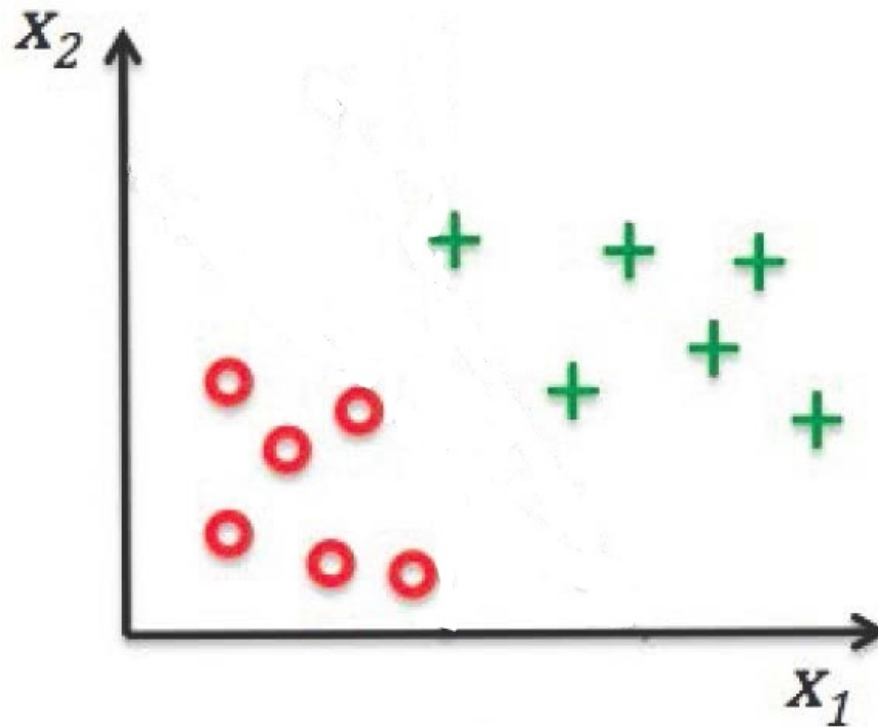
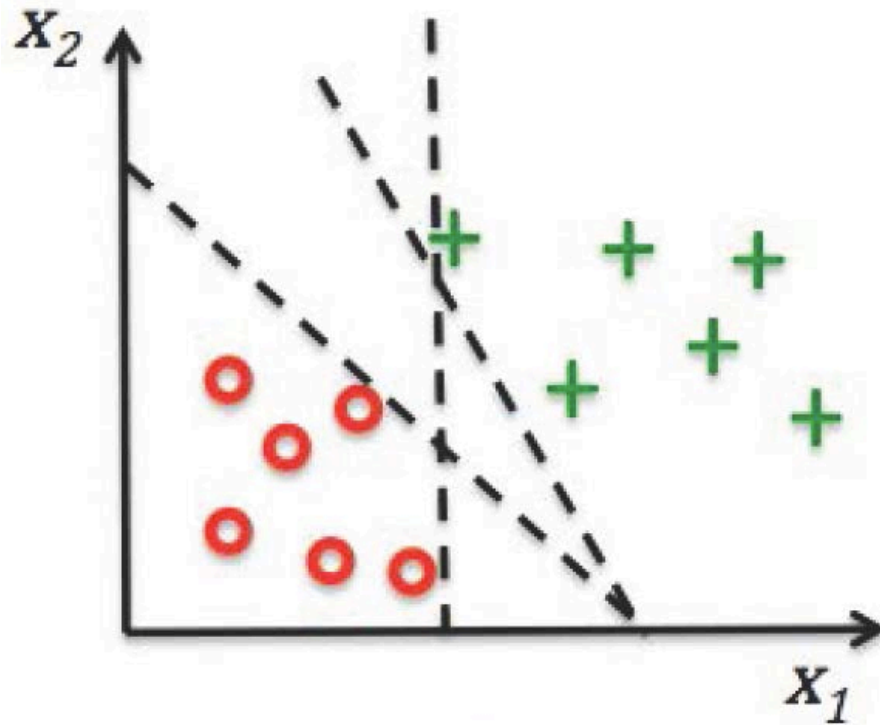


Support Vector Machines

Linearly separable case



Hard-margin classifications



Which hyperplane to use?

