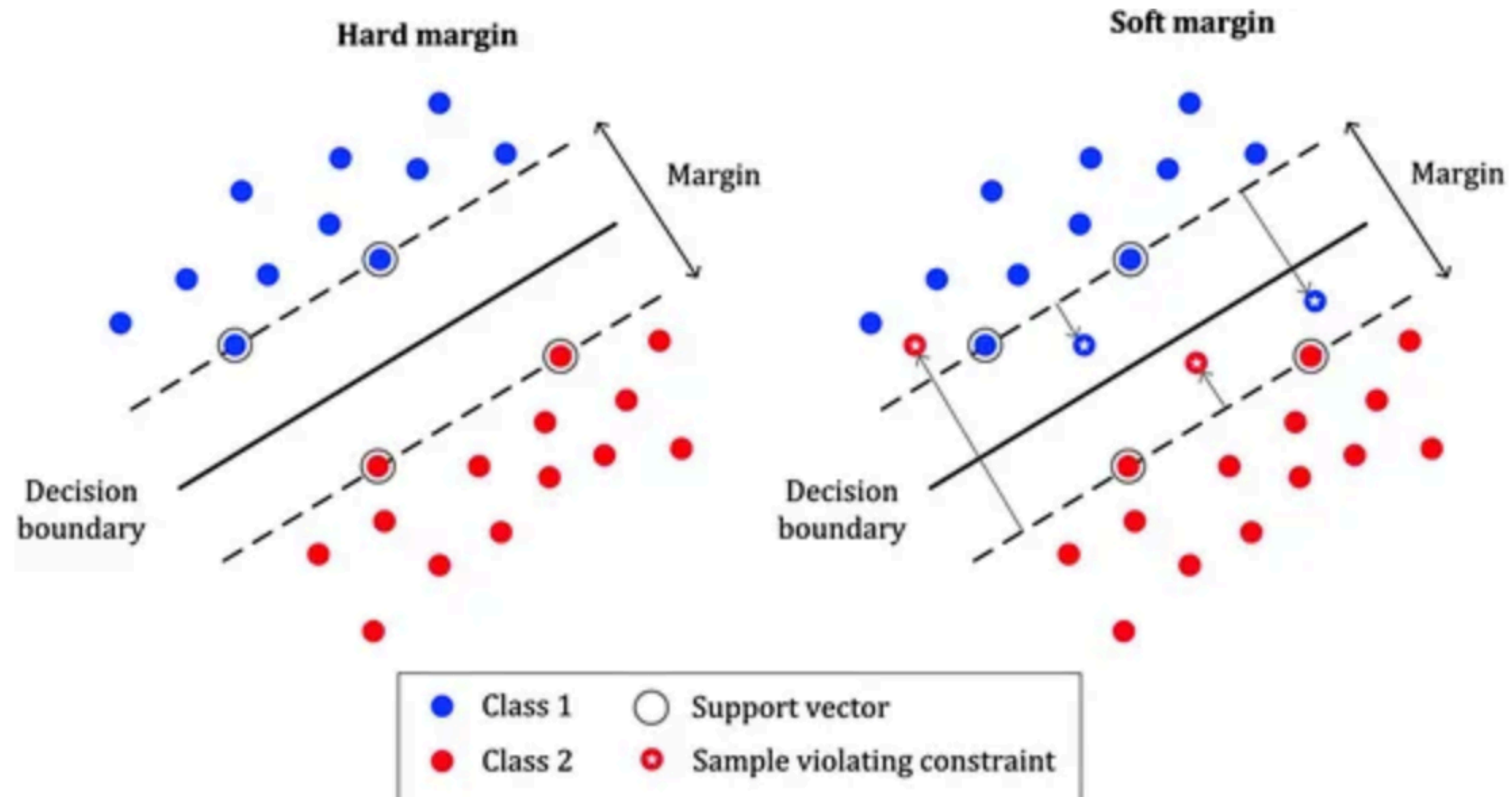


Image Credit: <https://medium.com/analytics-vidhya/how-to-classify-non-linear-data-to-linear-data-bb2df1a6b781>

