# Lab3\_SupportVectorMachine\_Report

#### 1. What's the difference between the different SVM kernels?

An SVM maps inputs into a (possibly higher-dimensional) feature space and finds a hyperplane that best separates classes (maximizes margin). The **kernel** function defines how input points are compared (i.e., the inner product in some feature space). Different kernels correspond to different feature mappings and therefore different shapes of decision boundary.

#### **Linear Kernel**

Decision Boundary Shape: Straight line / hyperplane

Hyperparameters: C

Good For: Linearly separable or high-dimensional sparse data (e.g. text)

Output score (decision\_function): Signed distance to the hyperplane

## **Polynomial Kernel**

Decision Boundary Shape: Polynomial curve (2nd, 3rd... degree)

Hyperparameters: degree, coef0, gamma, C

Good For: Data with feature interactions or curved relationships

Output score (decision\_function): Distance to polynomial decision surface

#### **RBF Kernel**

Decision Boundary Shape: Highly flexible, smooth nonlinear boundary

Hyperparameters: gamma, C

Good For: General-purpose nonlinear problems where the structure is unknown

Output score (decision\_function): Distance to nonlinear boundary in infinite-dimensional space

### 2. When would you use each one, and how do their outputs differ?

#### Linear kernel (kernel='linear')

- When the classes are separable or approximately separable by a linear boundary.
- Also ideal when you have very high dimensional features, even if data is noisy.
- Very fast for large datasets (use LinearSVC if you have a lot of samples).

## Polynomial kernel (kernel='poly', degree=d)

- When you suspect polynomial relationships or interactions among features (e.g., quadratic or cubic effects).
- Small- to medium-sized problems (higher degree increases complexity).
- Degree 2 or 3 is common (higher → risk of overfitting).

### Radial Basis Function (RBF) kernel (kernel='rbf') — most commonly used

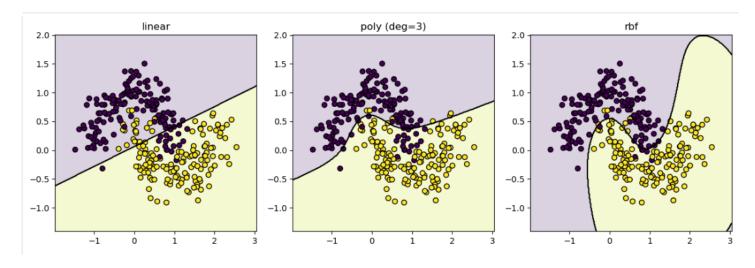
- Good default when you don't know the right kernel it's a general-purpose nonlinear kernel.
- It can model very complex nonlinear structure.
- Usually gives the best performance after proper tuning (C and gamma).
- Good for most small/medium tabular datasets.

As per the output, Higer ROC-AUC (better separation) between the classes in the decision\_function output.

The RBF model produces decision scores almost positives get higher scores than negatives, it is the highest among the three.

Polynomial kernel has the lowest ROC-AUC, some negatives are assigned high scores and some positives low scores (lower ranking ability).

Liner is in the middle, it separates reasonably well, but not as cleanly as RBF.



### Linear SVM classification report

Linear SVM classification report Consufion Matrix: [[8299, 242], [16, 121]] Classification Report precision recall f1-score support 0 1.00 0.97 0.98 8541 1 0.33 0.88 0.48 137 accuracy 0.97 8678 macro avg 0.67 0.93 0.73 8678 8678 weighted avg 0.99 0.97 0.98

Roc AUC Score: 0.9515356156692024

## Poly SVM classification report

Poly SVM classification report Consufion Matrix: [[8485, 56], [28, 109]] Classification Report precision recall f1-score support 0 1.00 0.99 1.00 8541 0.66 0.80 0.72 137 0.99 8678 accuracy 0.83 0.89 macro avg 0.86 8678 weighted avg 0.99 0.99 0.99 8678

Roc AUC Score: 0.9211933507503949

### RBF SVM classification report

RBF SVM classification report Consufion Matrix: [[8450, 91], [31, 106]] Classification Report precision recall f1-score 0.99 0.99 8541 0 1.00 1 0.54 0.77 0.63 137 0.99 8678 accuracy 0.88 macro avg 0.77 0.81 8678 0.99 weighted avg 0.99 8678 0.99

Roc AUC Score: 0.972283113568985