

MACHINE LEARNING WITH PYTHON

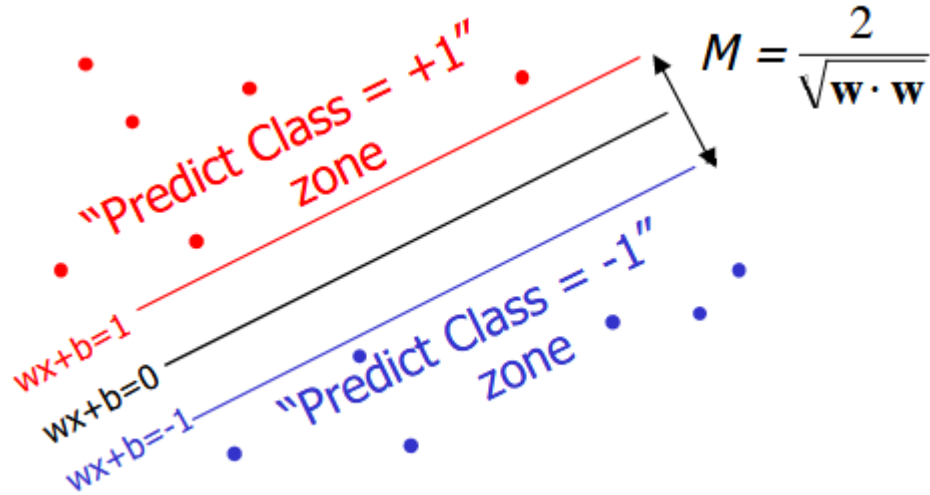
# SUPPORT VECTOR MACHINES

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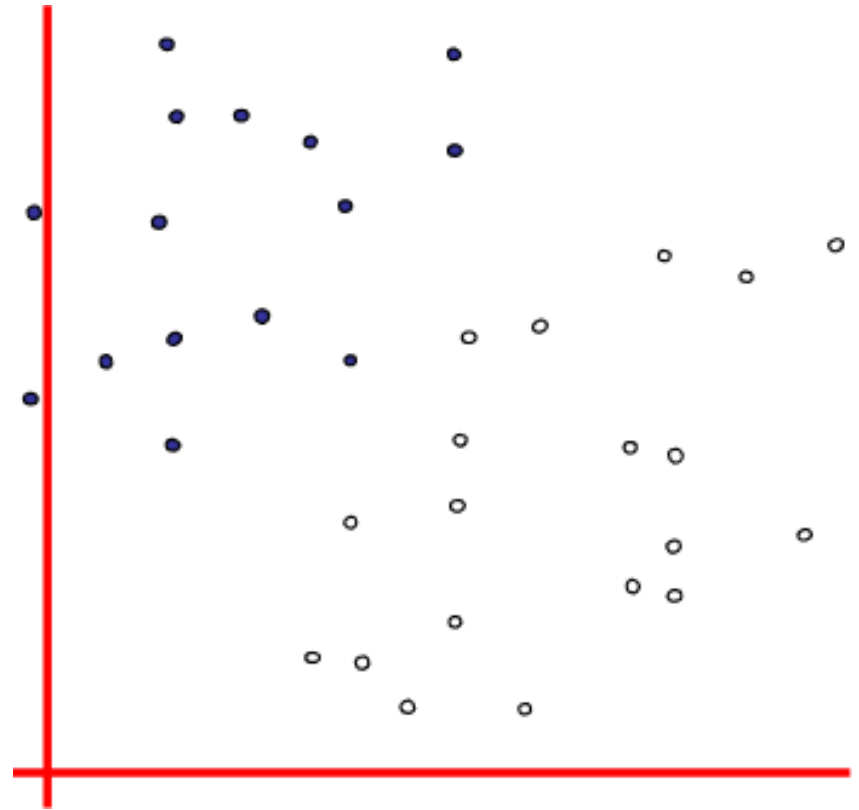
Themistoklis Diamantopoulos