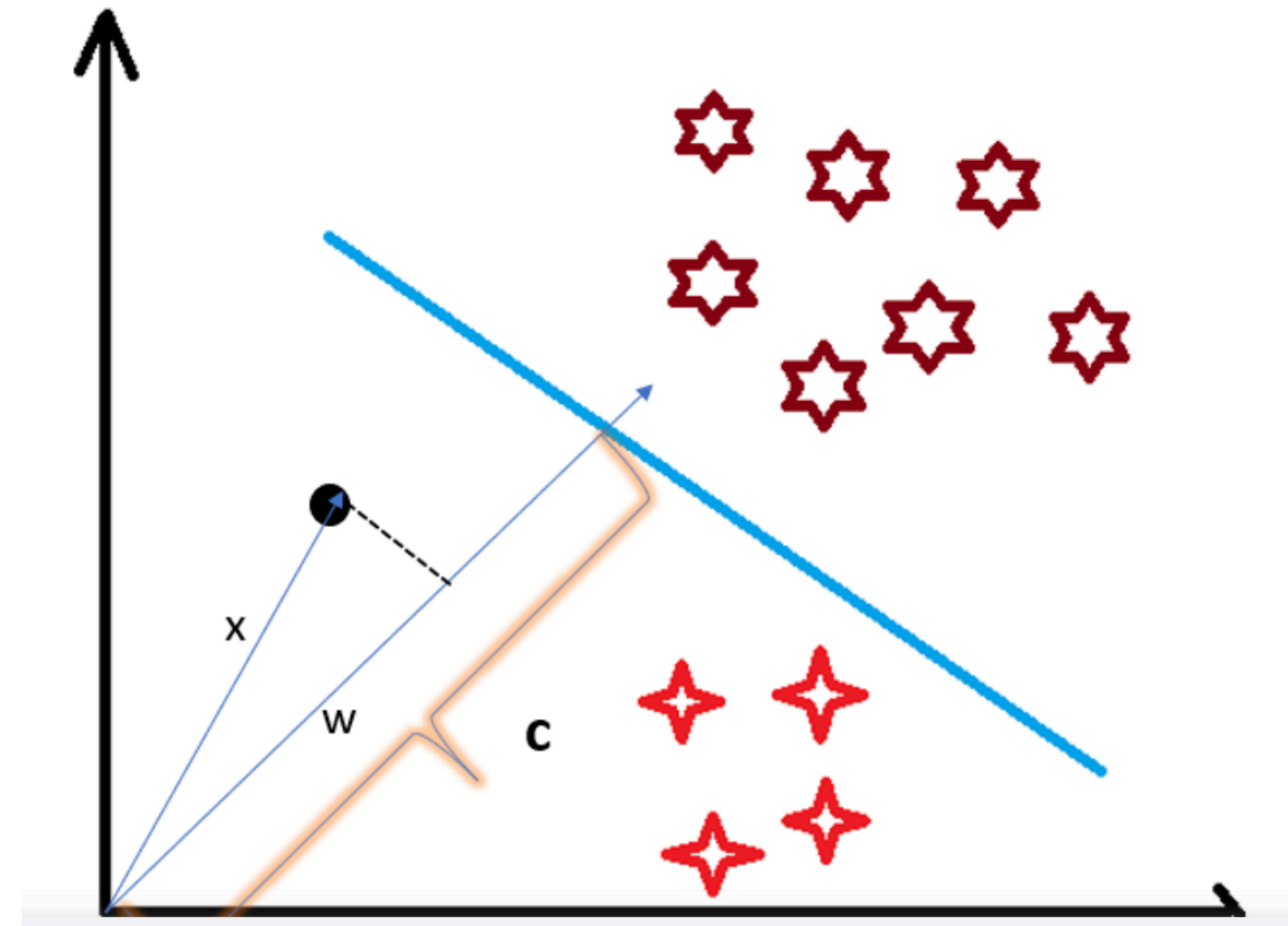
