

In partnership  
with



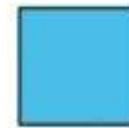
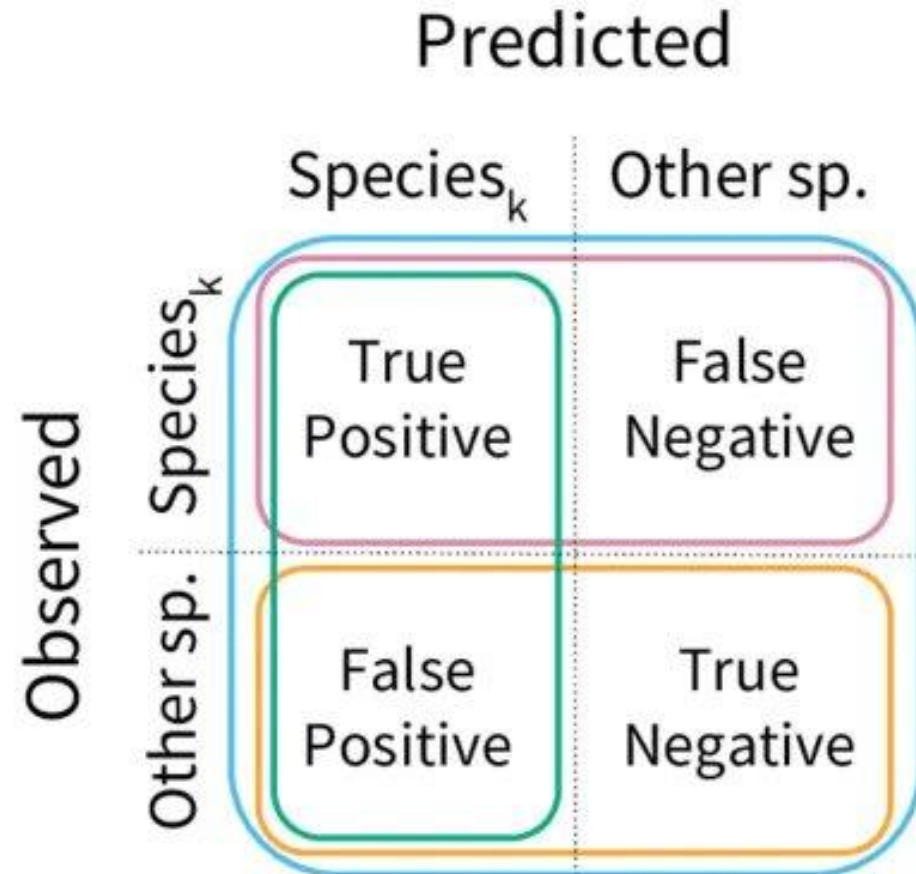
# Evaluation Metrics

# Evaluation Metrics

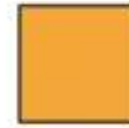
Evaluation metrics allow us to **quantify** how good or bad our model is, beyond just accuracy. They guide us in:

- Choosing between models
- Tuning models
- Understanding model behavior (e.g., bias, variance, imbalance)

# Evaluation Metrics



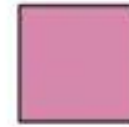
$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$



$$\text{Specificity} = \frac{TN}{TN + FP}$$



$$\text{Precision} = \frac{TP}{TP + FP}$$



$$\text{Recall} = \frac{TP}{TP + FN}$$

# COVID-19 detection

True Class			
		Positive	Negative
Predicated Class	Positive	TP	FP
	Negative	FN	TN

**True Positive (TP):** test says Positive, and reality Positive

**False Positive (FP):** test says Positive, and reality Negative

**False Negative (FN):** test says Negative, and reality Positive

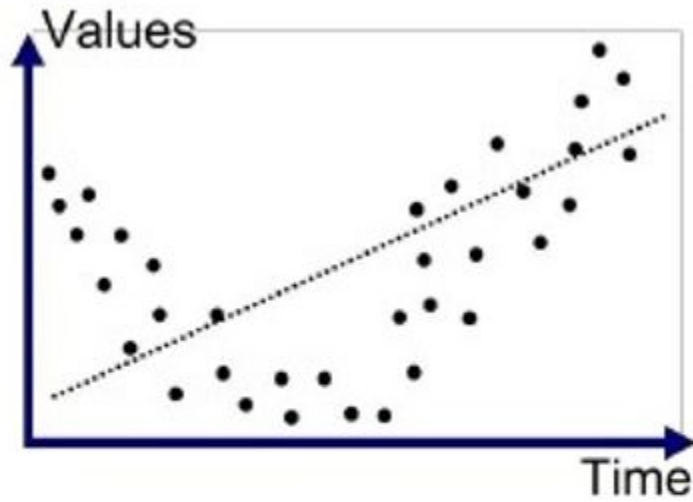
**True Negative (TN):** test says Negative, and reality Negative