# Maximum Margin

- Find optimal  $w$ ,  $b$  to maximize the margin

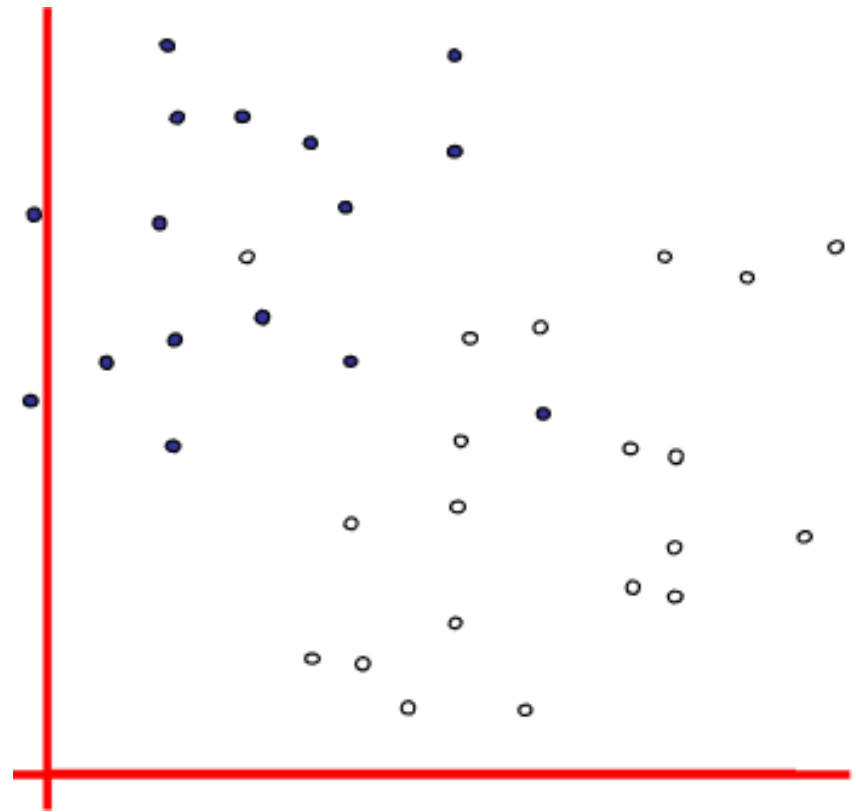
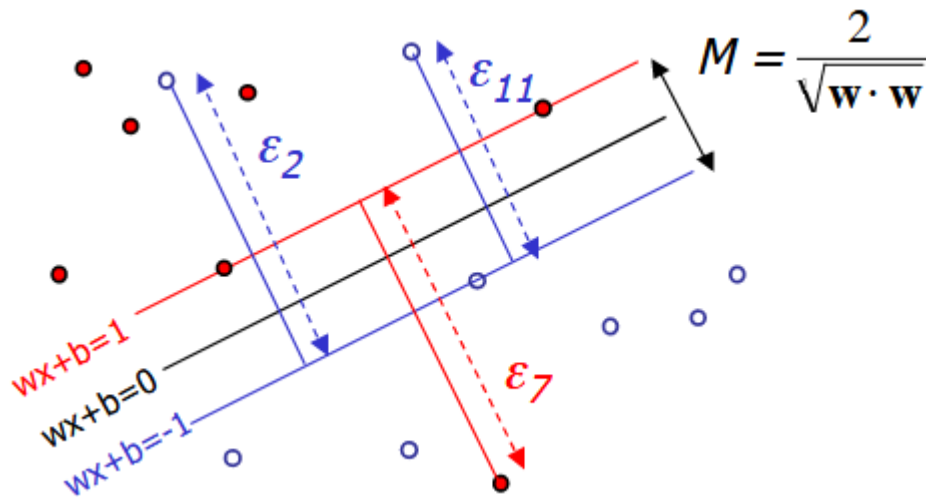