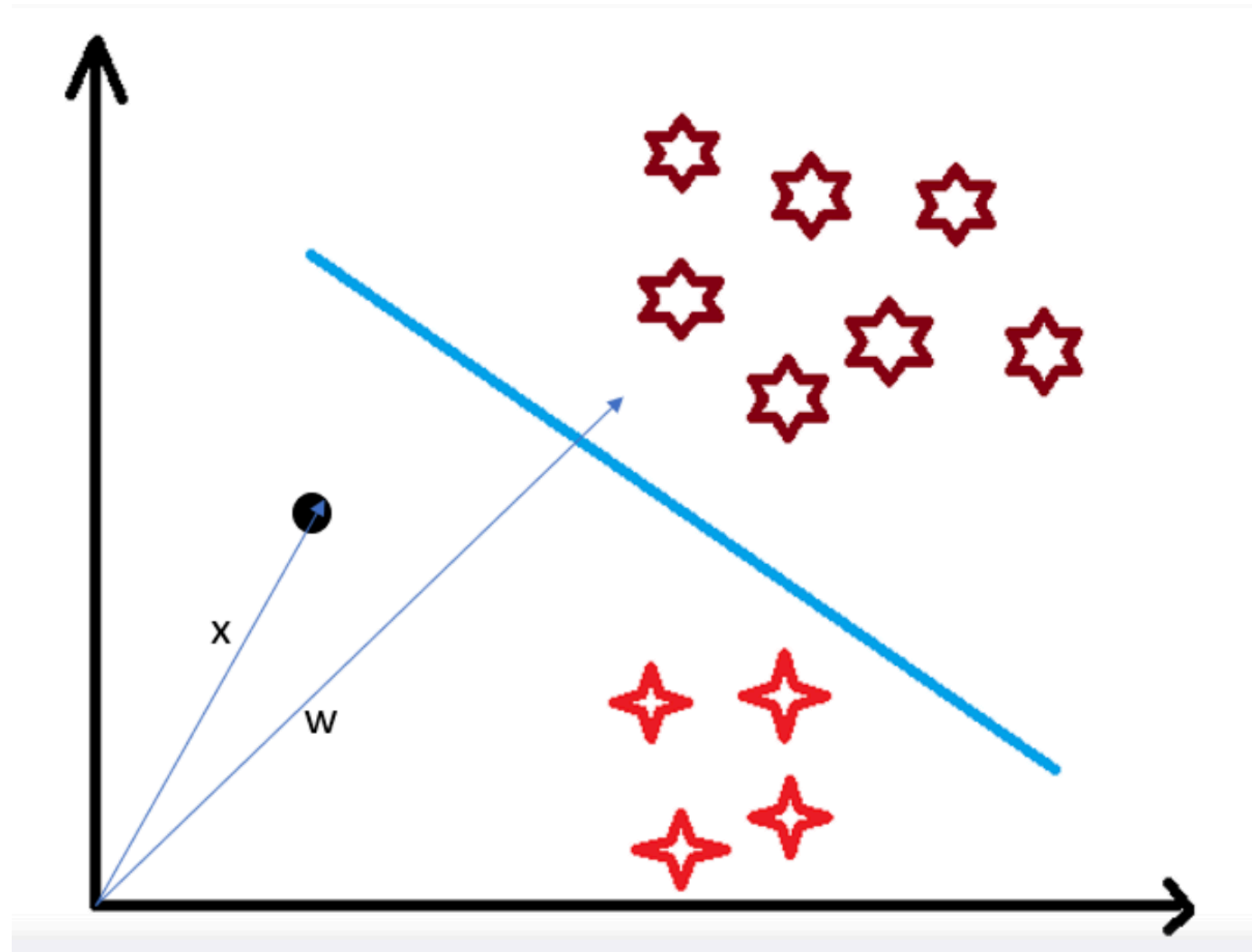
Hard and Soft Margin SVM