Perceptron

Separate the classes

Adaline

Minimize the cost function

Logistic Regression

Maximize the log-likelihood function

Source Vector Machine

Maximize the **Margin**

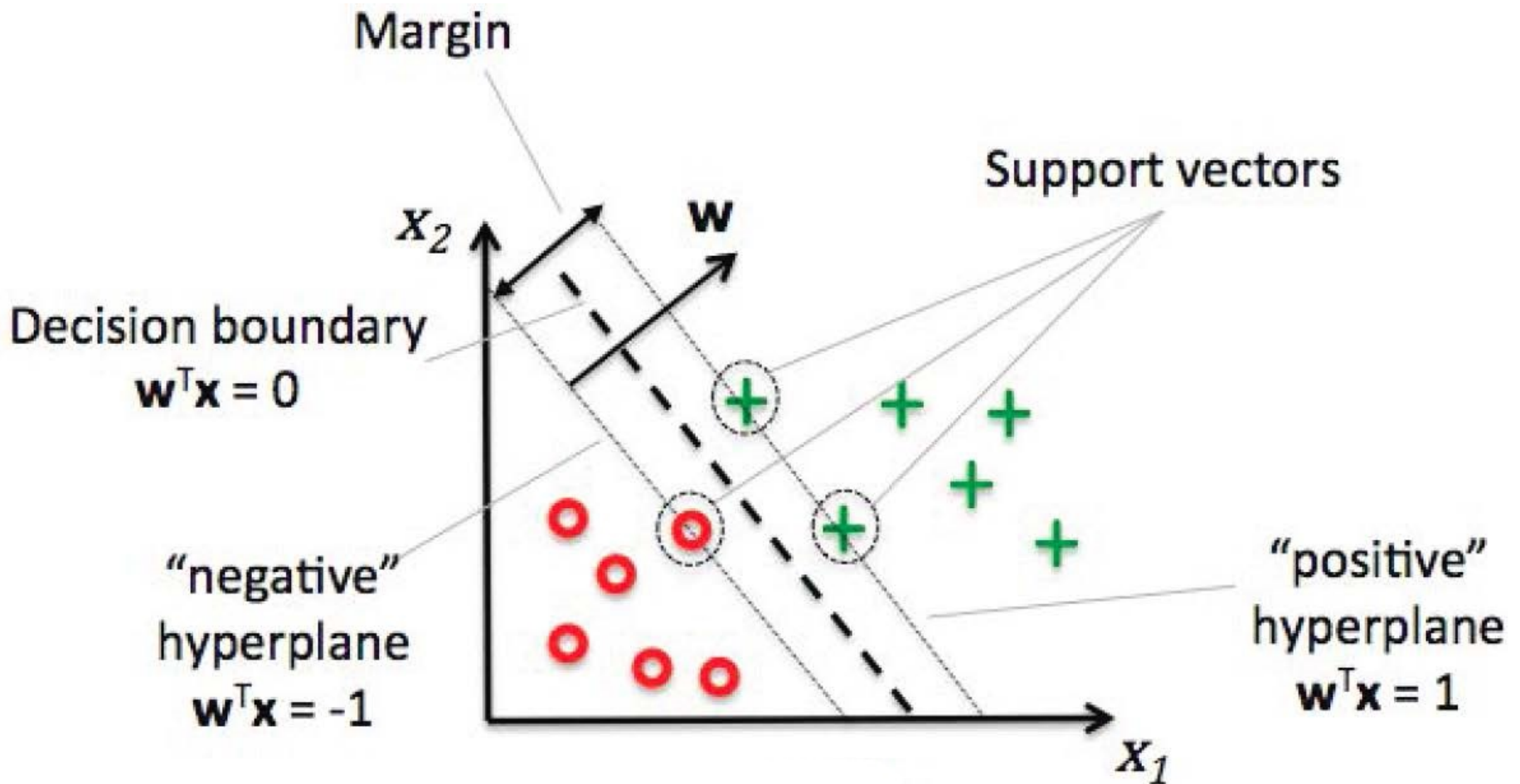


STOP

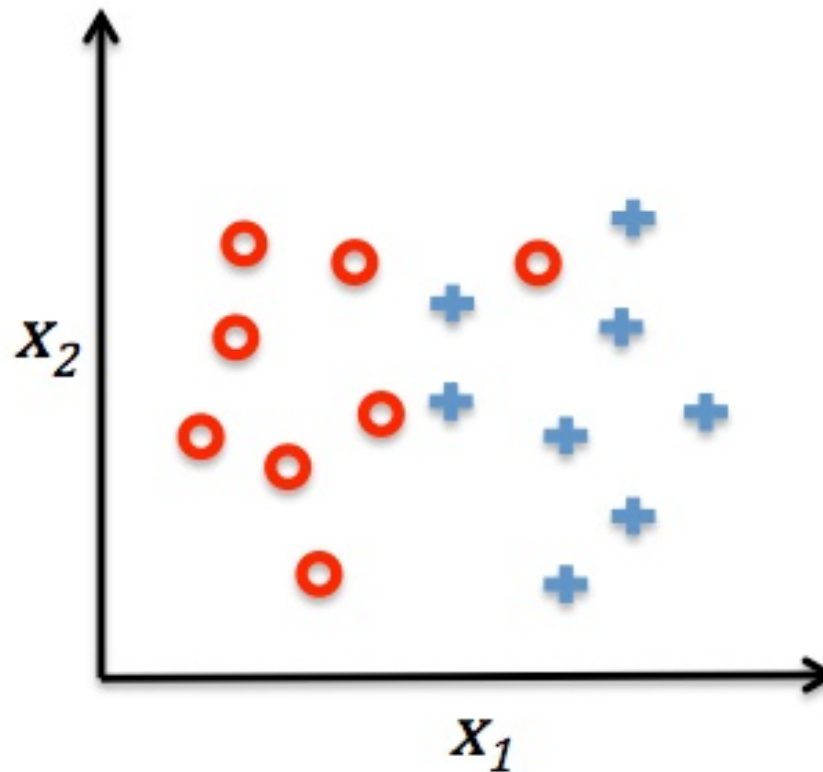
Hard-margin classification

- Choose a pair of parallel hyperplanes such that the hyperplanes and the space between them separate the classes.
- Label one hyperplane as the **Positive** hyperplane and the other as the **Negative** hyperplane (in a OvA or OvA case, the Positive hyperplane includes at least one sample from the One class).
- Define the **Margin** to be the distance between the two hyperplanes
- Choose the two hyperplanes that maximize the **Margin**.
- Designate the hyperplane equidistant between the Positive and Negative hyperplanes as the **Decision Boundary**.
- Label the samples on the Positive and Negative hyperplanes as **Support Vectors**.

