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Subject- Application of machine learning in industries

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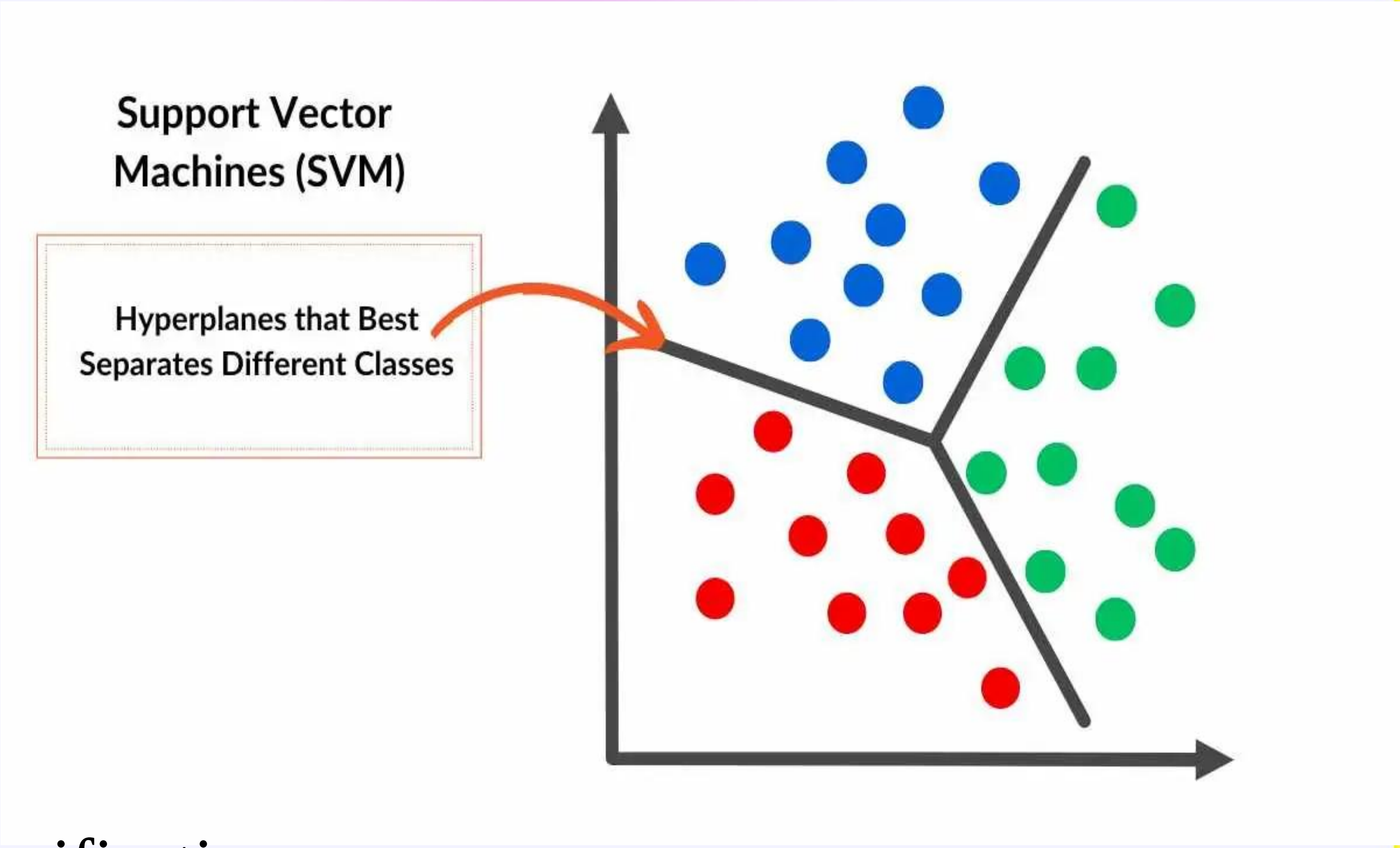
Support Vector Machine (SVM)

•Support Vector Machine (SVM) is a supervised machine learning algorithm used for classification and regression tasks.

•It finds the optimal decision boundary (hyperplane) to separate different classes in a dataset.

•SVM is widely used in image recognition, text classification, and bioinformatics.



Why Use SVM?