SVM vs LOGISTIC REGRESSION

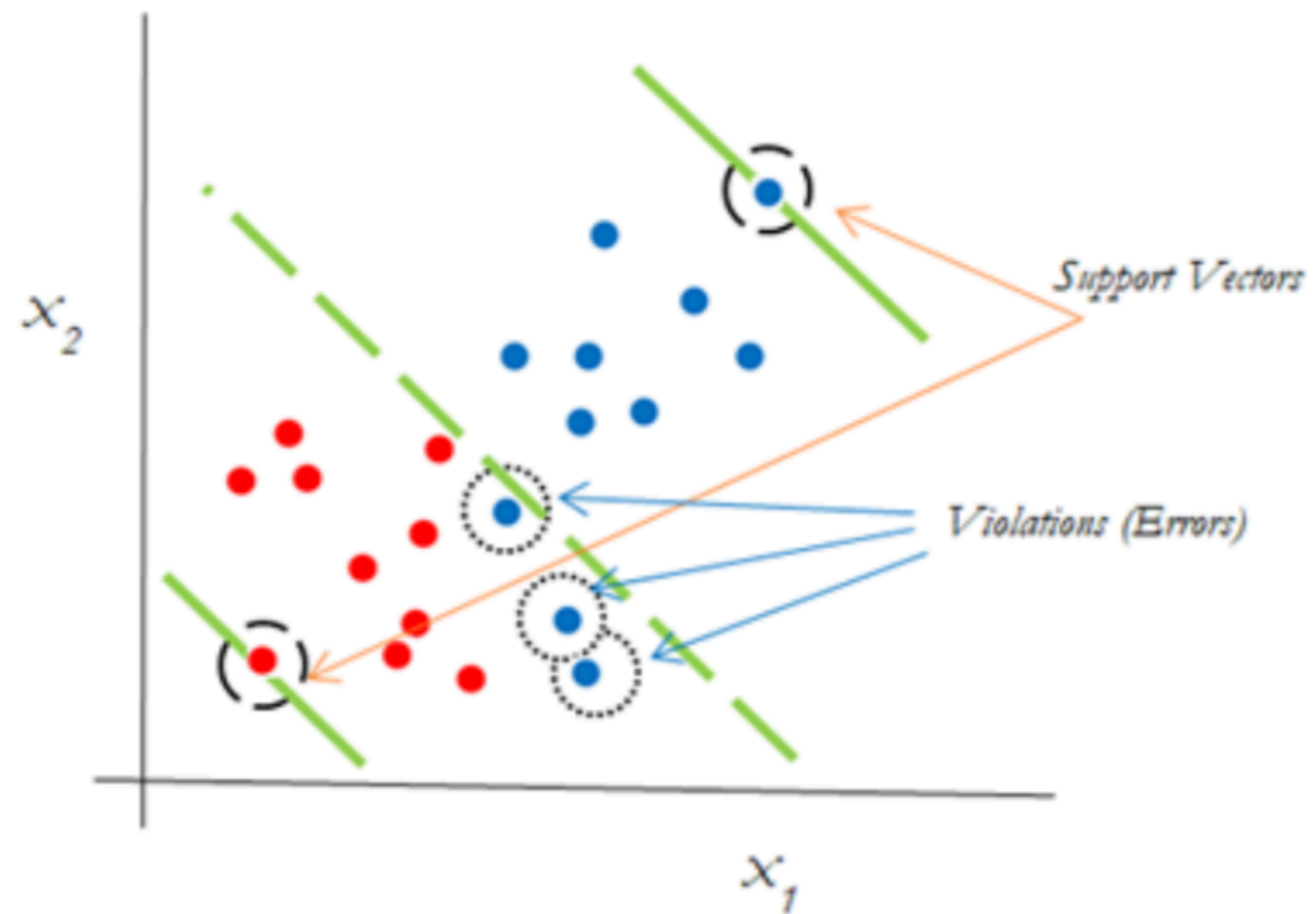
- Logistic Regression for **classification**, whereas SVM for **classification and Regression**.
- SVM tries to find the “**best**” **margin** (distance between the line and the support vectors) that separates the classes and this reduces the risk of error on the data, while logistic regression does not, instead it can have different decision boundaries with different weights that are near the optimal point.
- Use **SVM when you have large number of feature vectors** and there is a clear decision boundary in the dataset. Otherwise use Logistic Regression.
- SVM is defined such that it is **defined in terms of the support vectors only**, we don't have to worry about other observations since the margin is made using the points which are closest to the hyperplane (support vectors), whereas in logistic regression the classifier is defined over all the points. Hence SVM enjoys some natural speed-ups.