# F1 Score

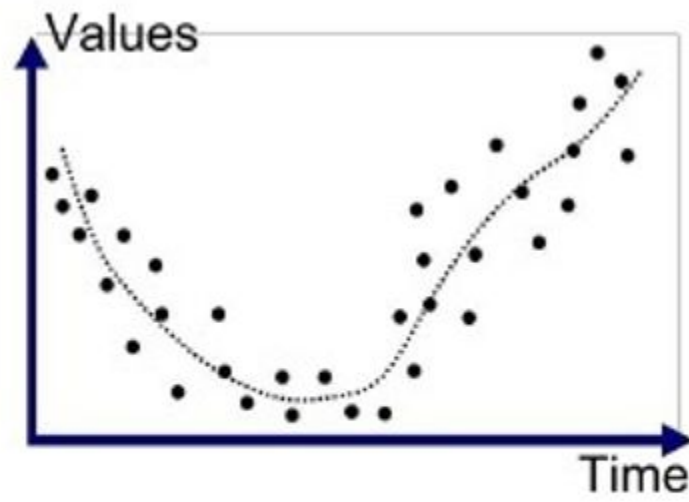
$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

- Harmonic mean of precision and recall
- Useful when you need balance between precision and recall

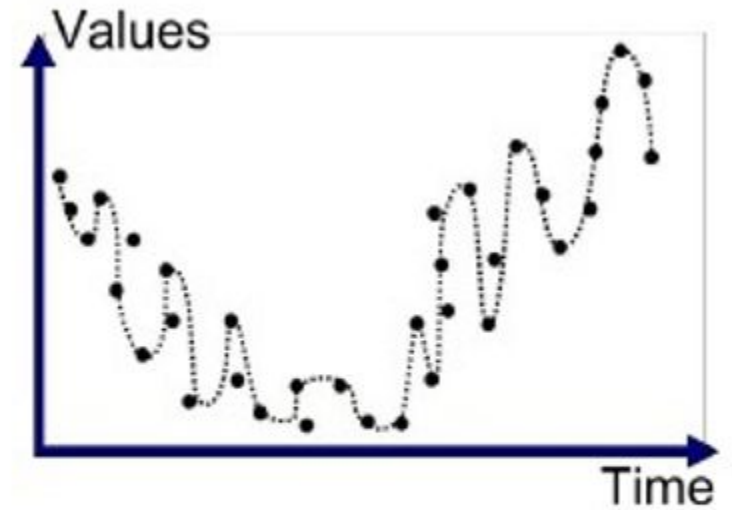
# Overfitting and Underfitting



Underfitted



Good Fit/Robust



Overfitted

# Overfitting

- **Memorizes training data.**
- **Performs well on training set.**
- **Performs poorly on test/validation set.**

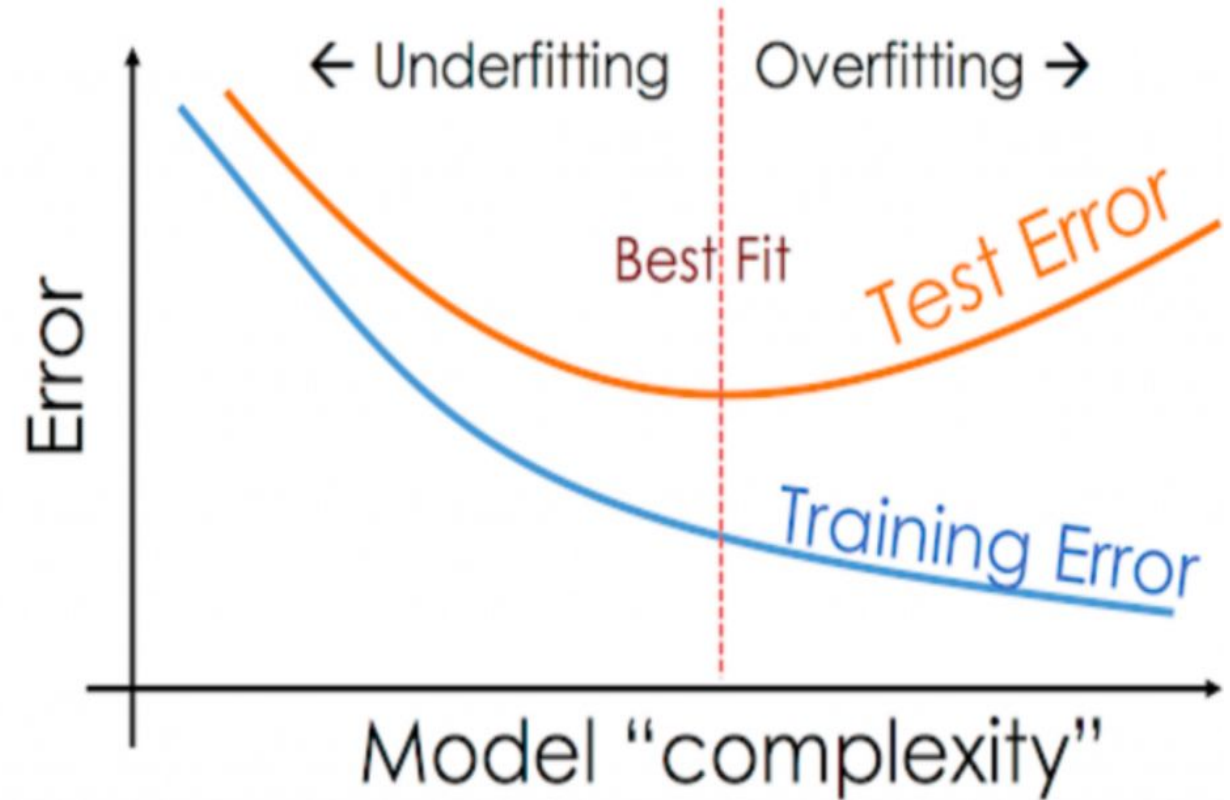
# Underfitting

- **High training error**
- **High validation/test error.**
- **Model too simplistic.**