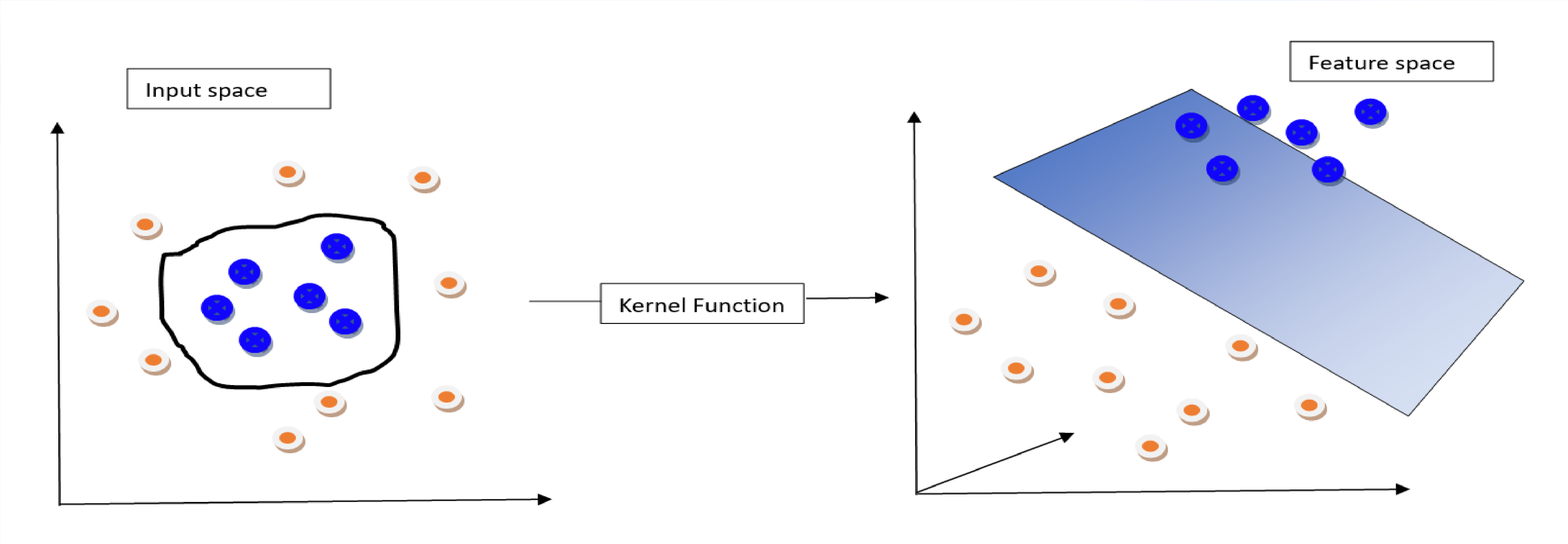
•Works well for both linear and non-linear classification.
•Effective when the number of features is greater than the number of samples.
•Robust against overfitting, especially in high-dimensional spaces.
•Can handle outliers better than other classifiers.

How SVM Works?

•SVM tries to find the best hyperplane that maximizes the margin between two classes.

•The points closest to the hyperplane are called Support Vectors.

•The larger the margin, the better the generalization of the classifier.



TYPES OF KERNELS IN SVM

The various types of Kernels in SVM are:

1. Linear Kernel: The linear kernel computes the inner product of input vectors, used for linearly separable data. It’s efficient and straightforward, ideal when a linear decision boundary can separate the classes.
2. Polynomial Kernel: The polynomial kernel maps data into higher dimensions using polynomial functions, capturing more complex relationships. It’s effective for moderately non-linear data and offers flexibility in decision boundaries based on the polynomial degree.
3. Radial Basis Function (RBF) Kernel: The RBF kernel uses distance between points to map data into a higher-dimensional space, allowing for highly flexible decision boundaries. It’s ideal for non-linear, complex datasets, commonly used in classification tasks.
4. Sigmoid Kernel: The sigmoid kernel uses the hyperbolic tangent function, similar to neural network activation functions. It’s less commonly used but works well in binary classification problems where decision boundaries resemble a sigmoid curve.

Question:

You are given the following equation related to the dimensionality of an SVM kernel:

$$f(x) = p + \sqrt{roll} + E0$$

where:

$p = 1/\sqrt{2}$,

$roll = 129$

$E0 = 0.6$

a) Compute the value of f(x).

b) Using f(x) , derive the general form of SVM kernel equations for different types of kernels (Linear,
Polynomial, RBF and Sigmoid) in terms of λ. Provide the final kernel equations incorporating D
and explain how λ is related to it.

Solution:

SVM kernal equation

Let kernal function be

$$f(x) = P + \sqrt{\text{Roll No.(last 3 digit)}} + \epsilon_0$$

where

$$P = \frac{1}{\sqrt{2}} \approx 0.7071$$

$$\text{Roll No.} = 129$$

$$\epsilon_0 = 0.6$$

$$\therefore f(x) = \frac{1}{\sqrt{2}} + \sqrt{129} + 0.6$$

$$= 0.7071 + 11.357 + 0.6$$

$$= 12.664$$

Taking celling values of $12.664 = \lceil 12.664 \rceil$

$$= 13$$

for Limear kenmal:-

$$K(x_i, x_j) = f(x).x_i \times x_j$$

$$= 13(x_i \cdot x_j)$$

for polymomial kenmal:-

$$K(x_i, x_j) = (x_i \cdot x_j + c)^d$$

usimg $f(x)$ to scale:

$$K(x_i, x_j) = (x_i \cdot x_j + f(x))^d$$

$$= (x_i \cdot x_j + 13)^d$$

Radial Basis function (RBF) kernal :-

$$k(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2)$$

$$\left(\gamma = \frac{1}{f(x)} = \frac{1}{12.664} \approx 0.0789 \right.$$

$$\therefore k(x_i, x_j) = \exp\left(-0.078 \| x_i - x_j \|^2\right)$$

Sigmoid kernal :-

$$k(x_i, x_j) = \tanh(\alpha(x_i \cdot x_j) + c)$$

using $f(x)$ to scale c :

$$k(x_i, x_j) = \tanh(\alpha(x_i \cdot x_j) + 13)$$

CONCLUSION

Support Vector Machine (SVM) is a powerful supervised learning algorithm used for classification, regression, and anomaly detection. It is highly effective in handling high-dimensional data and complex decision boundaries using the kernel trick.

• It finds the optimal hyperplane to maximize the margin between classes.

• Kernels enable SVM to handle non-linear data by transforming it into higher-dimensional spaces.

• Popular kernels include Linear, Polynomial, RBF, and Sigmoid.