SVM

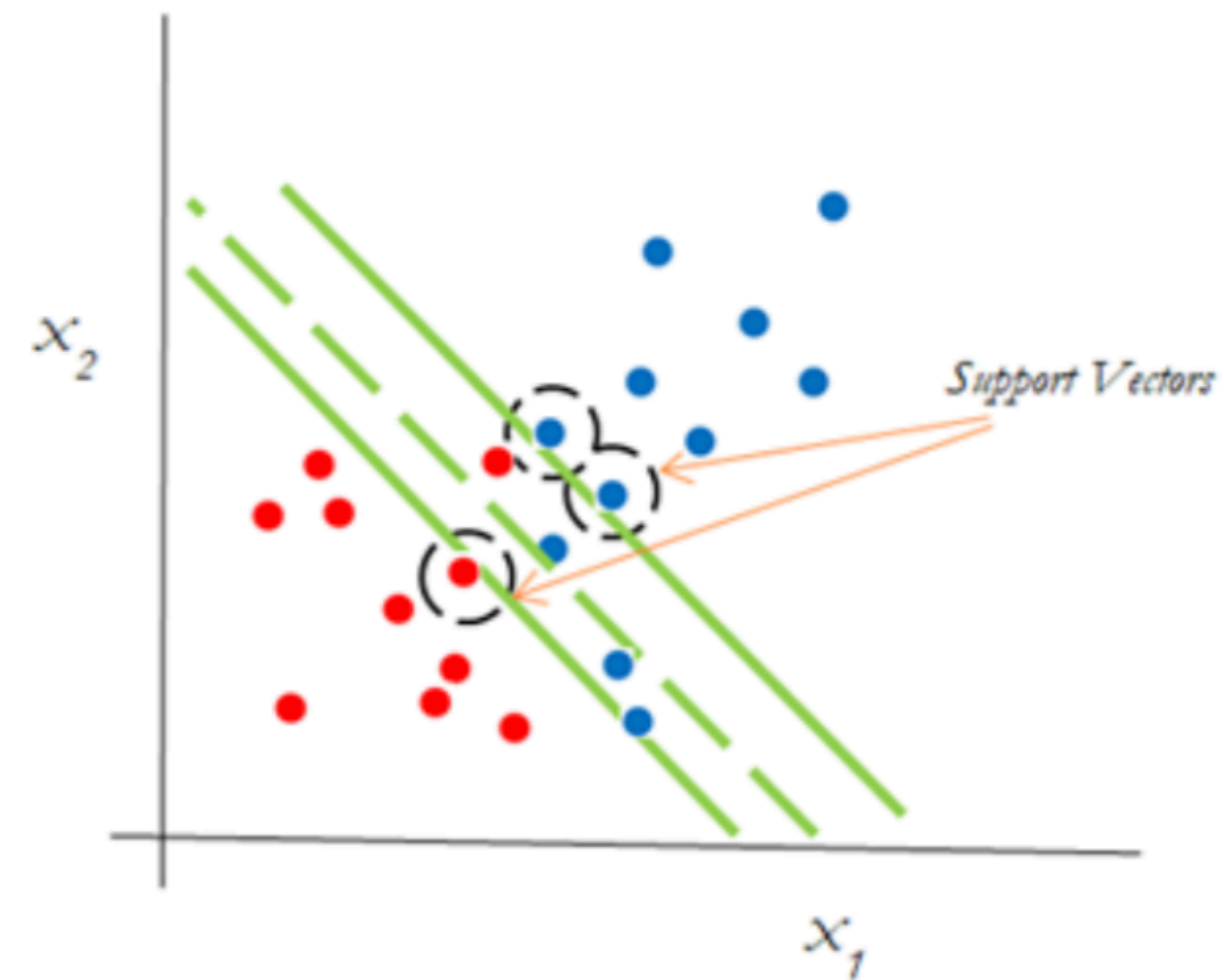


Impact of C parameter in SVM

Support Vector Classifier with large value of C



Support Vector Classifier with small value of C



Use of Dot Product in SVM

$$\vec{X} \cdot \vec{w} = c \text{ (the point lies on the decision boundary)}$$

$$\vec{X} \cdot \vec{w} > c \text{ (positive samples)}$$

