

# **Institute of Technology of Cambodia**

**Seminar**

**Lecturer: Chann Sophal**

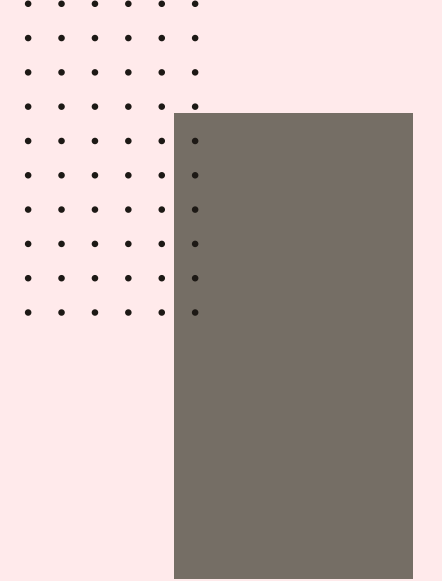
**Room 4**

**Tuning Kernel Parameters**

## **Members Name:**

<b>1. OUN VIKRETH</b>	<b>e20200485</b>
<b>2. KEO VONMONYROTH</b>	<b>e20200759</b>
<b>3. PHUN SREYPICH</b>	<b>e20200179</b>
<b>4. SENG VATHANAK</b>	<b>e20200463</b>
<b>5. NOR PHANIT</b>	<b>e20200241</b>
<b>6. HUN SOKRARITH</b>	<b>e20201218</b>
<b>7. HONG KIMLENG</b>	<b>e20200766</b>

# Table Of Contents



01

Exploring the parameters associated with different kernel functions

02

Understanding the effects of kernel parameters on SVM model complexity and generalization

03

Techniques for selecting appropriate kernel parameters (e.g., grid search, cross-validation)