# Handling Overfitting and Underfitting

- **Overfitting**
  - Increasing the model complexity
  - Reducing regularization
  - Adding features to training data
- **Underfitting**
  - Adding more data
  - Data augmentation
  - Regularization
  - Removing features from data



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# Classification

# Classification

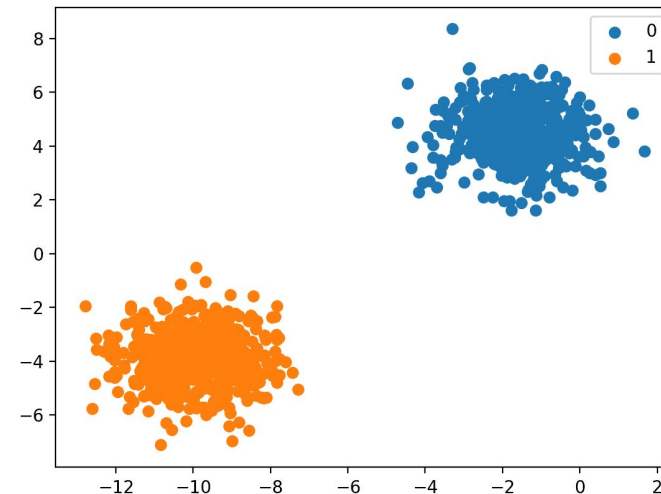
Classification is a fundamental task in supervised machine learning where the goal is to assign discrete labels to input instances based on their features by building a decision boundary that separates the data points into distinct classes based on the input features.

## Key Classification Techniques:

- Logistic regression
- K nearest neighbors
- Support vector classification (SVM)
- Naïve-Bayes

# Binary Classification

- Binary classification involves predicting between **two possible outcomes**.
- This is the simplest form of classification, with examples such as email **spam detection** (spam or not spam) or disease prediction (positive or negative).
- The model learns to **separate the data points into two distinct classes** based on their features.



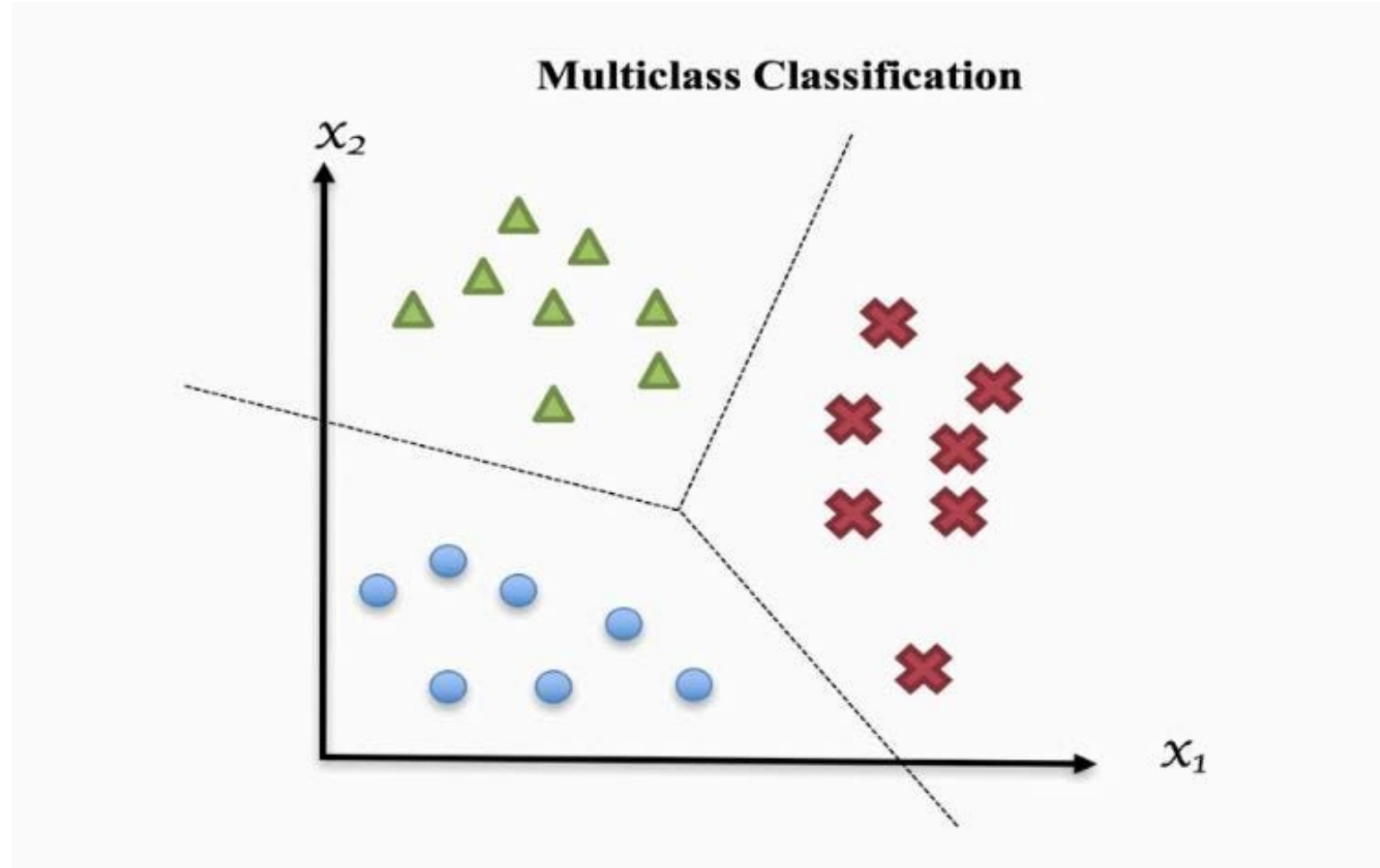
# Multi-Class Classification

Each instance (data point) belongs to exactly one class out of multiple possible classes.

