



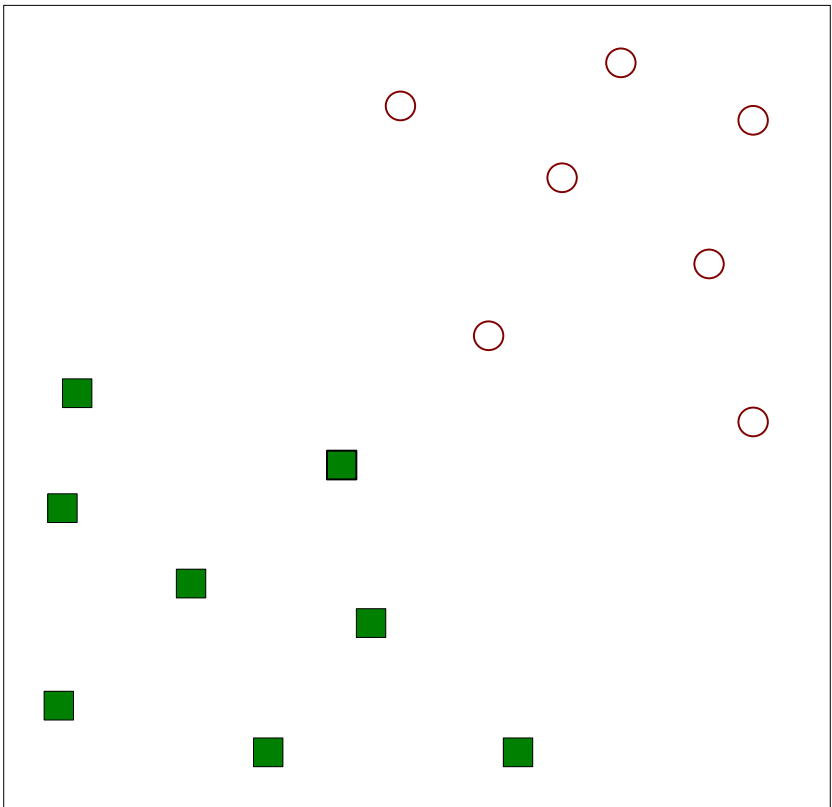
# Support Vector Machine



Support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis.

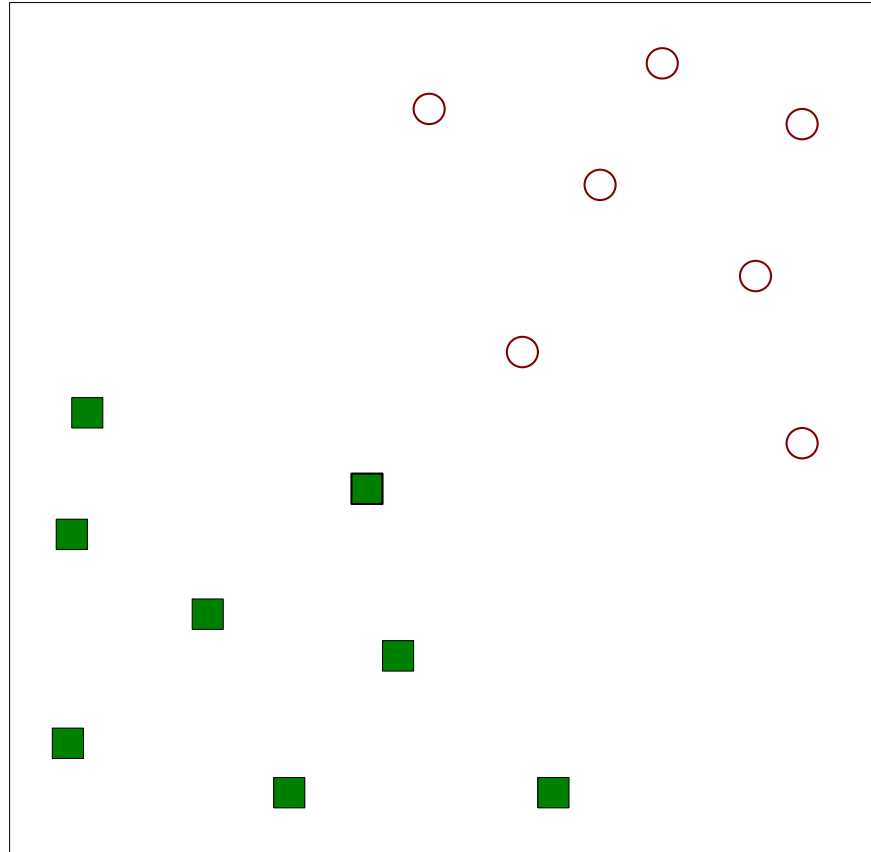


How to separate these points?