Maximize the margin



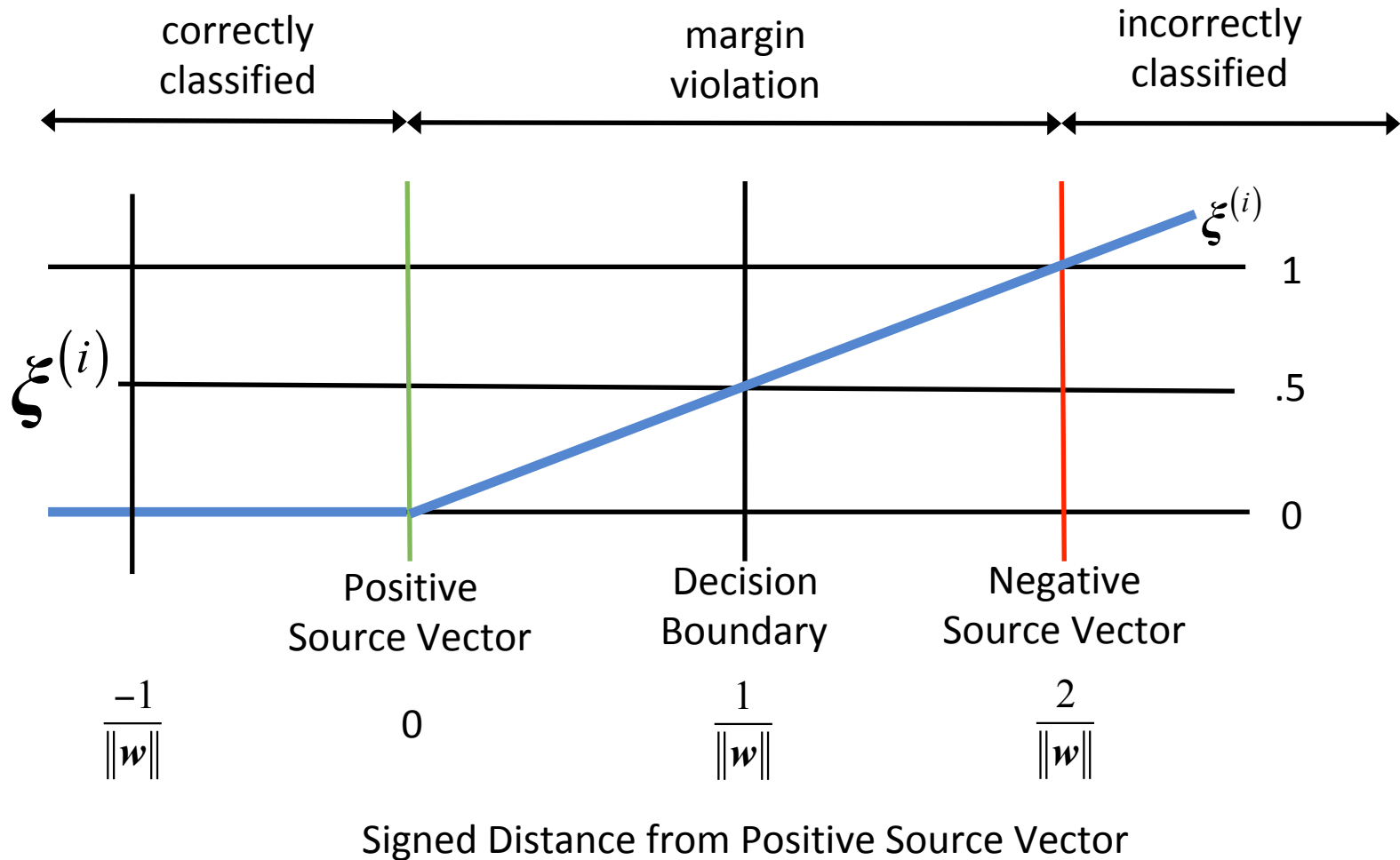
Linearly inseparable case



Soft-margin classifications

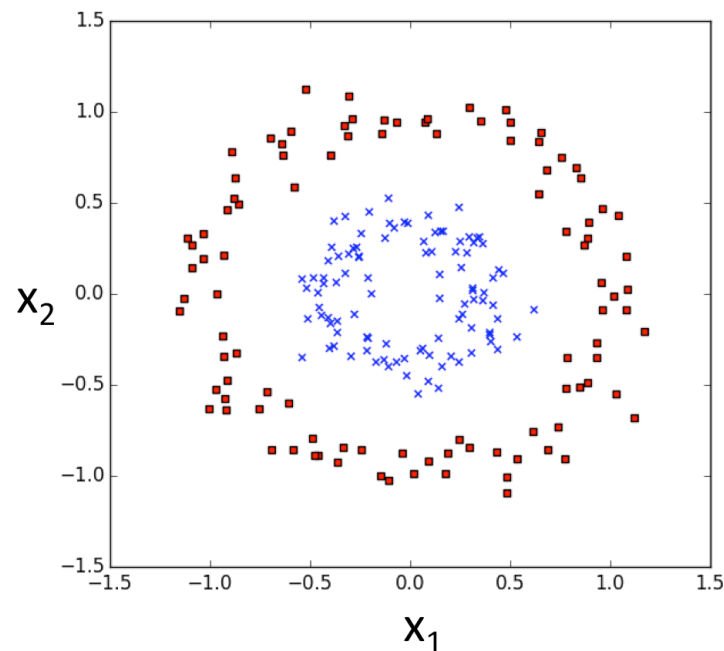
- Slack Variable using a Hinge Loss Function

Slack-variable hinge-loss function



Solving non-linear problems with a SVM

- So far, we've used hyperplanes to divide the regions corresponding to one class from those corresponding to others.
- But for some problems, surfaces other than hyperplanes are more appropriate.



