



# **Foundations of Machine Learning (CS 725)**

## **FALL 2024**

**Lecture 20:**  
- SVMs and Kernels

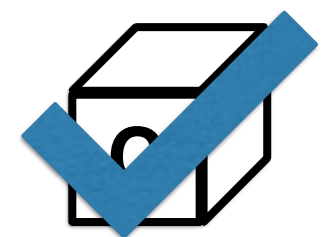
Instructor: Preethi Jyothi

# Question

Recall the soft-margin SVM where each  $(\mathbf{x}_i, y_i)$  is associated with a  $\xi_i$  and the objective contains a term  $C \sum_i \xi_i$ . Say we impose an additional constraint that  $\forall i, \xi_i = \xi_1$ . What can we say about the minimum value of the objective function under the modified constraints, say  $\alpha$ , in comparison to the minimum under the original constraints, say  $\beta$ ?

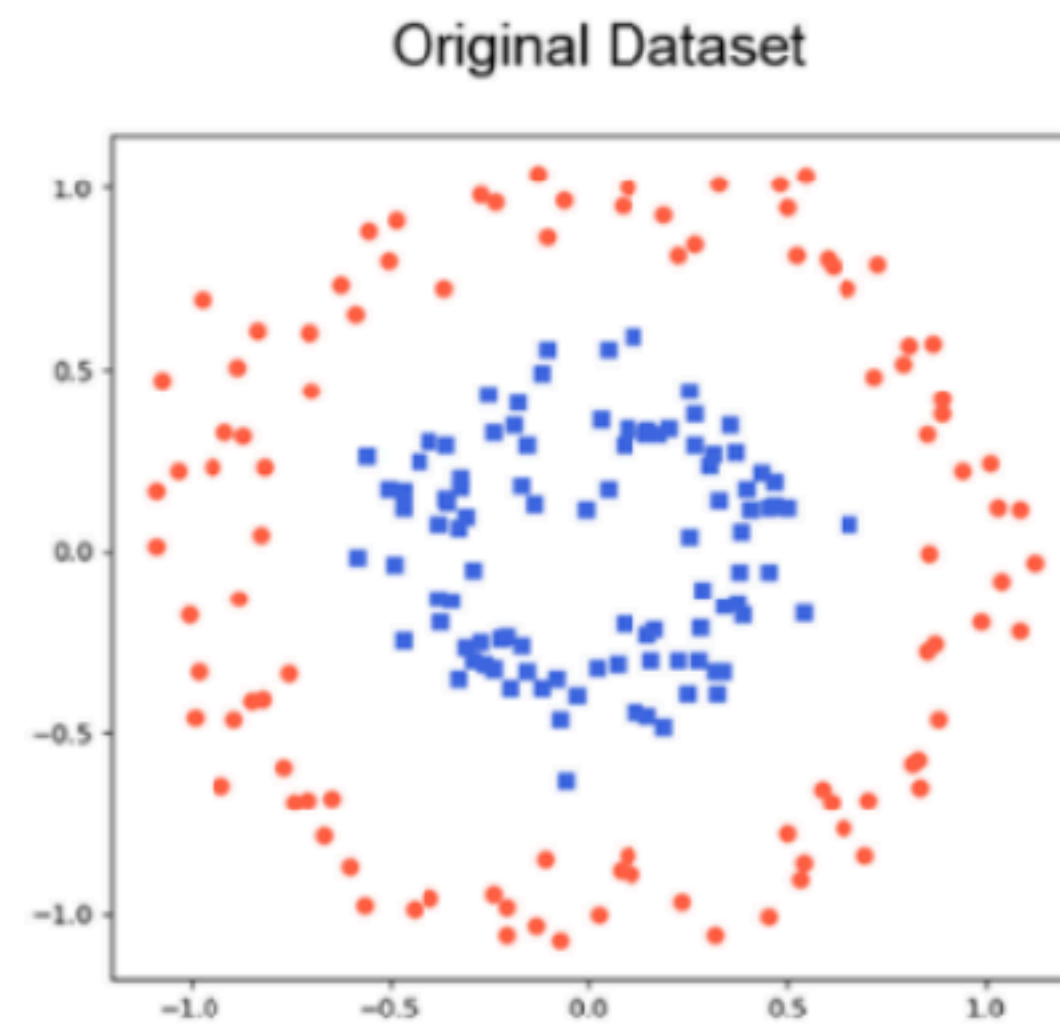
  $\alpha = \beta$

  $\alpha \leq \beta$

  $\alpha \geq \beta$

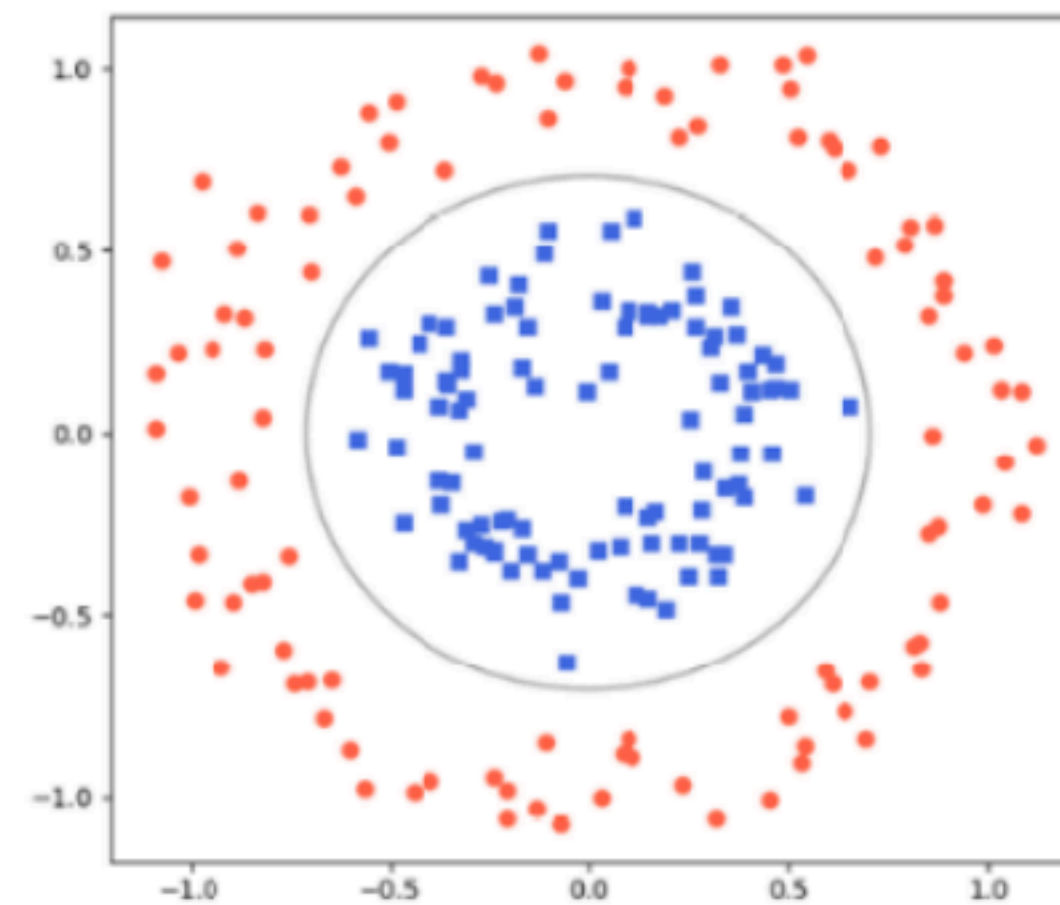
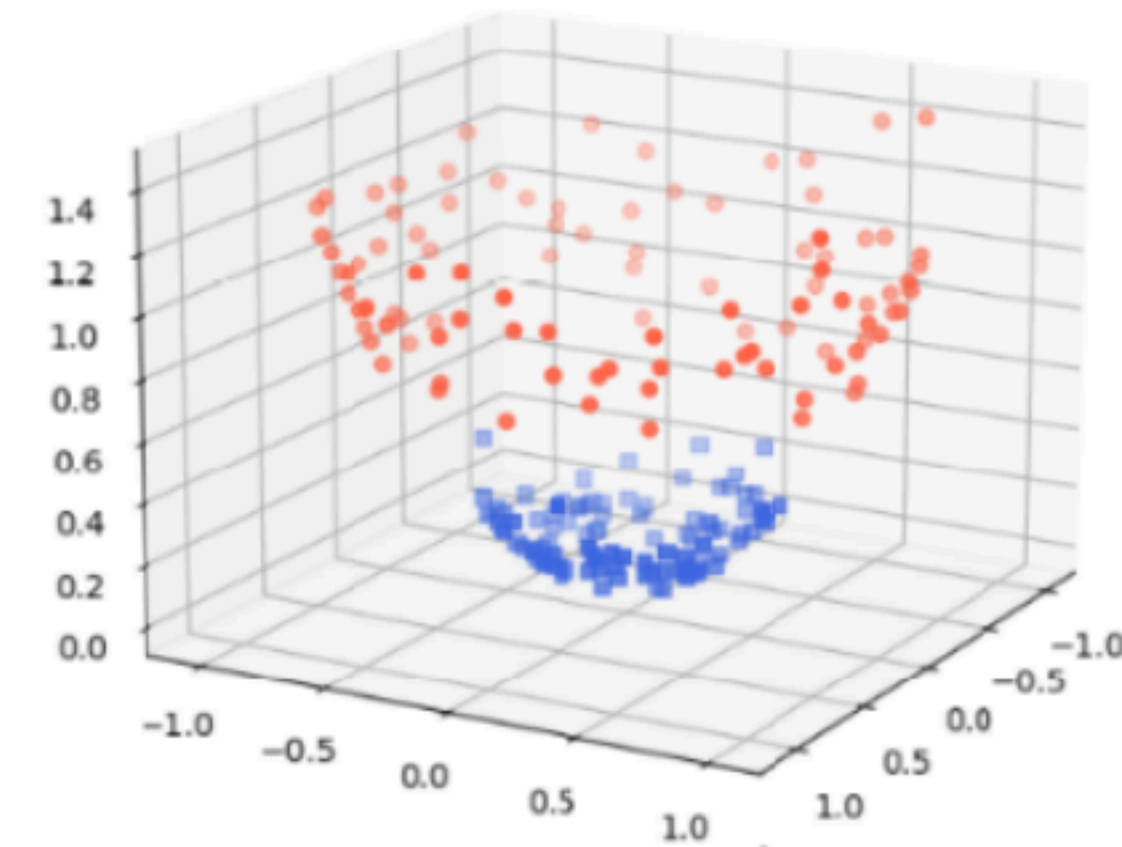
$\beta$  is the minimum value under fewer constraints; guaranteed to be at least as good (if not better) than  $\alpha$  obtained with additional constraints.