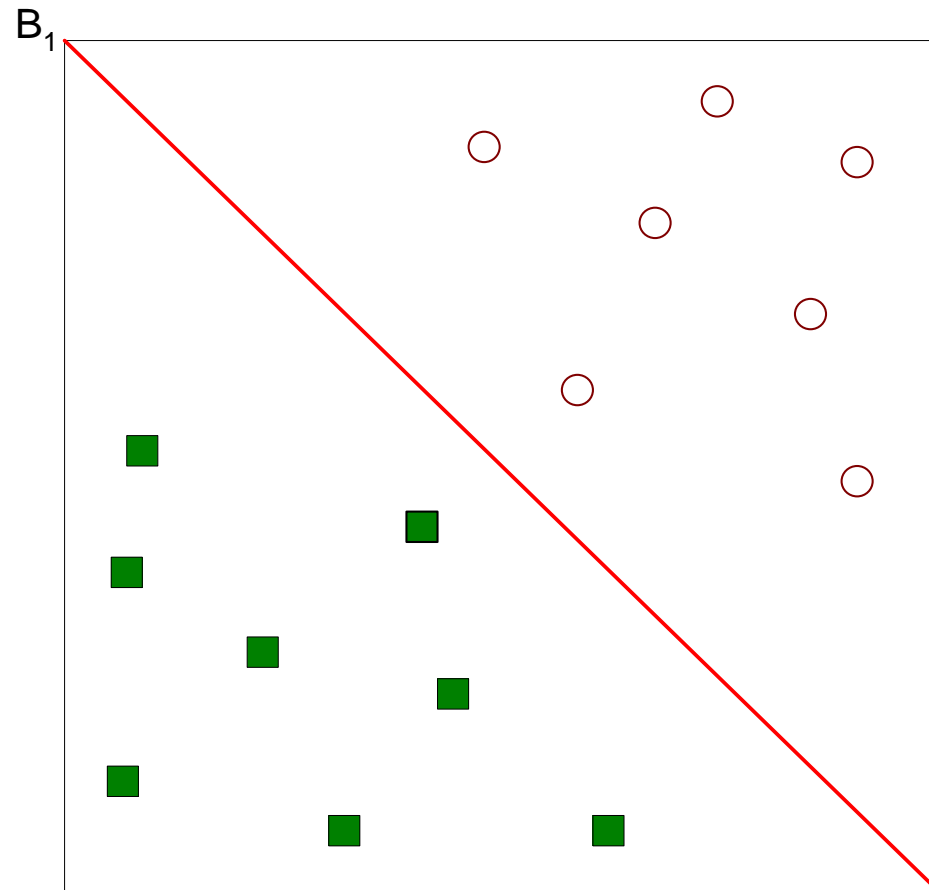
# Support Vector Machines



- Find a linear hyperplane (decision boundary) that will separate the data



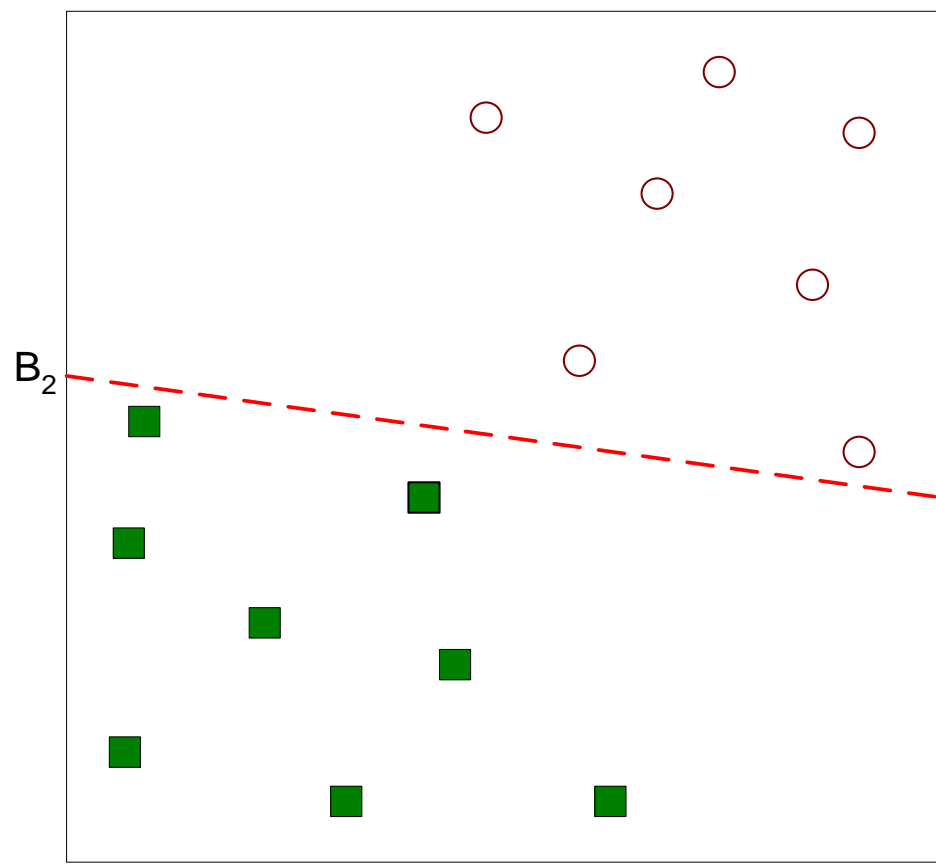
# Support Vector Machines



- One Possible Solution



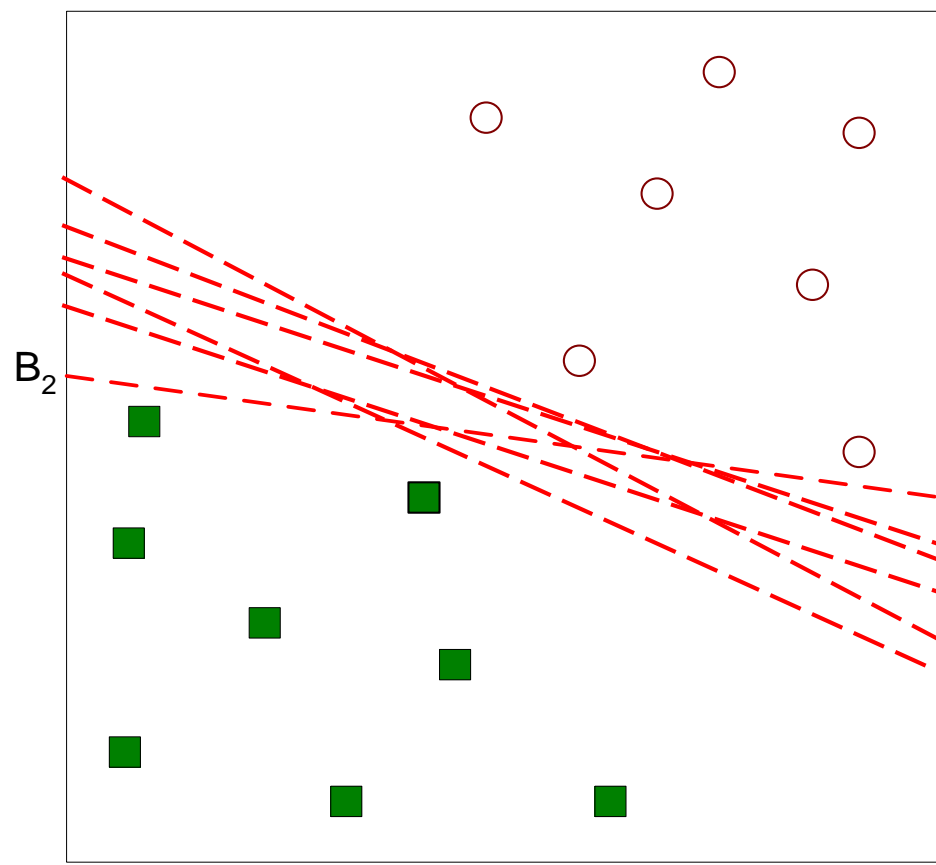
# Support Vector Machines



- Another possible solution



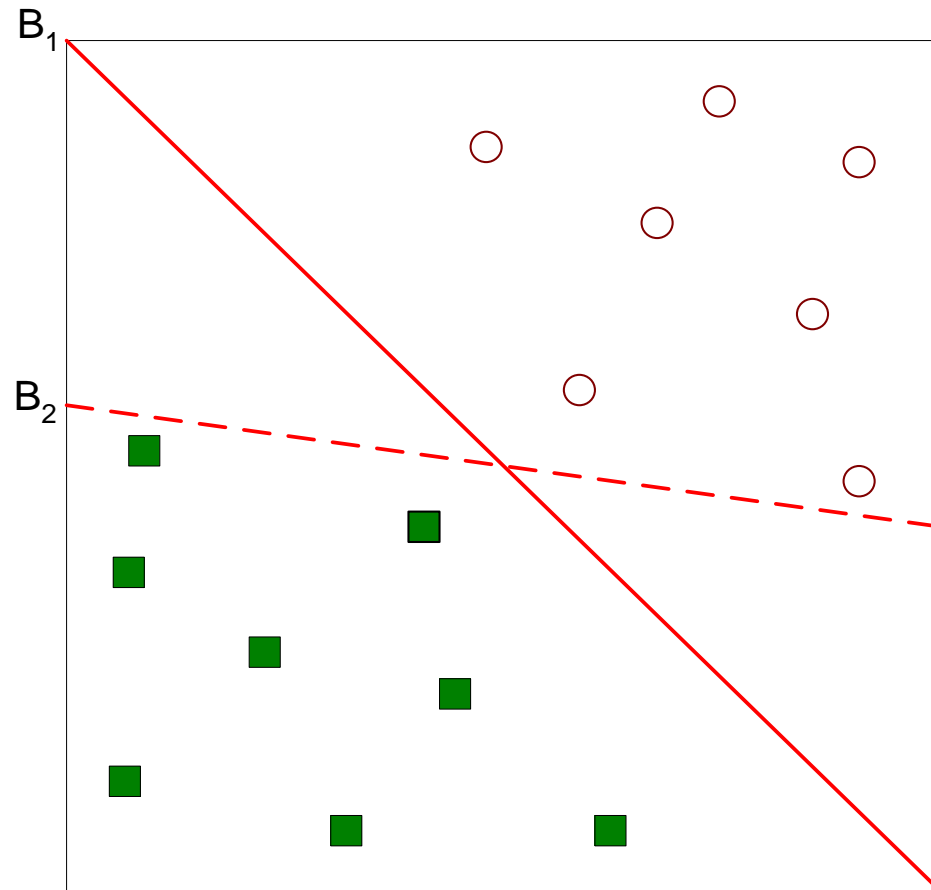