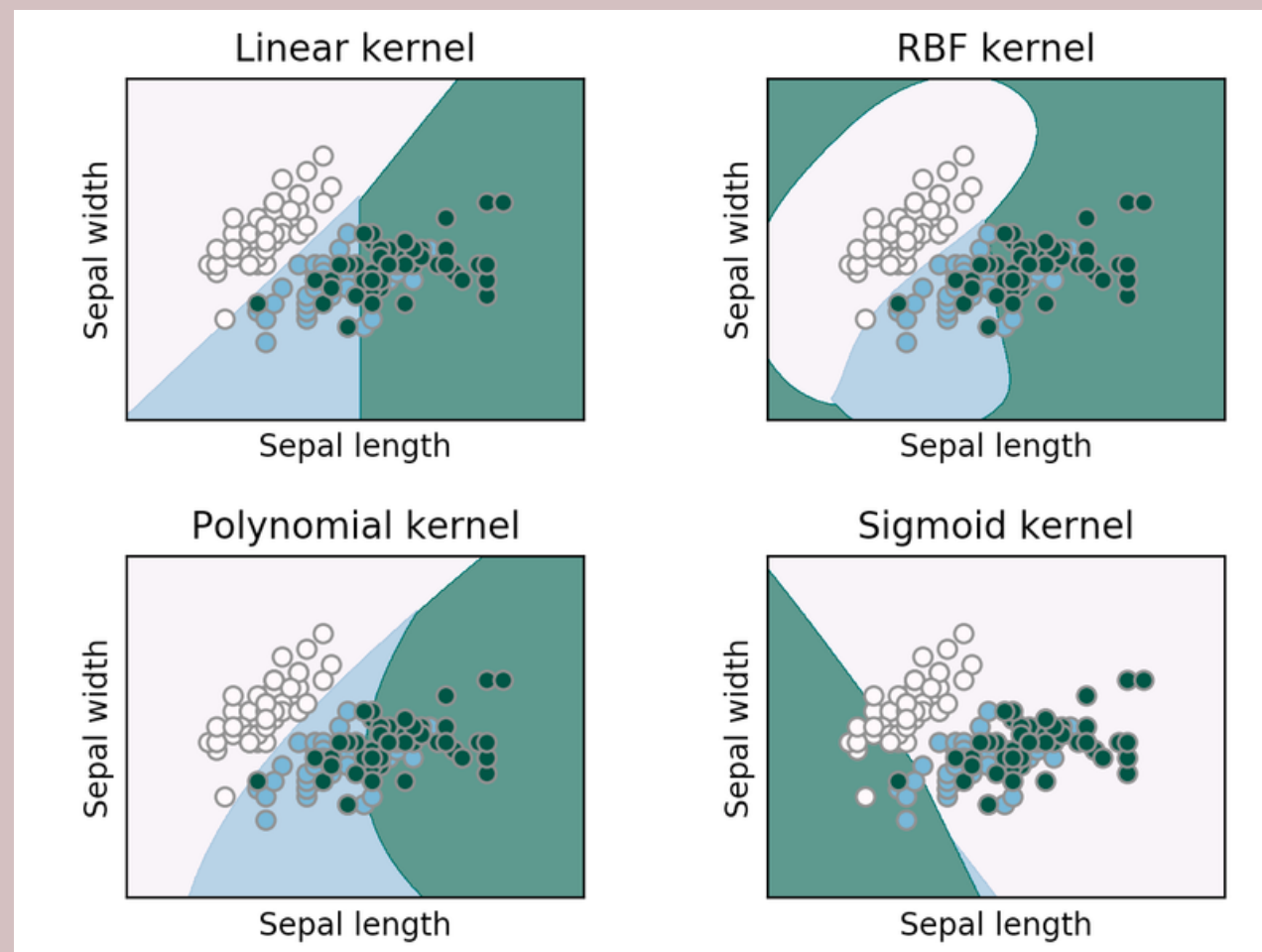
04

Discussing the trade-offs and considerations when tuning kernel parameters in SVM