# Gaussian Kernel



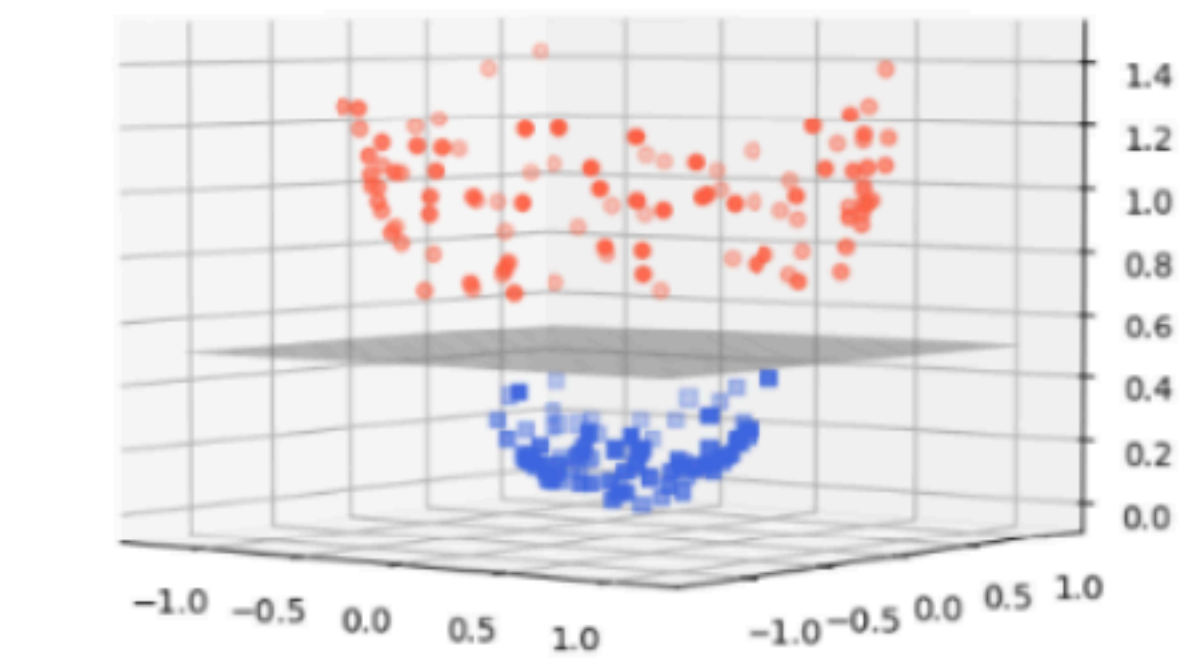
$$\phi$$

Projection into higher-dimensional space



Decision boundary projected in original feature space

$$\phi^{-1}$$



Learn decision boundary