# Support Vector Machines



- Other possible solutions



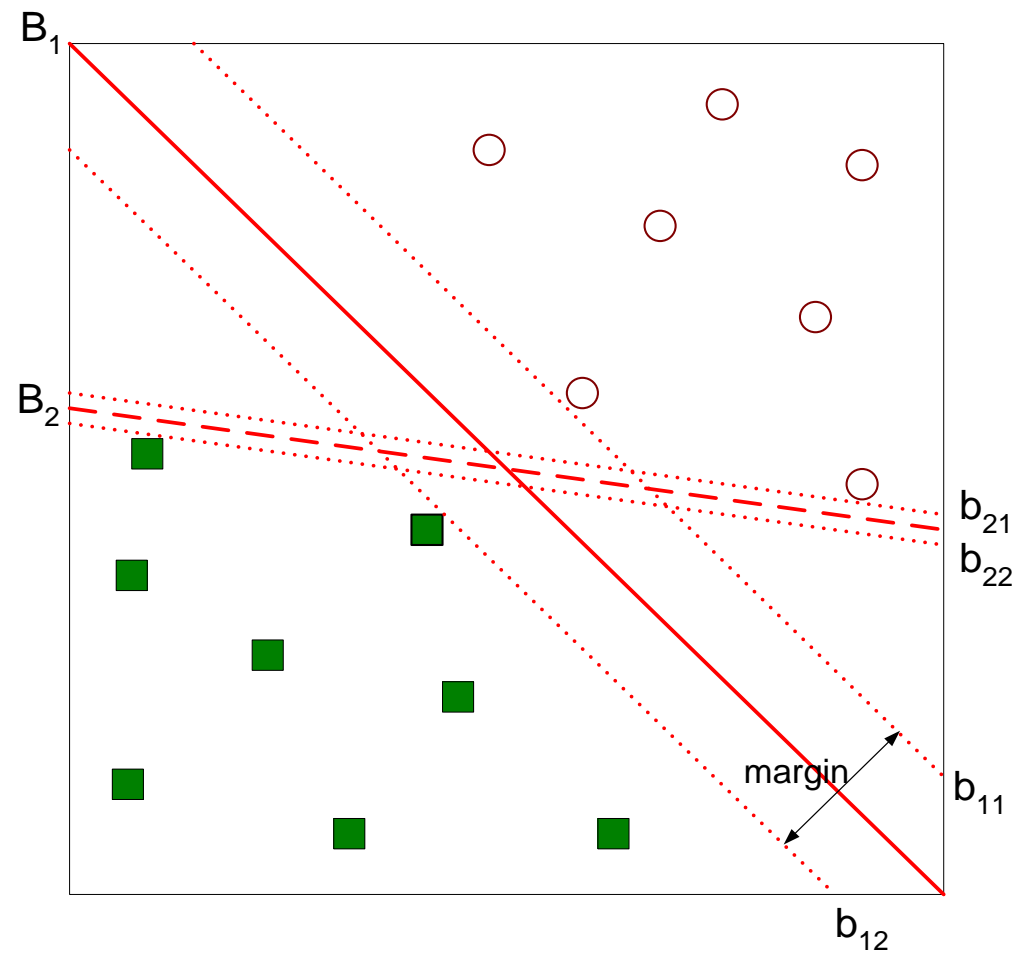
# Support Vector Machines



- Which one is better?  $B_1$  or  $B_2$ ?
- How do you define better?



# Support Vector Machines



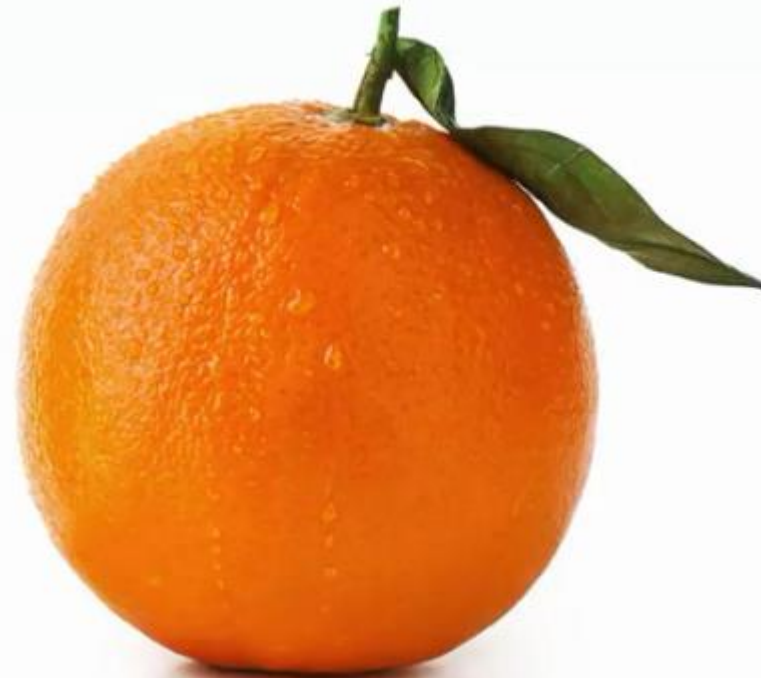
- Find hyperplane **maximizes** the margin  $\Rightarrow$   $B_1$  is better than  $B_2$