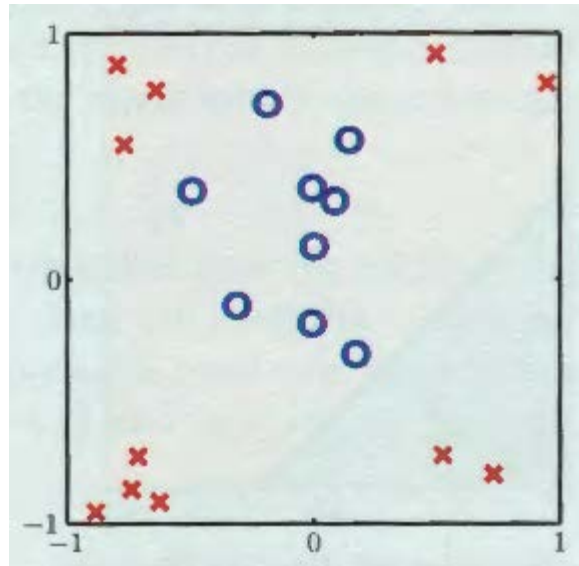
Solving non-linear problems with a SVM

1. Transform the training data onto a higher dimensional feature space using a mapping function, $\phi(\cdot)$.
2. Train a linear SVM model to classify the transformed data in this new feature space.
3. Transform new, previously unseen, data using the same mapping function, $\phi(\cdot)$ as was used in Step 1 and classify the new, transformed data using the SVM trained in Step 2.