Example:

- Classifying types of fruit: apple, banana, orange — each fruit is only one type.
- Handwritten digit recognition (0-9), each image is exactly one digit.
- Output: One class label per instance.

# Multi-Class Classification



# Multi-Label Classification

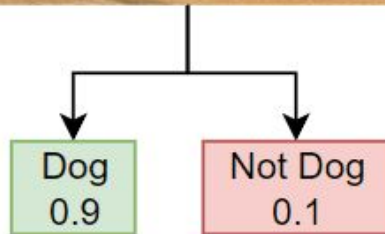
Each instance can belong to multiple classes simultaneously.

## Example:

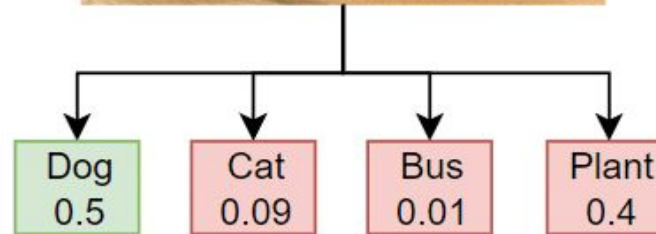
- Tagging a news article with multiple topics like politics, sports, and economy at the same time.
- Detecting objects in an image: an image can contain both a dog and a cat.

**Output:** A set (or vector) of labels per instance.

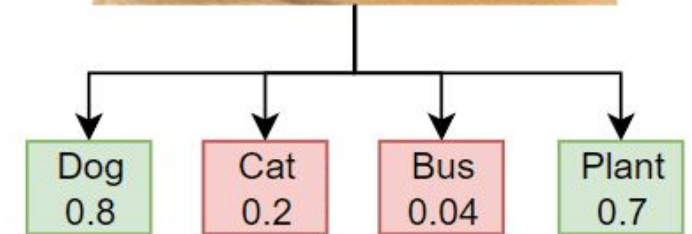
## Binary Classification



## Multiclass Classification



## Multilabel Classification





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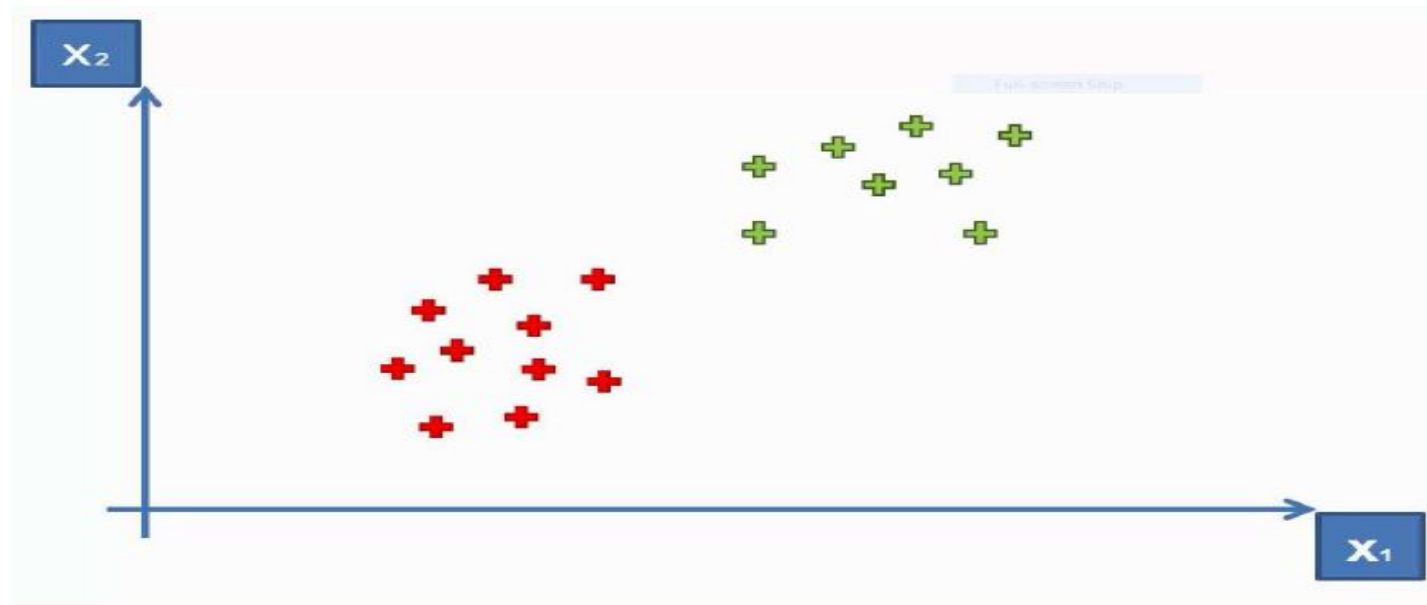


# Support Vector Machine

# SVM

Support Vector Machine (SVM) is a **supervised** machine learning algorithm used for **classification** and sometimes regression problems.