- Minimize  $\frac{1}{2} w \cdot w$



# Maximum Margin with Noise

- Allow misclassification errors

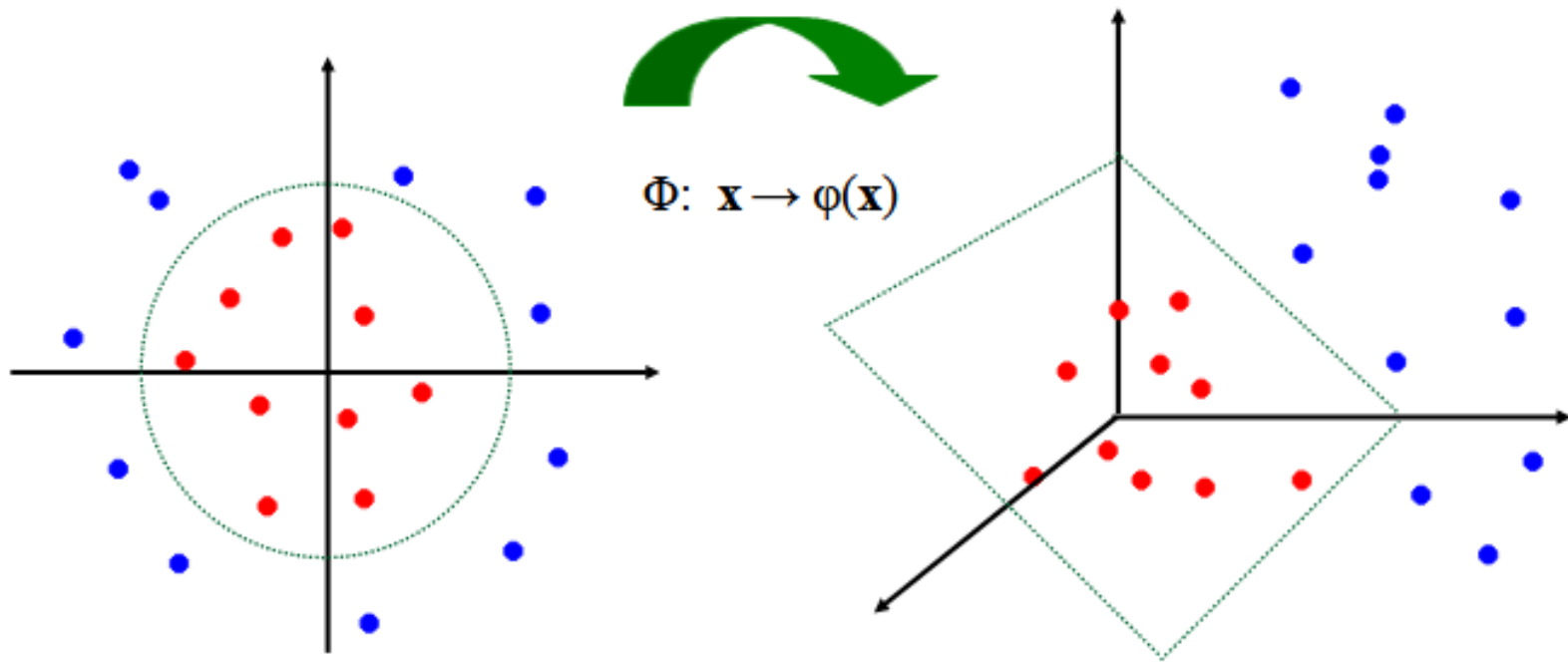


- Minimize  $\frac{1}{2} \mathbf{w} \cdot \mathbf{w} + C \sum_k \varepsilon_k$

controls tolerance of misclassification

# Transformation with Kernels

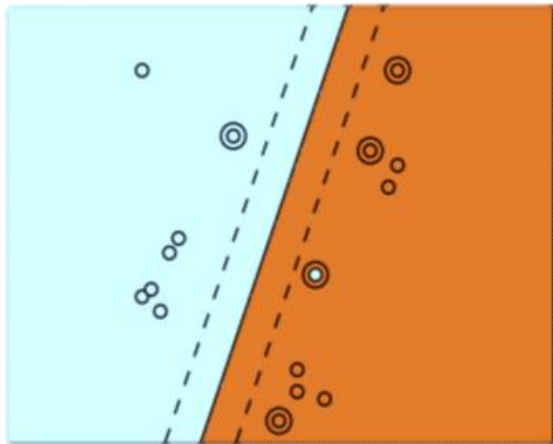
- Non-linearly separable data  $\rightarrow$  linearly separable data



- Kernel trick:  $K(\mathbf{x}, \mathbf{x}') = \varphi(\mathbf{x})^T \varphi(\mathbf{x}')$
- Linear, Polynomial, tanh