# What's So Special About SVMs?

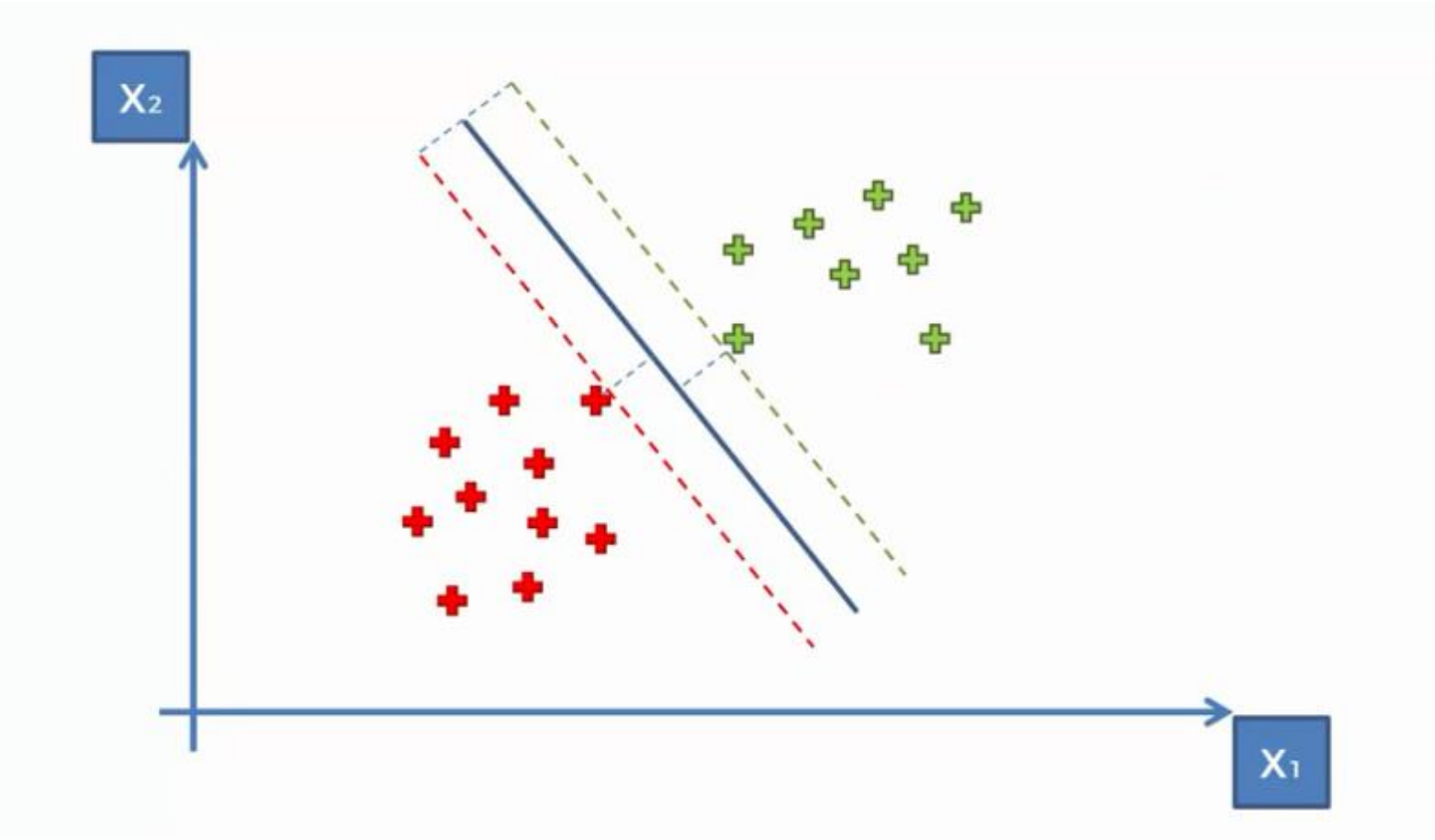


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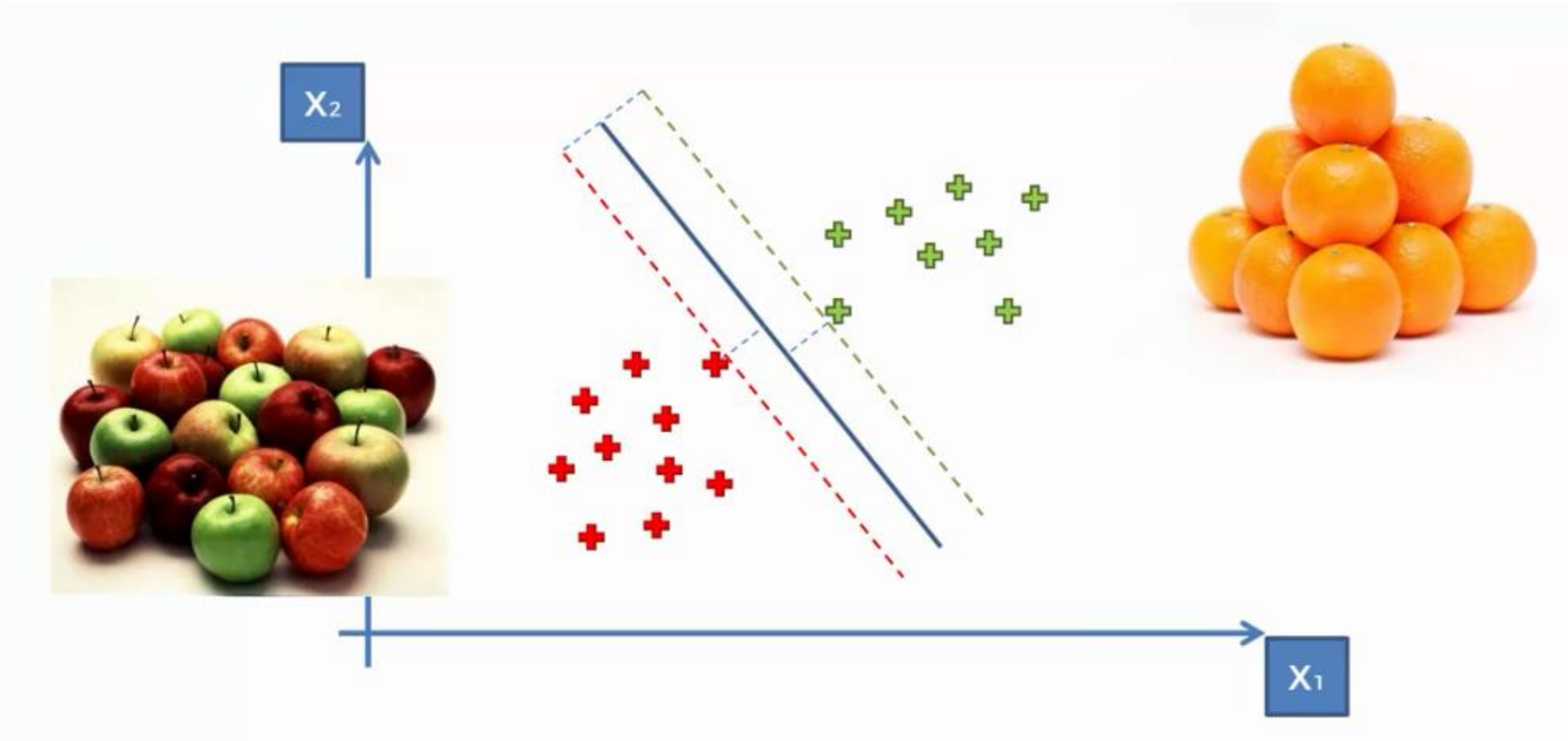


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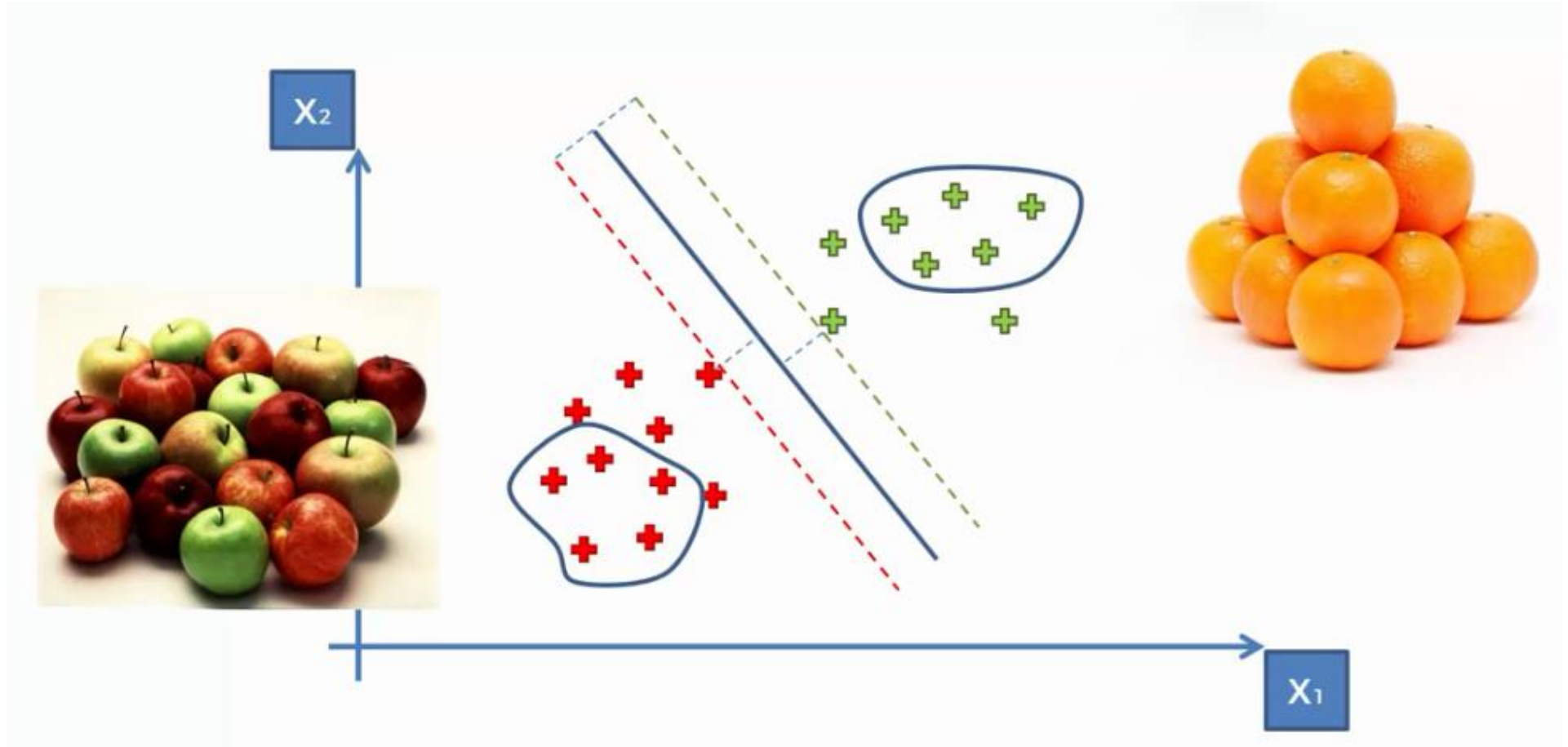


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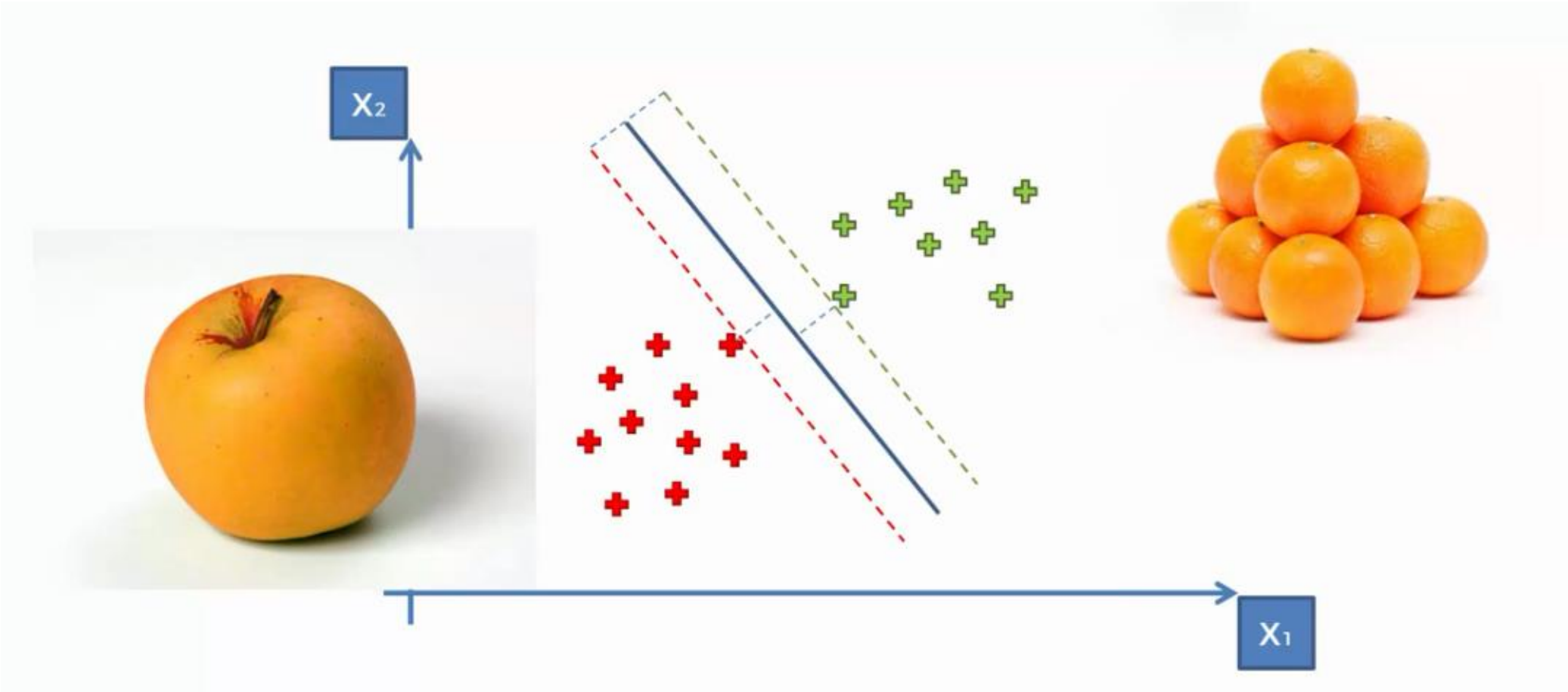