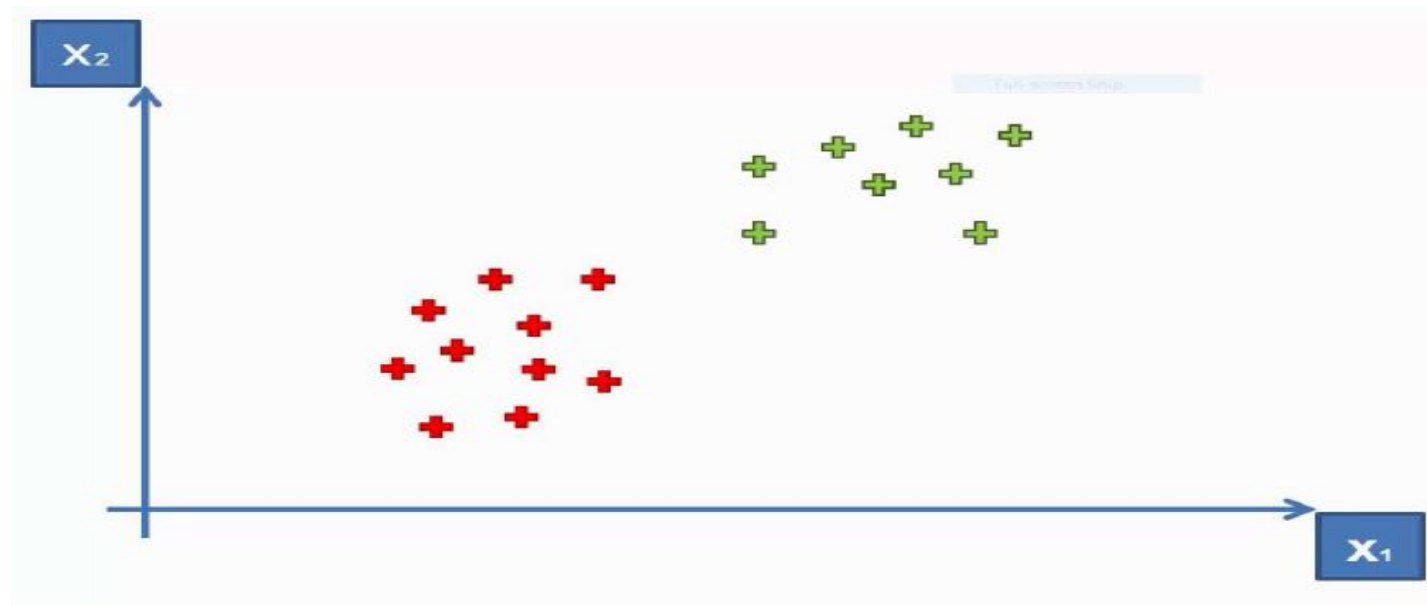
Its **main idea** is to find the best boundary (hyperplane) that separates different classes..