$$\vec{X} \cdot \vec{w} < c \text{ (negative samples)}$$

Margin in SVM

$$\vec{X} \cdot \vec{w} - c \geq 0$$

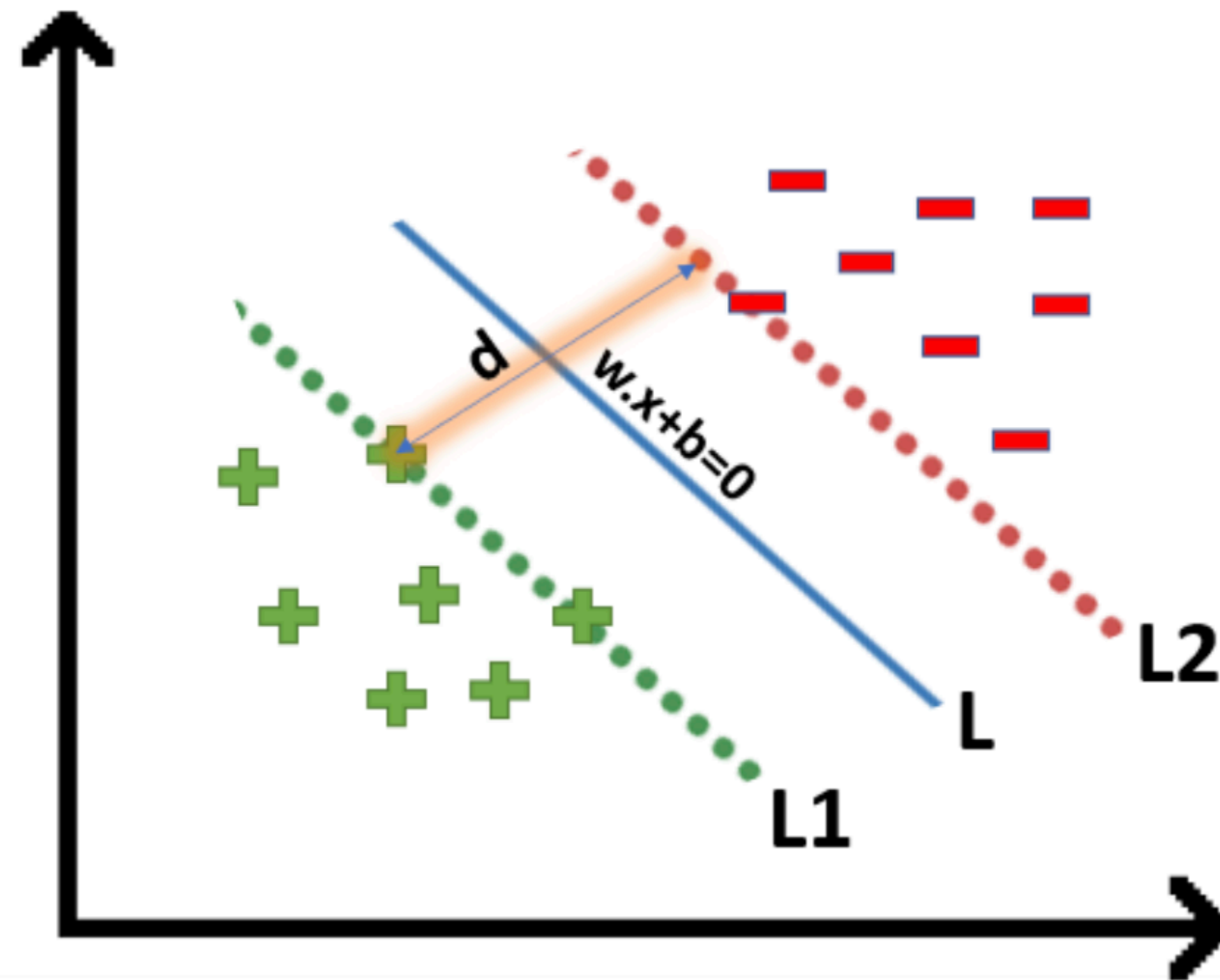
putting $-c$ as b , we get

$$\vec{X} \cdot \vec{w} + b \geq 0$$

hence

$$y = \begin{cases} +1 & \text{if } \vec{X} \cdot \vec{w} + b \geq 0 \\ -1 & \text{if } \vec{X} \cdot \vec{w} + b < 0 \end{cases}$$