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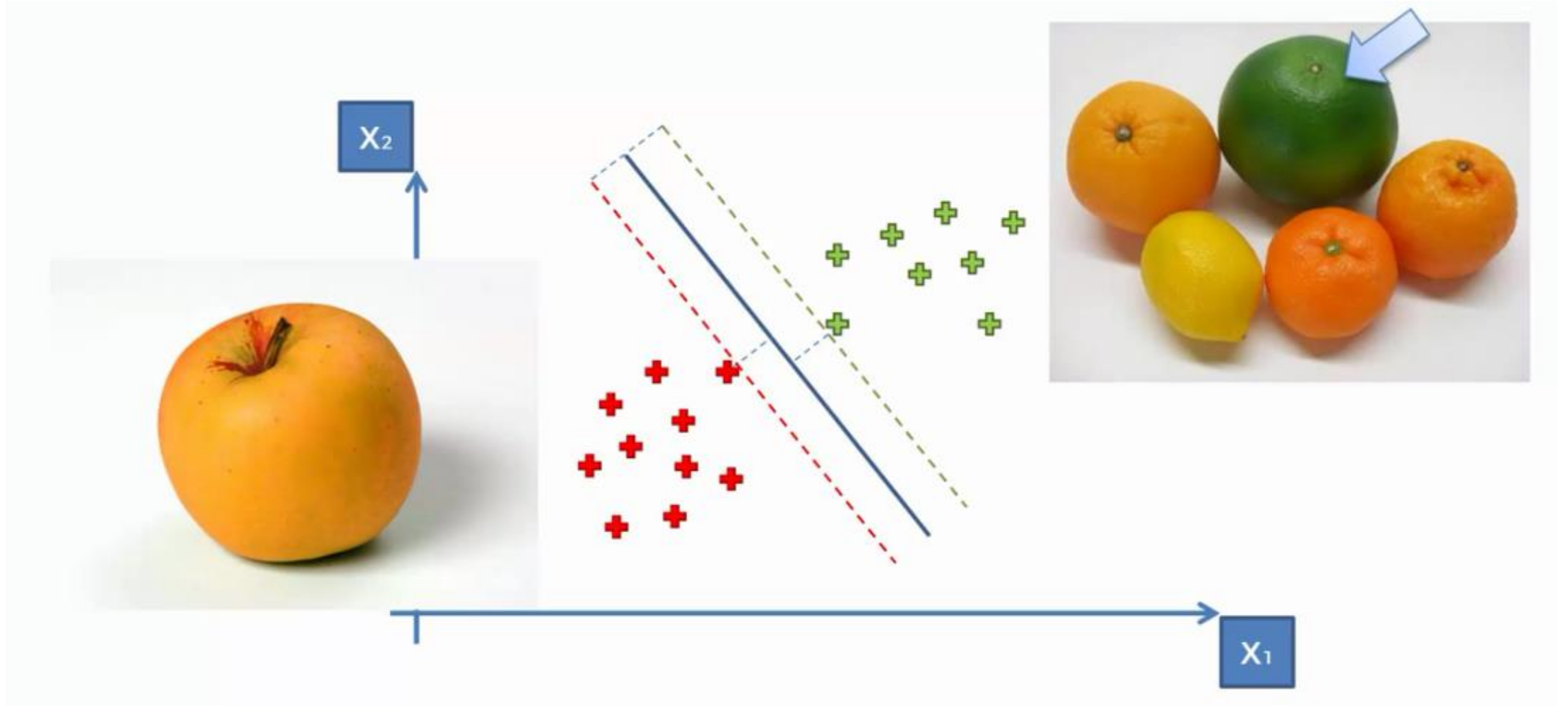


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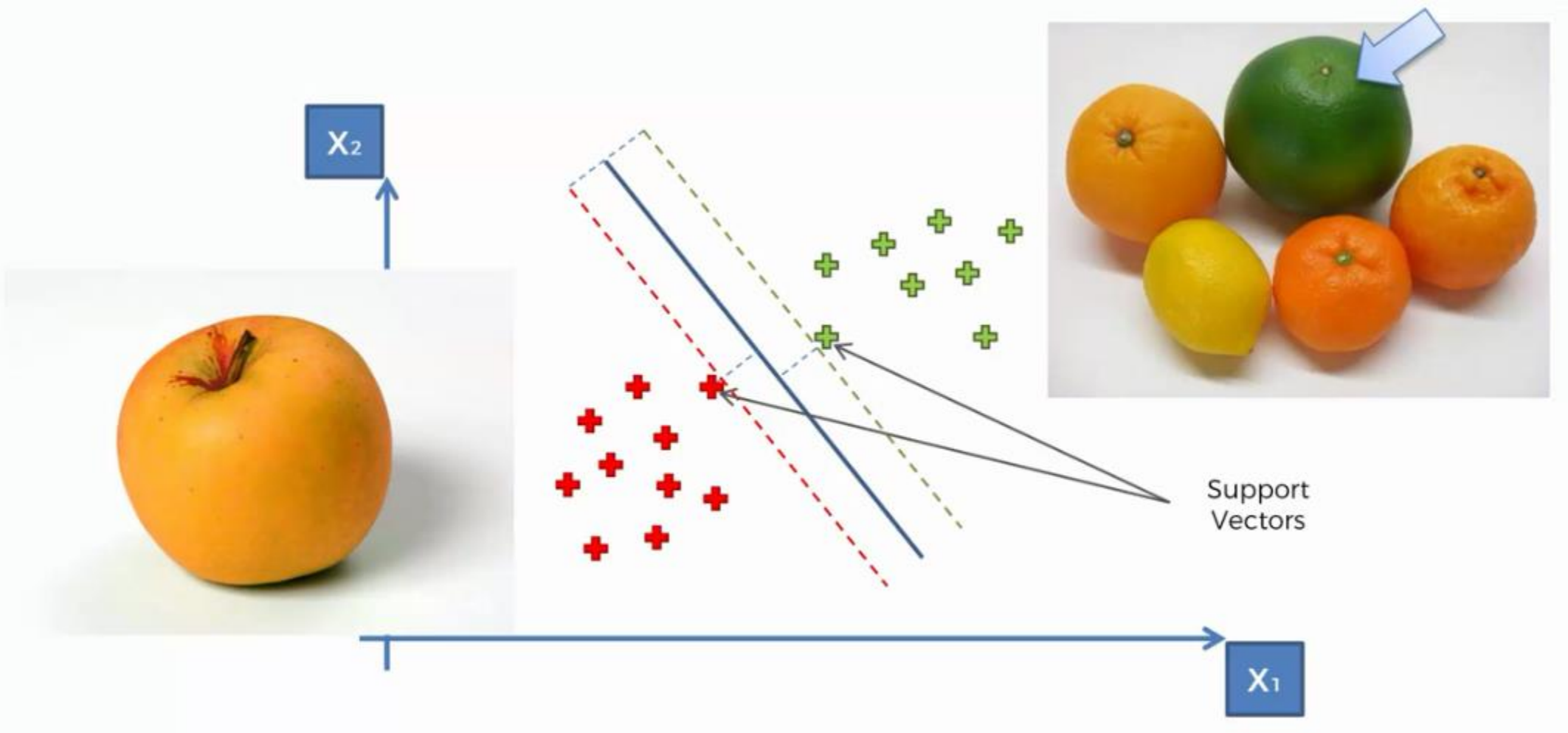