# SVM

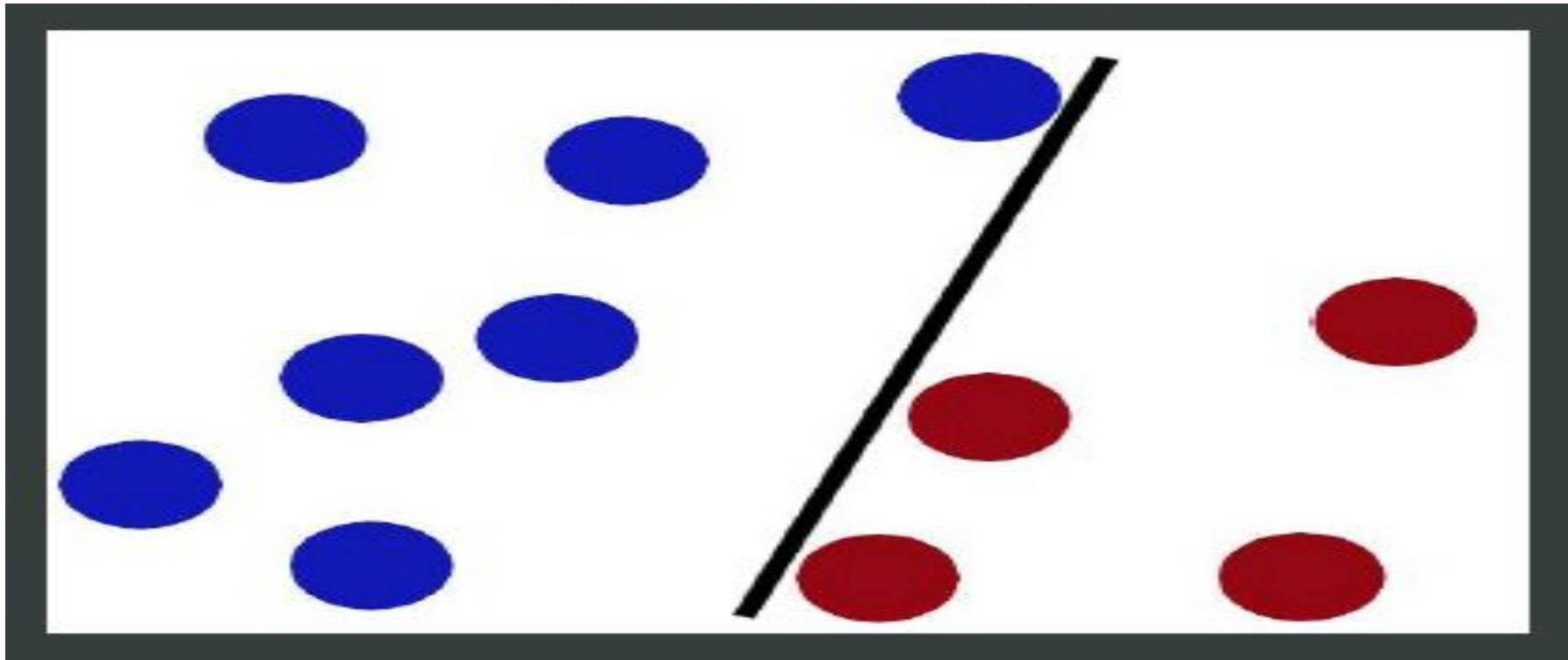
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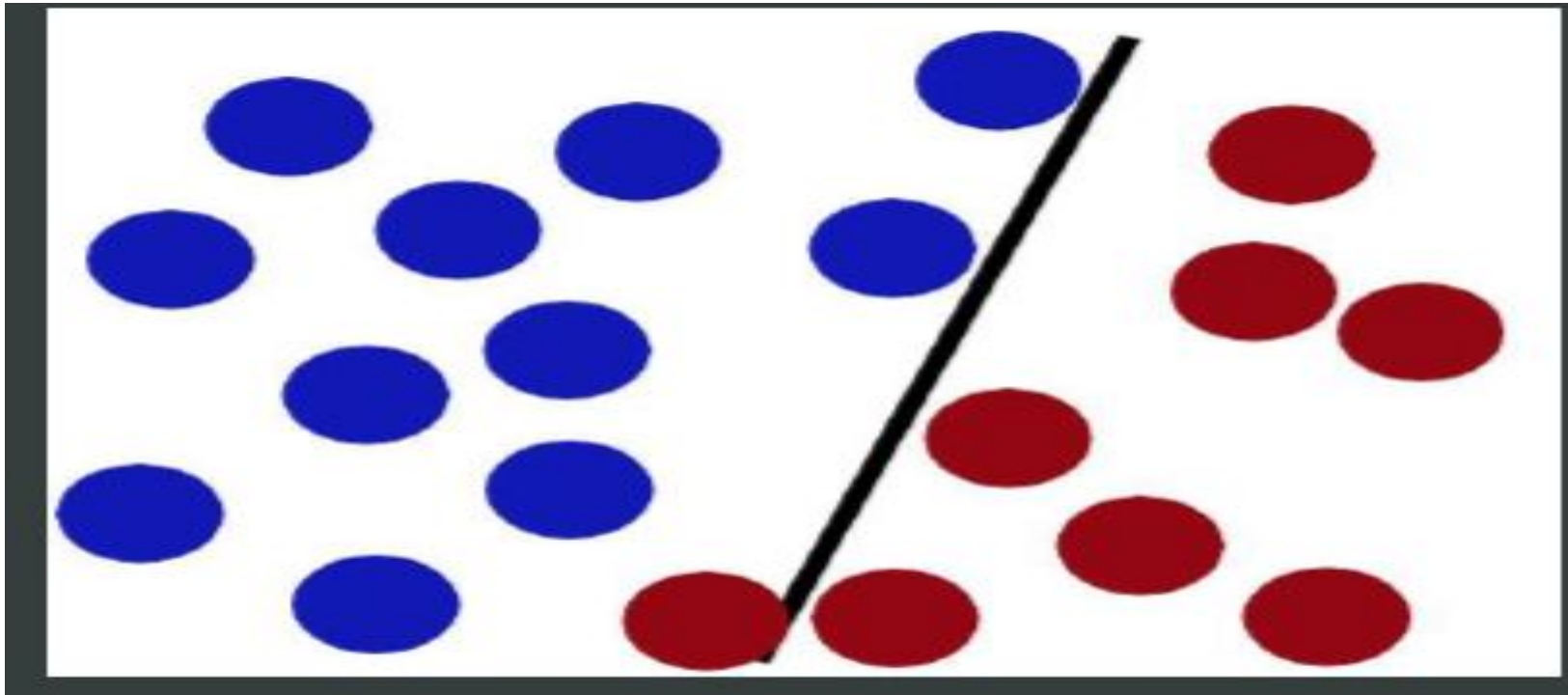
# Support Vector Machine (SVM) – Example 1

- We have **2 colors of balls** on the table that we want to separate, we get a stick and put it on table, pretty well right?