# 1. Exploring the parameters associated with different kernel functions

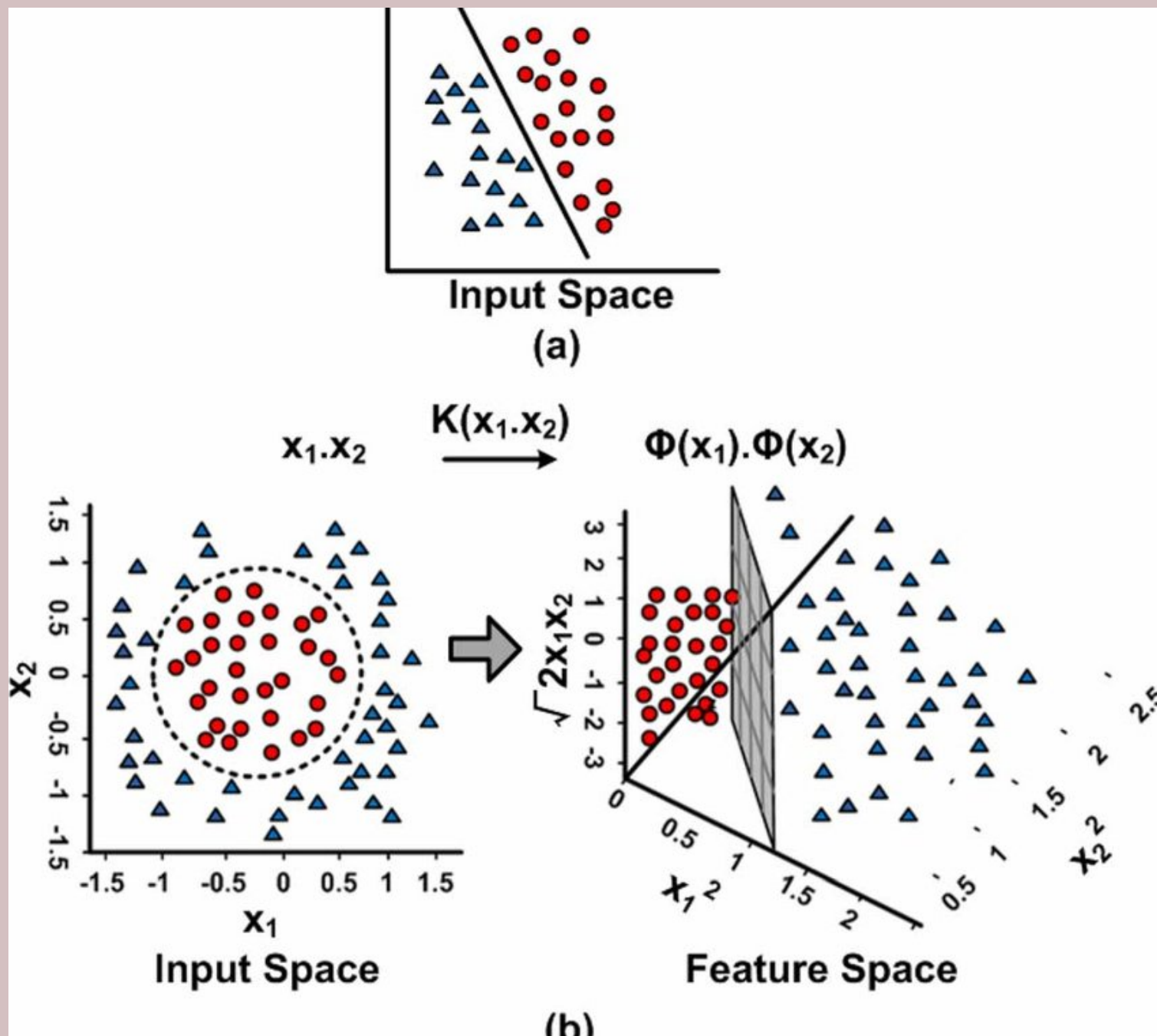
There are 4 main kernel in svm

- **Linear kernel:** It has no parameters. It simply calculates the dot product between feature vectors in the original space.
- **Polynomial kernel:** It has parameters such as degree ( $d$ ) and coefficient of the polynomial term ( $c$ ).
- **Gaussian (RBF) kernel:** It has a parameter called gamma ( $\gamma$ ), which controls the width of the Gaussian curve.
- **Sigmoid kernel:** It has parameters like coefficient ( $c$ ) and intercept ( $r$ ).

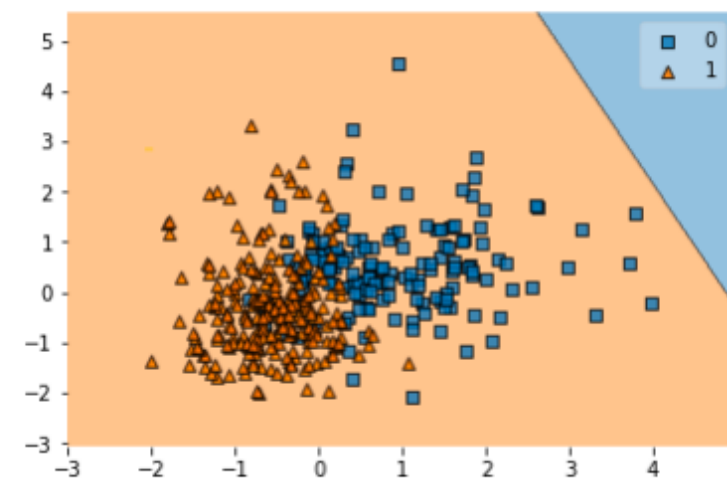


## 2. Understanding the effects of kernel parameters on SVM model complexity and generalization

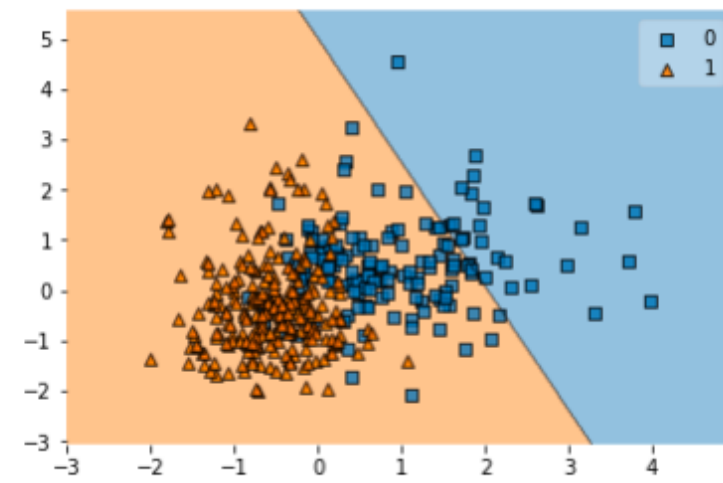
- Kernel parameters have a significant impact on the complexity and generalization ability of SVM models.
- Higher parameter values can lead to more complex decision boundaries, potentially resulting in overfitting the training data.
- Lower parameter values tend to produce simpler boundaries, which may underfit the data and result in poor generalization.
- The choice of kernel parameters should aim for an optimal balance between model complexity and generalization performance.