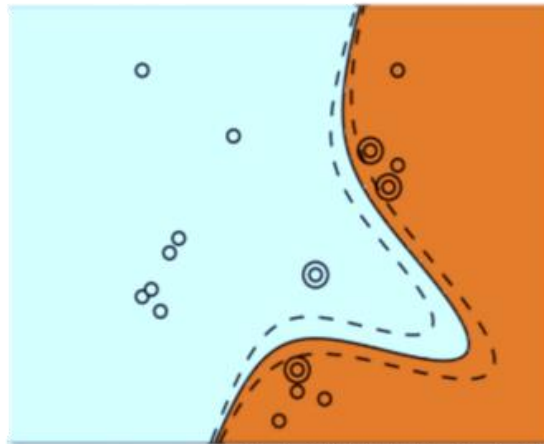
# Different types of Kernels

Linear Kernel



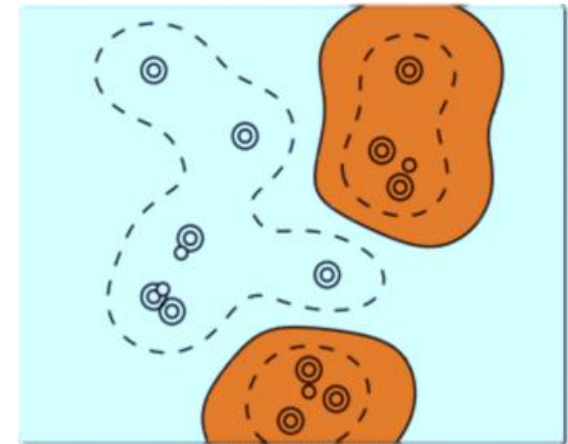
$$K(x, x') = x^T x'$$

Polynomial Kernel



$$K(x, x') = (x^T x' + 1)^d$$

RBF Kernel



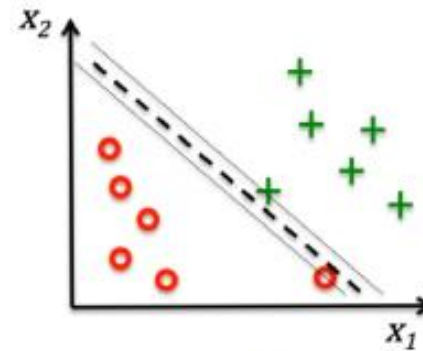
$$K(x, x') = e^{-\frac{\|x - x'\|^2}{2\sigma^2}}$$

$1/2\sigma^2 = \gamma$

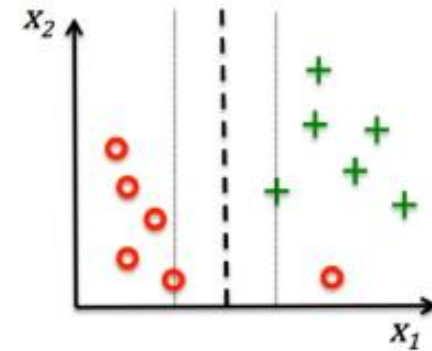
controls the width  
of the RBF kernel

# Overfitting

- Parameter C
  - Large C  $\rightarrow$  More error penalization
  - Small C  $\rightarrow$  Allow more errors
- Parameter gamma
  - Large gamma  $\rightarrow$  Exact data fit
  - Small gamma  $\rightarrow$  Generalization

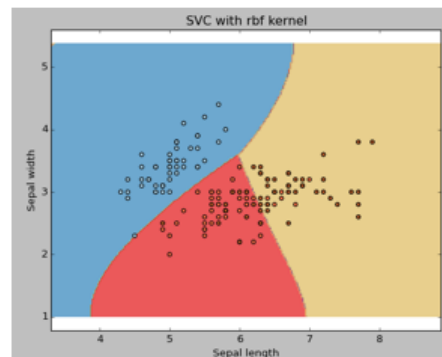


Large value for parameter C

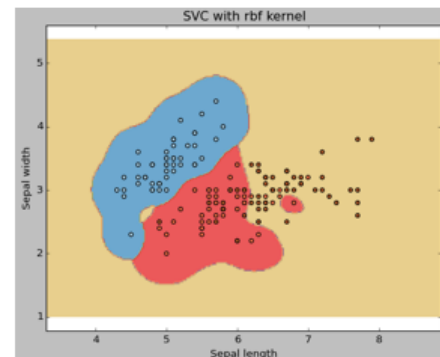


Small value for parameter C

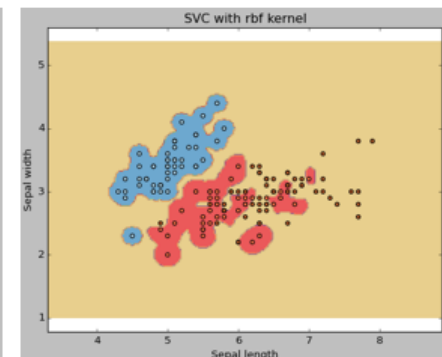
gamma=0



gamma=10



gamma=100



# Validation

- Split data in two parts
  - Use 1 part for training and 1 part for testing
  - Compare the errors
- Cross-validation
  - Divide dataset in k-folds
  - Use k-1 parts for training and 1 for testing
  - Repeat for all folds
  - Determine a metric value