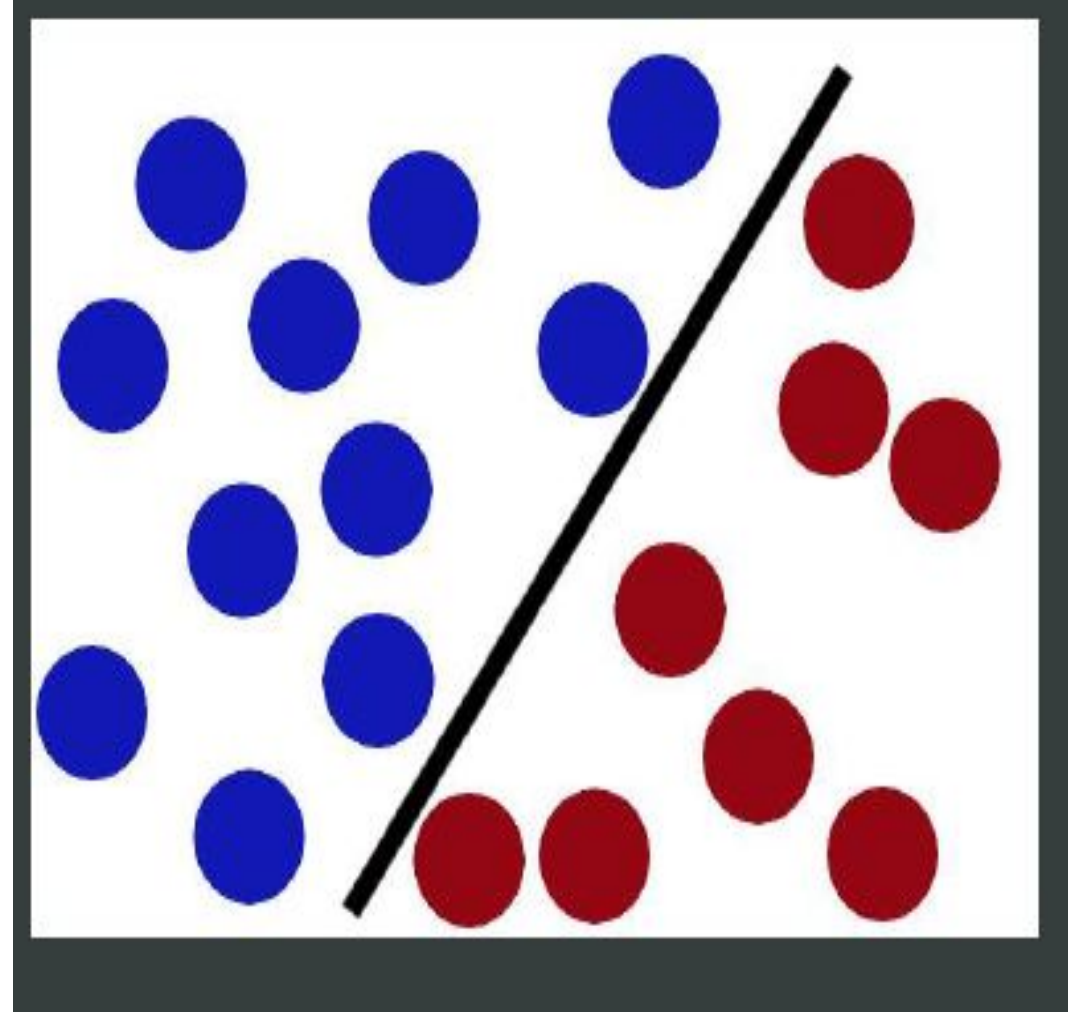
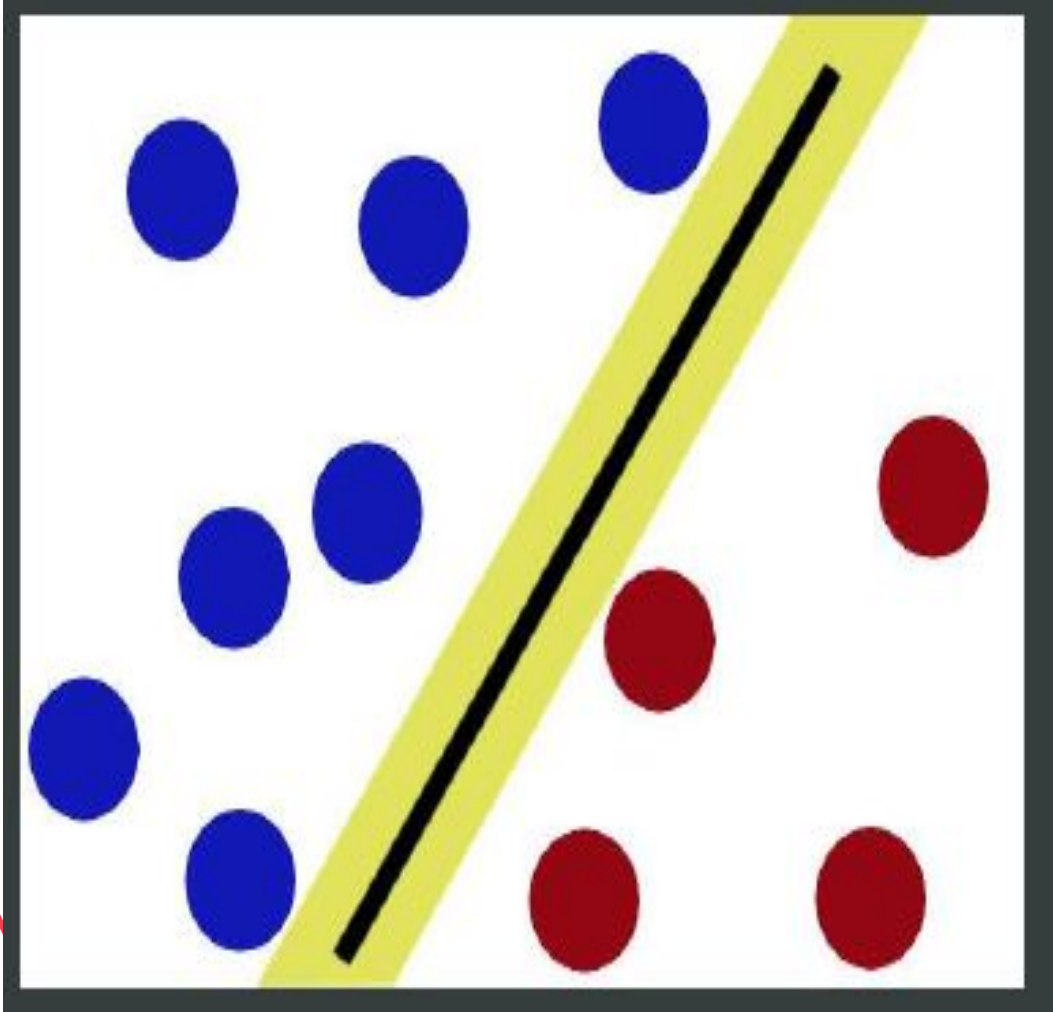
# Support Vector Machine (SVM) – Example 1