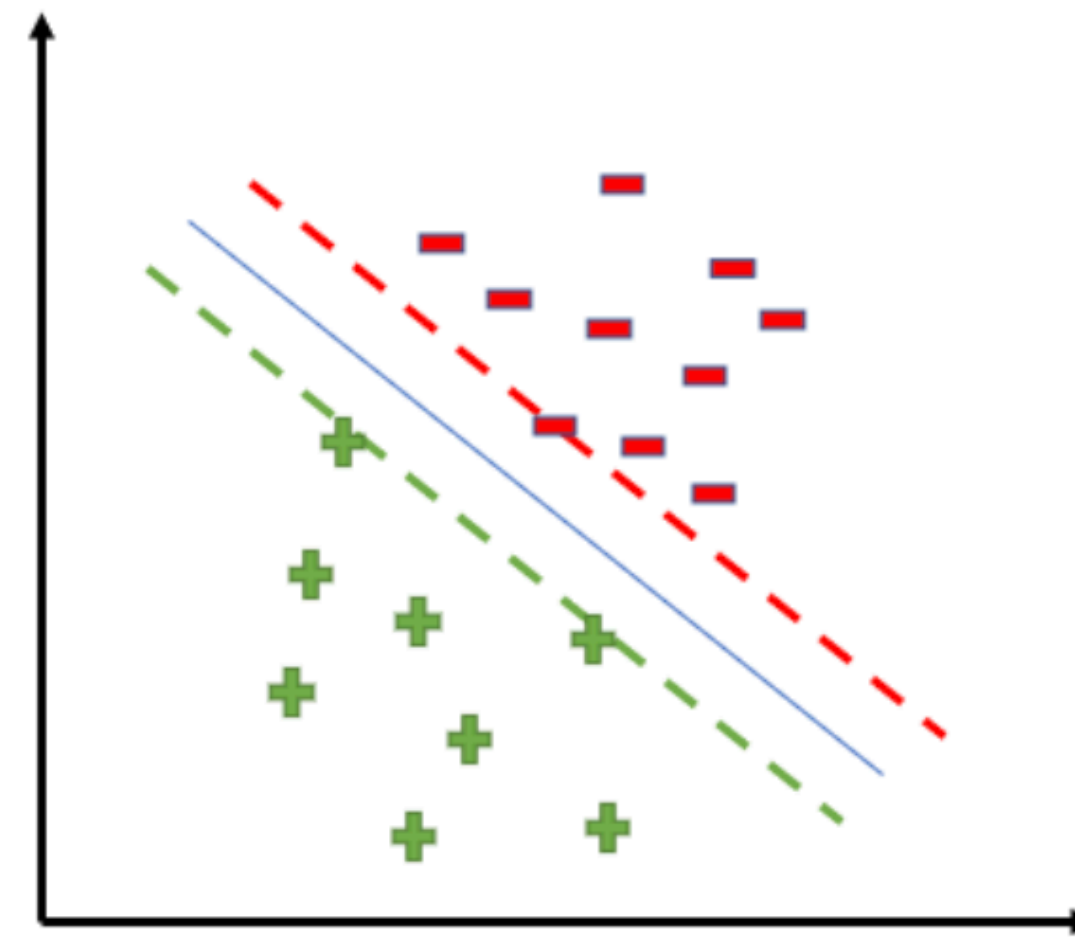
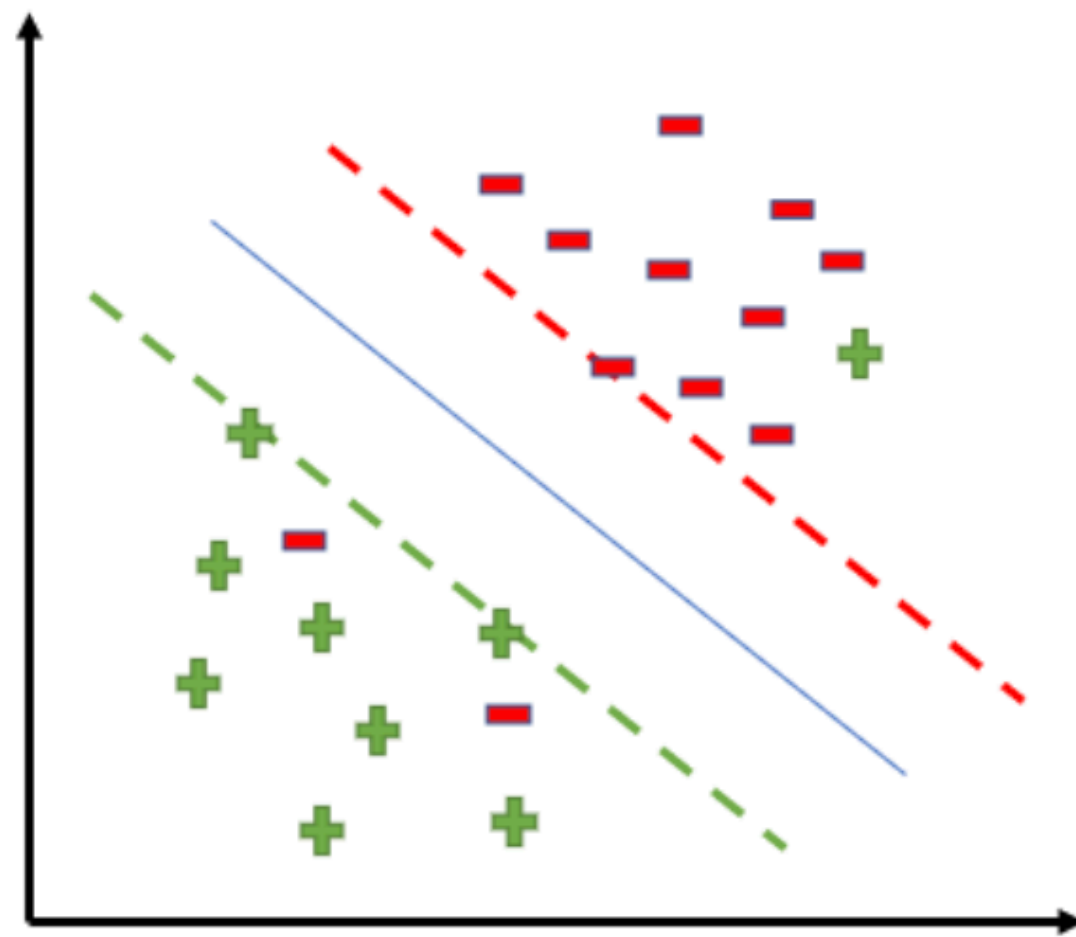
Margin in SVM



Optimization function and its constraints

$$\operatorname{argmax}(\mathbf{w}^*, b^*) \frac{2}{\|\mathbf{w}\|} \text{ such that } y_i(\vec{w} \cdot \vec{X} + b) \geq 1$$

Which one is better model ?