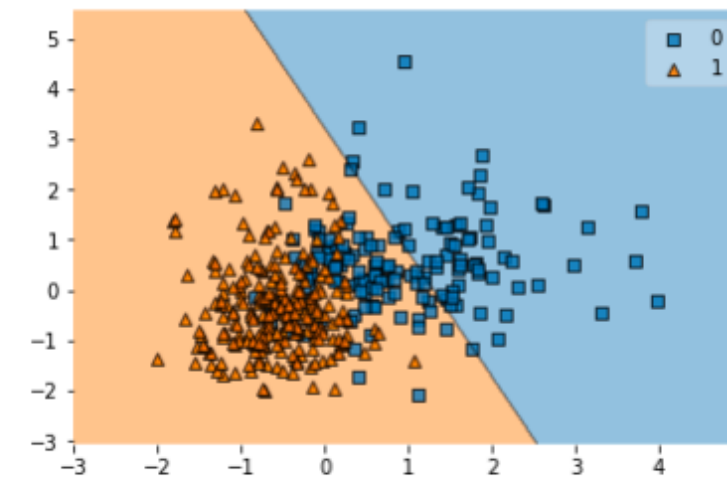




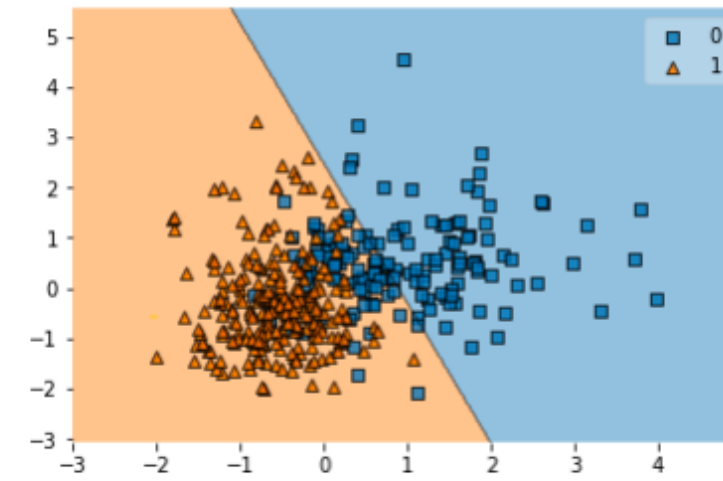
**C = 0.001**  
**Accuracy: 62.6%**



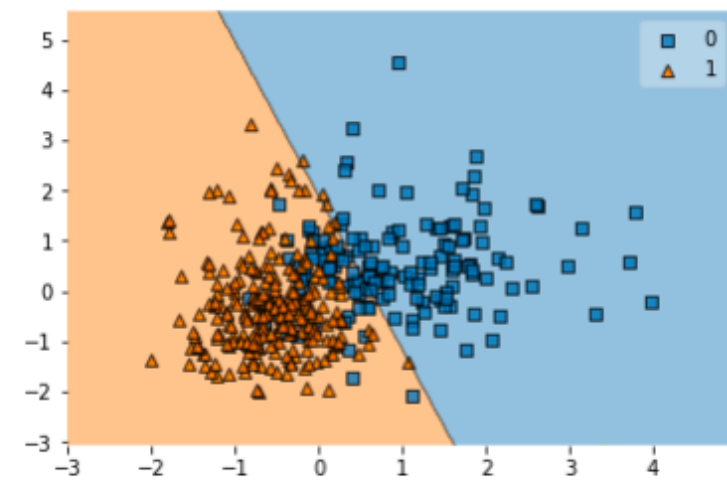
**C = 0.002**  
**Accuracy: 71.3%**



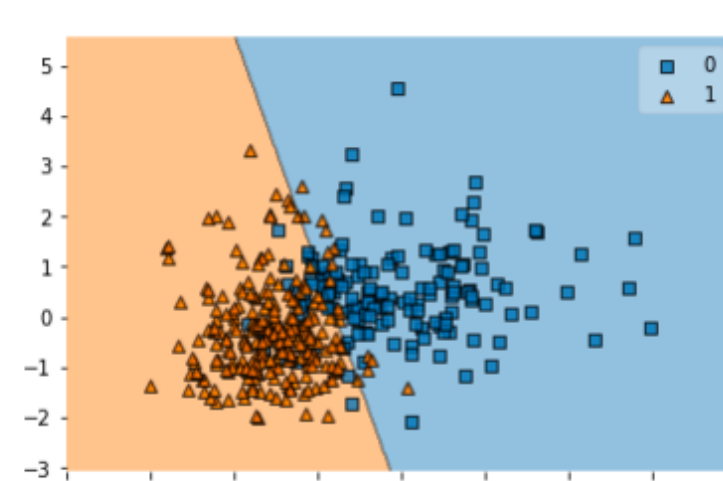
**C = 0.003**  
**Accuracy: 81.3%**



**C = 0.005**  
**Accuracy: 81.7%**



**C = 0.01**  
**Accuracy: 89.5%**



**C = 10.0**  
**Accuracy: 90.1%**

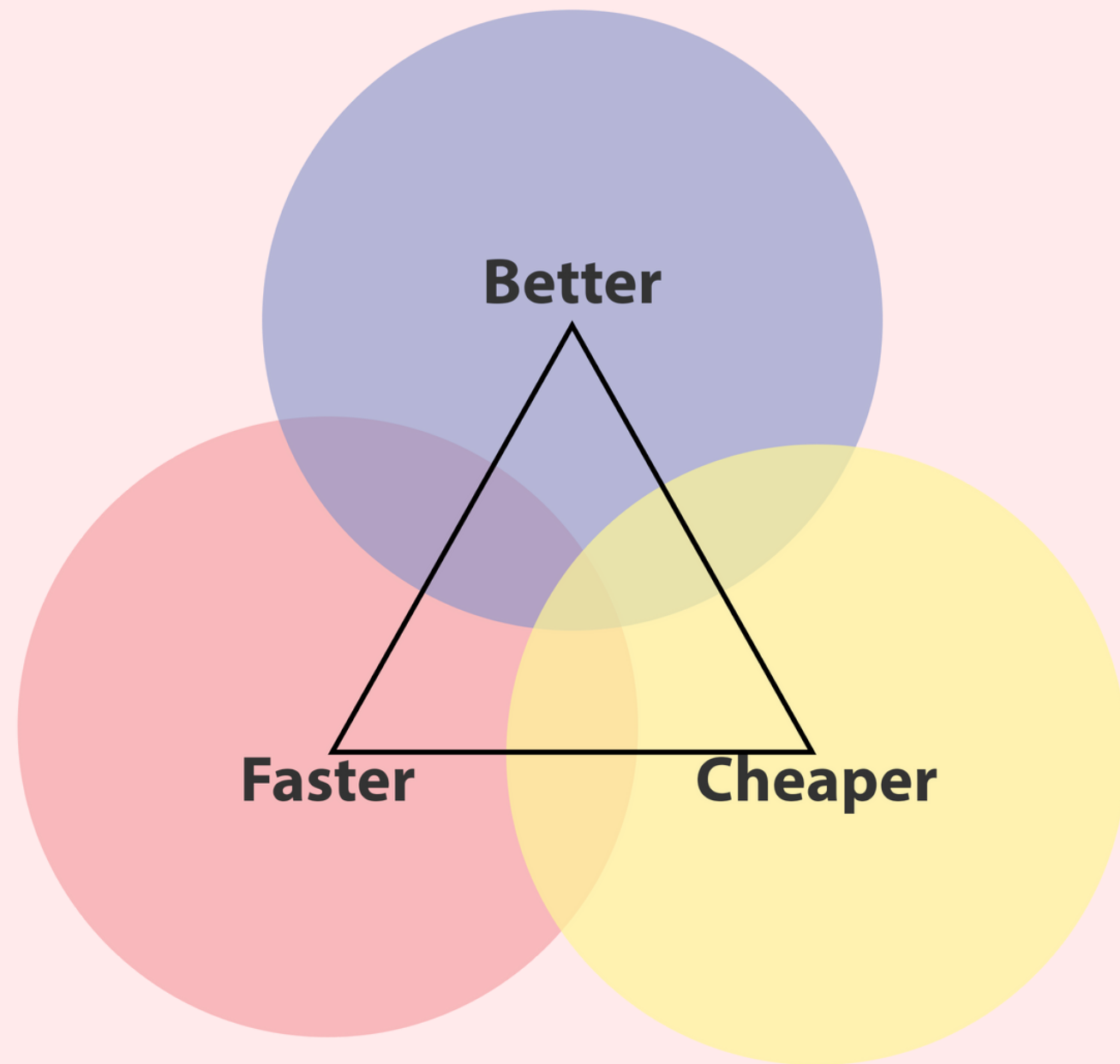
### 3. Techniques for selecting appropriate kernel parameters (e.g., grid search, cross-validation)

- Grid Search
- Cross-Validation
- Random Search
- Bayesian Optimization

## 4. Discussing the trade-offs and considerations when tuning kernel parameters in SVM

By carefully considering these trade-offs and utilizing techniques like grid search, cross-validation, random search, and Bayesian optimization, you can effectively tune the kernel parameters in SVM to achieve improved model performance.

- Computational Cost:
- Overfitting
- Interpretability
- Prior Knowledge



Thanks you  
For watching