- Some **villain** comes and places more balls on the table, it kind of works but one of the balls is on the **wrong side** and there is probably a **better place to put the stick now**.



# Support Vector Machine (SVM) – Example 1

- SVMs try to put the stick in the best possible place by having as **big a gap** on either side of the stick as possible.
- **Solution - Next Slide**



# Support Vector Machine (SVM)

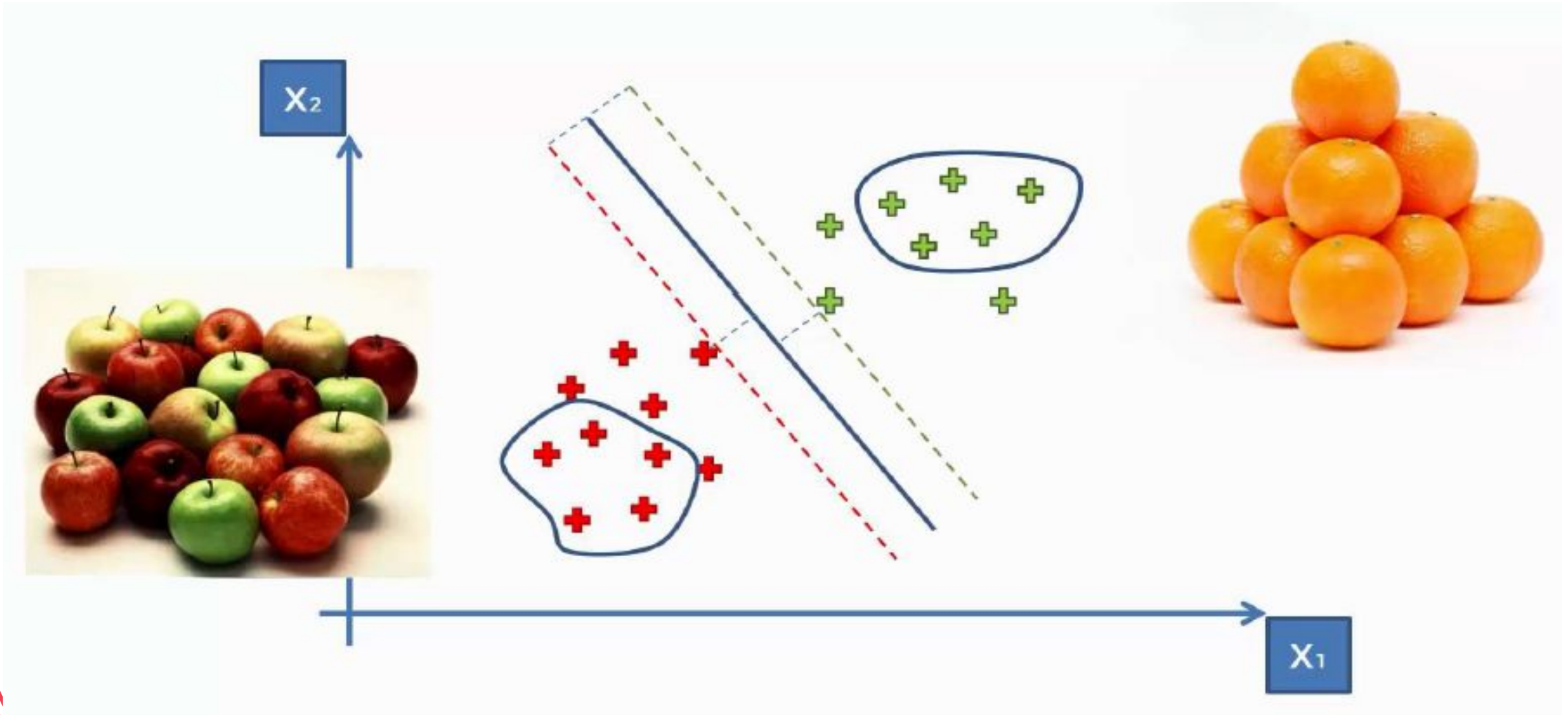
- **Hyperplane:** A decision boundary that separates classes.
- **Margin:** The distance between the hyperplane and the closest points from each class.
- **Support Vectors:** The data points that lie closest to the hyperplane — they “support” the decision boundary.



# Support Vector Machine (SVM) - Example



# Support Vector Machine (SVM) - Example



# Support Vector Machine (SVM) - Example