Kernel Methods

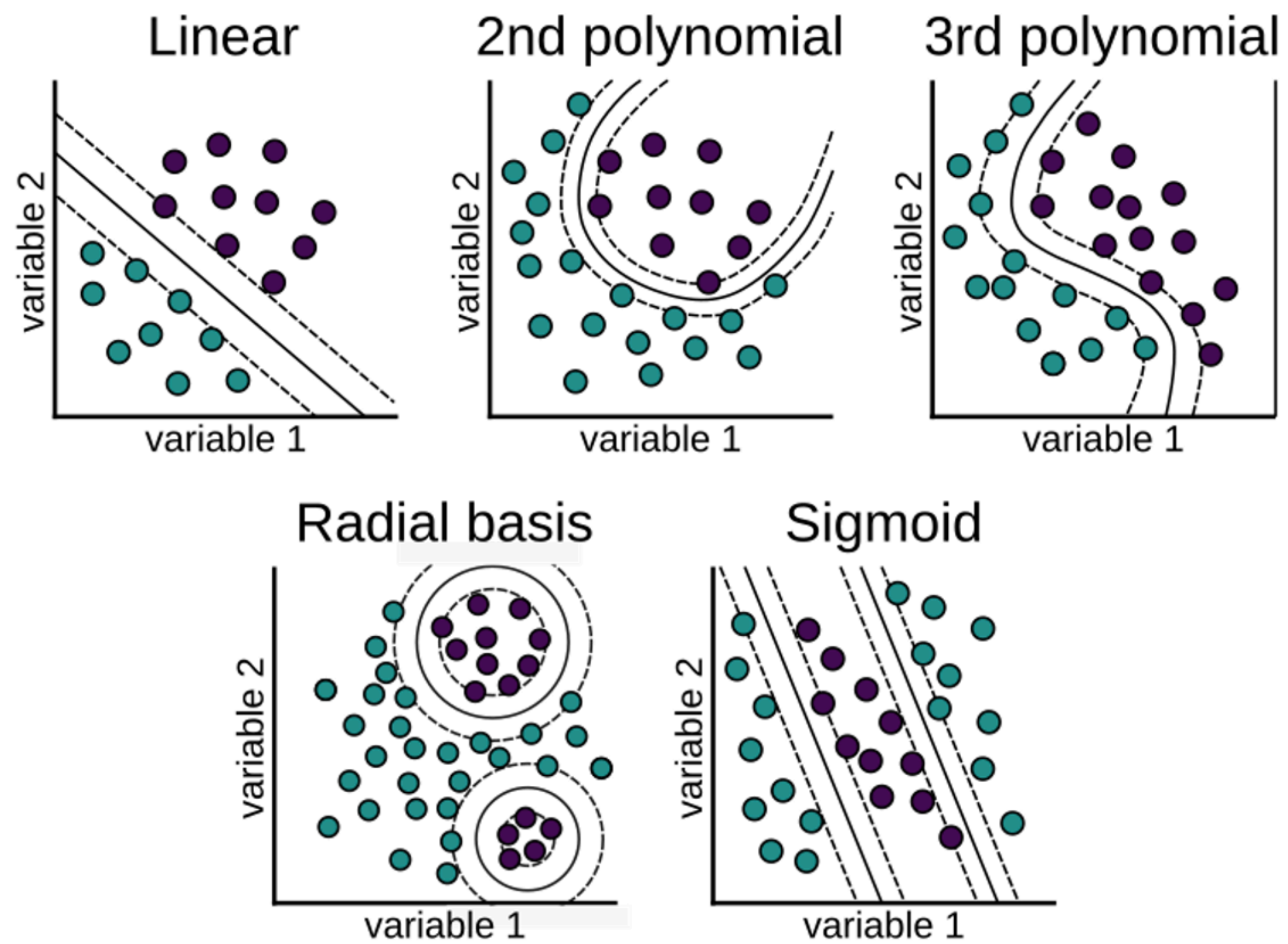
The main idea behind kernel methods in SVMs is to map the input data into a higher dimensional feature space, where it is possible to find a hyperplane that separates the classes with maximum margin.

The mapping from the original input space to the feature space is performed using a kernel function.

Types of kernel functions :

- Linear kernel
- Polynomial kernel
- Radial basis function (RBF) kernel
- Sigmoid kernel

Kernel Methods



Support Vector Machine

Here are some key points about SVMs:

- Maximal Margin Classifier
- Linear and Non-Linear Classification
- Dual Formulation
- Kernels
- Overfitting
- Applications