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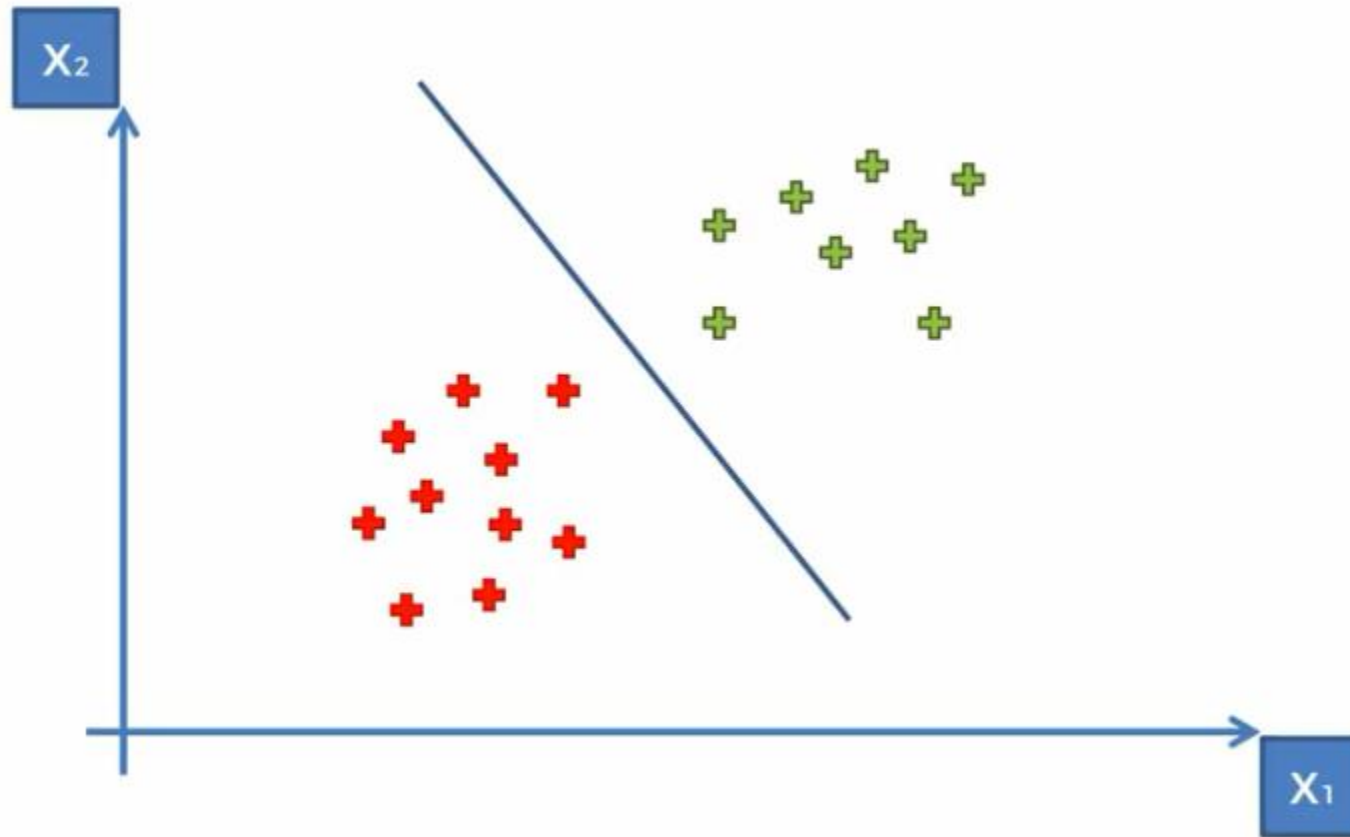


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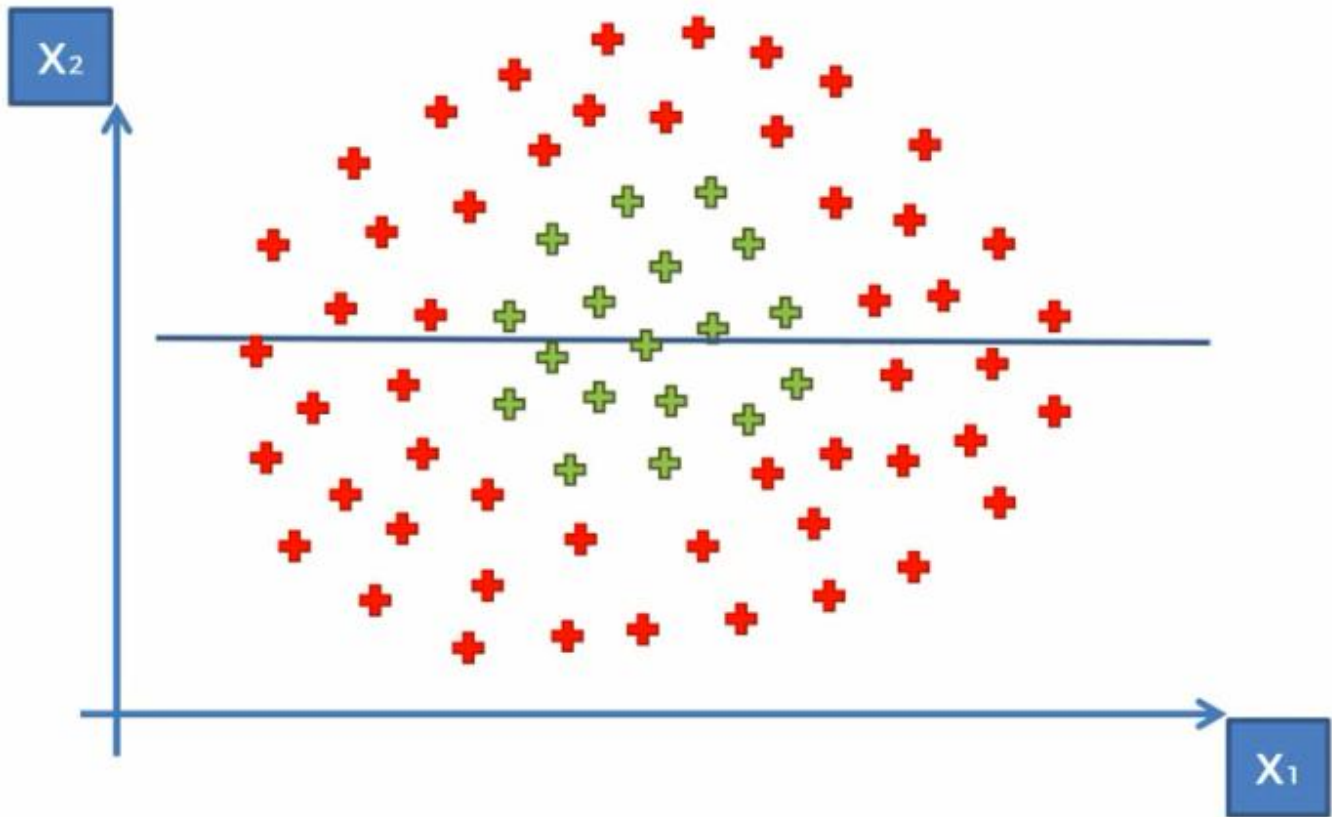


SVM separates these points





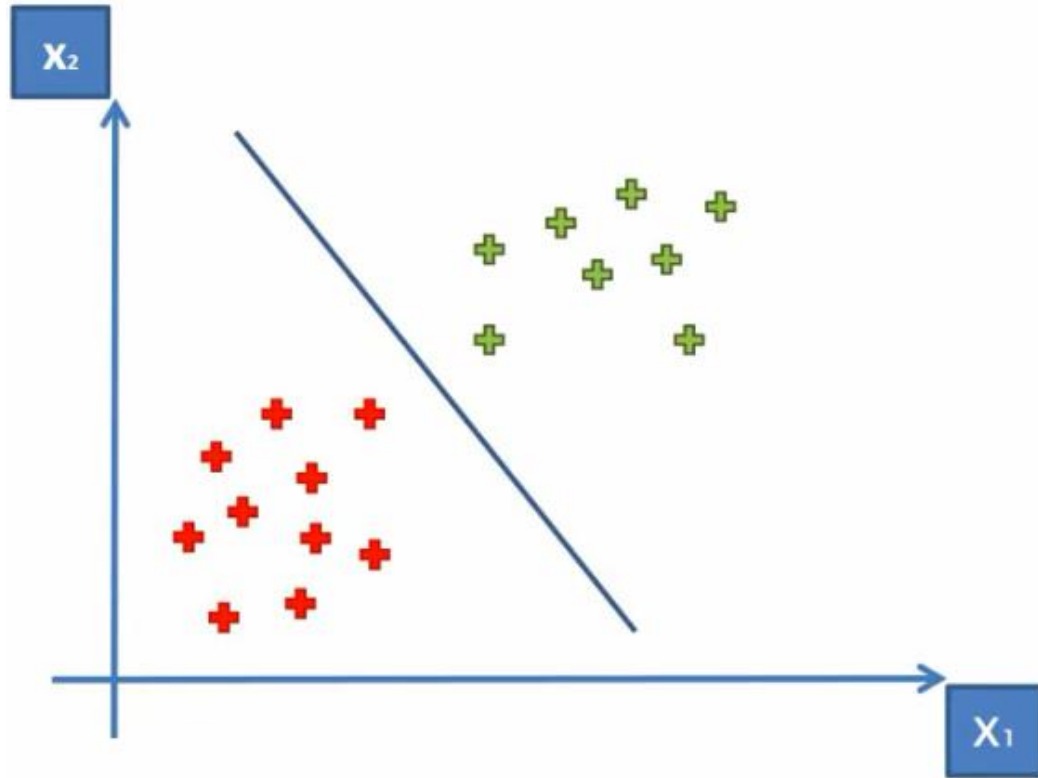
What about these points?



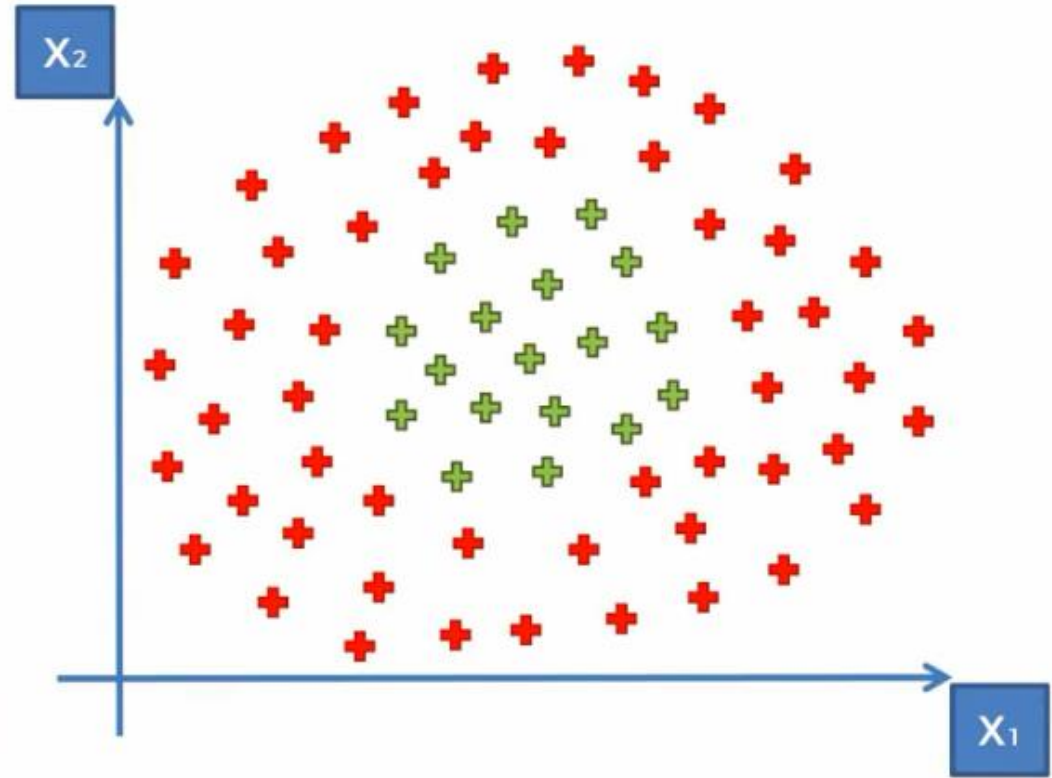


# Linearly Separability

Linearly Separable



Not Linearly Separable





# A Higher-Dimensional Space



# Mapping to a higher dimension





# Mapping to a higher dimension

$$f = x - 5$$





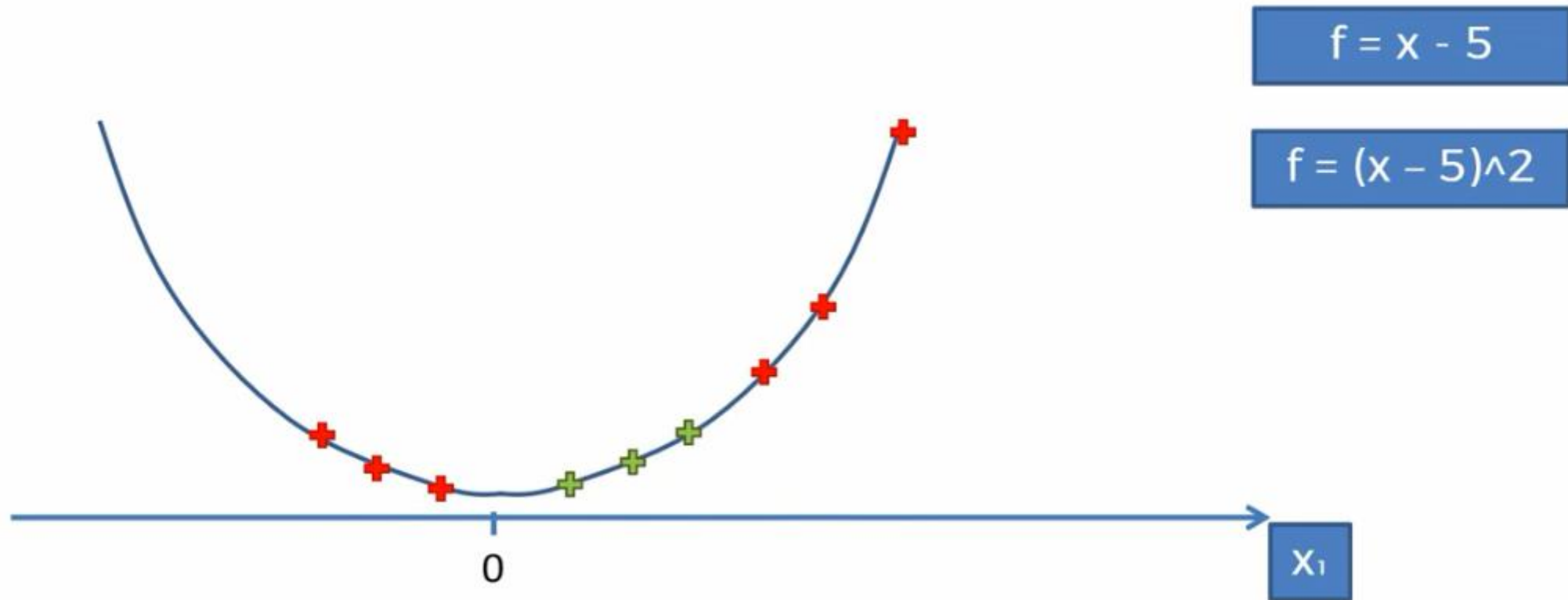
# Mapping to a higher dimension

$$f = x - 5$$



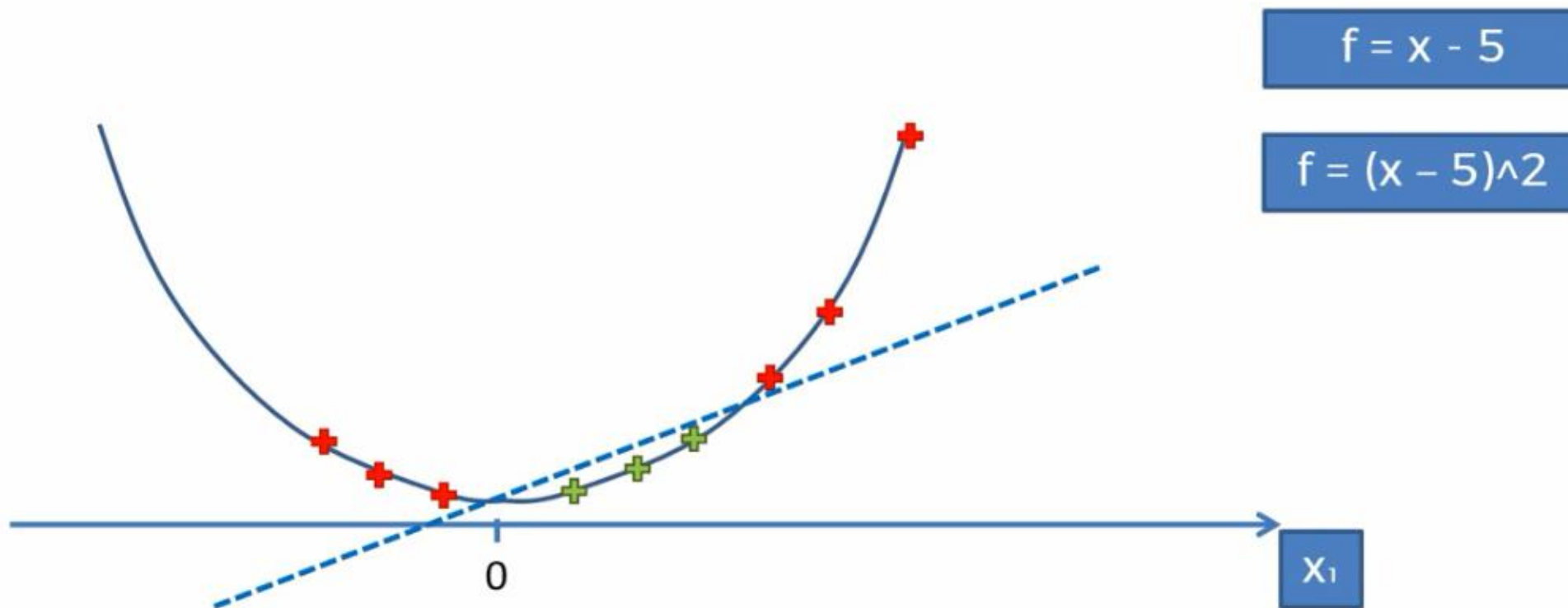


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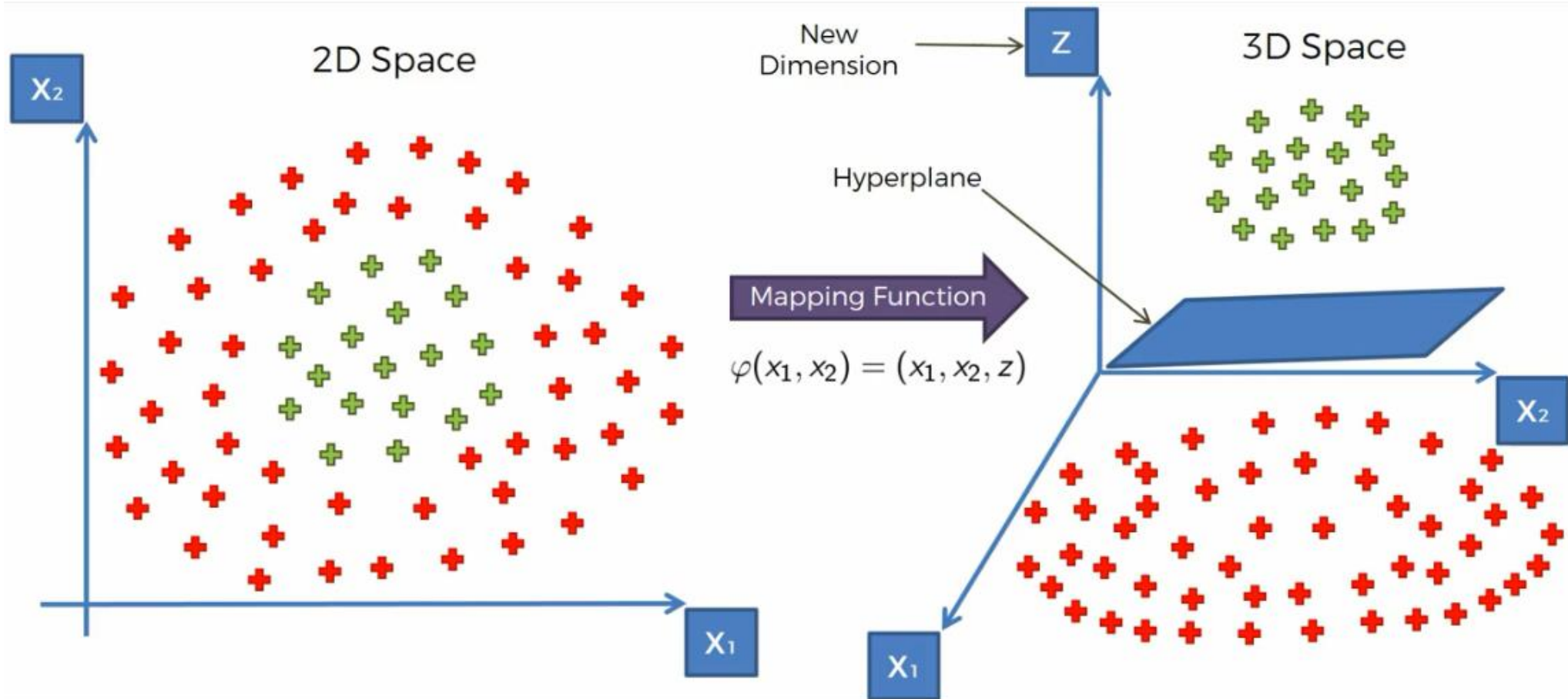


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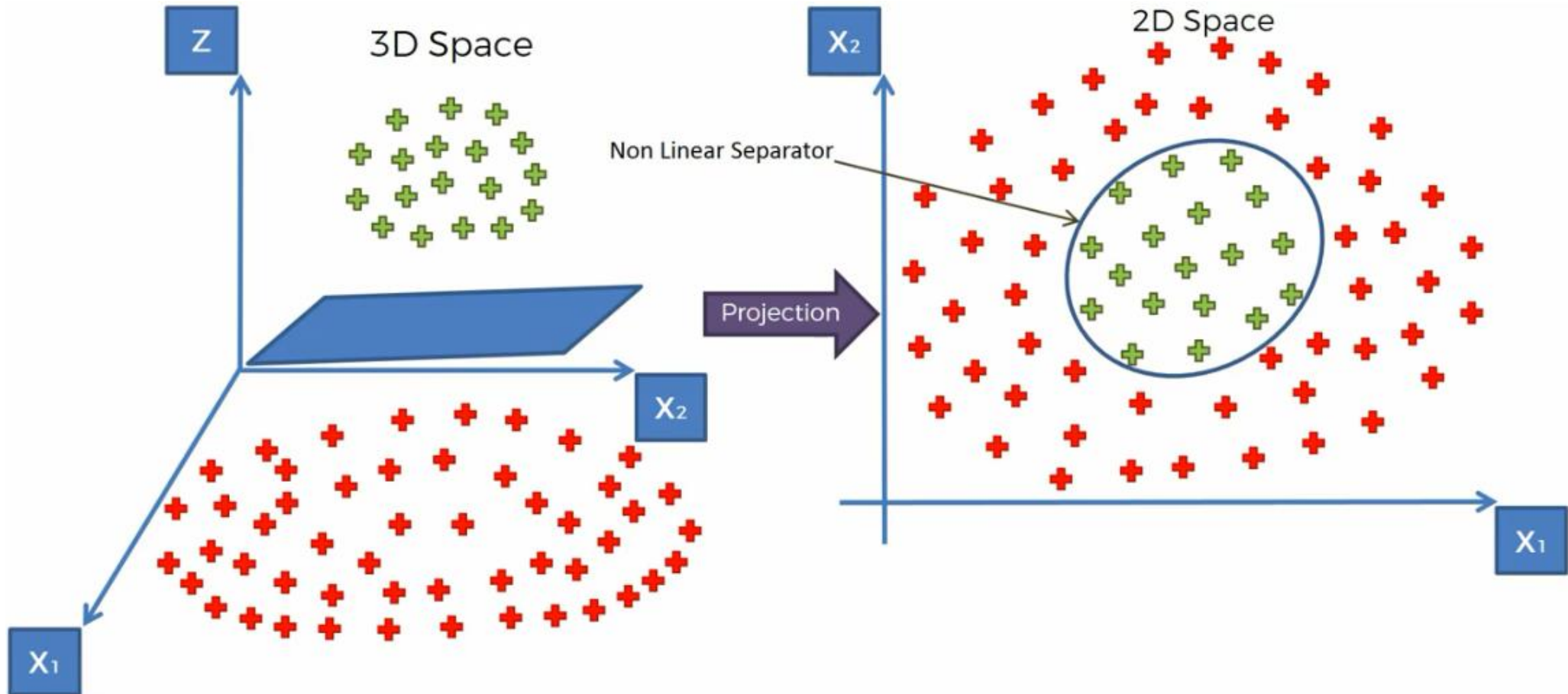


# Mapping to a higher dimension





# Projecting back to 2D space





# Drawback

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



# Characteristics of SVM

- Since the learning problem is formulated as a convex optimization problem, efficient algorithms are available to find the global minima of the objective function (many of the other methods use greedy approaches and find locally optimal solutions)
- Overfitting is addressed by maximizing the margin of the decision boundary, but the user still needs to provide the type of kernel function and cost function
- Difficult to handle missing values
- Robust to noise
- High computational complexity for building the model