OR

3. Transform the decision boundary determined in Step 2 using $\phi^{-1}(\cdot)$, the inverse of the mapping function used in Step 1, and classify new, previously unseen data using transformed decision boundary.

Non-linear example

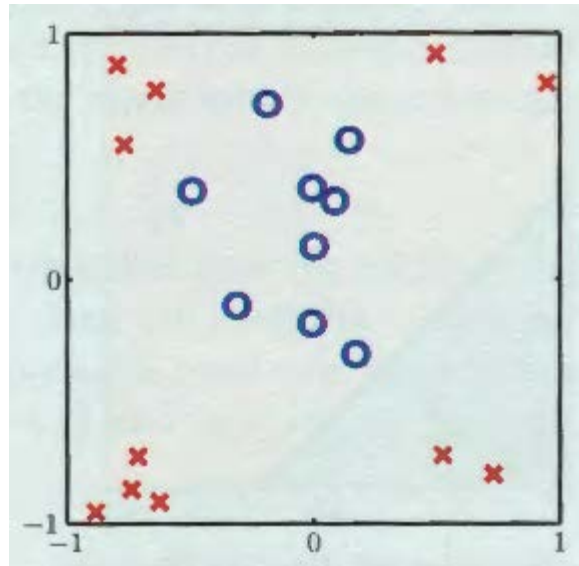


Original Data

$$\mathbf{x}^{(i)} \in X$$

Example is from **Learning From Data, A Short Course**, Yaser S. Abu-Mostafa, Malik Magdon-Ismail, Hsuan-Tien Liu, AMLBook.com, 2012; I highly recommend the book)

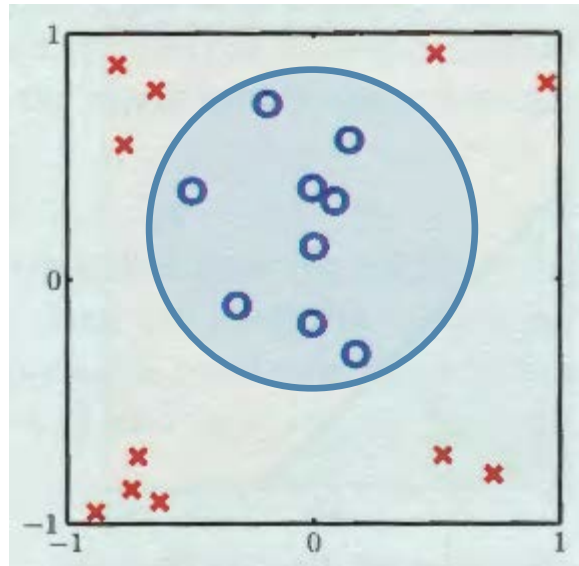
Data is not linearly separable; nor is it close to being so



Original Data

$$\mathbf{x}^{(i)} \in X$$

Possible non-linear decision boundary in X -space



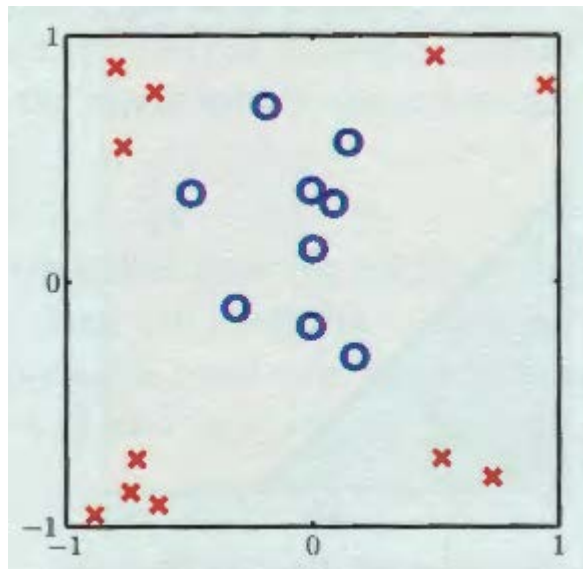
Original Data

$$\mathbf{x}^{(i)} \in X$$

with a possible non-linear decision boundary

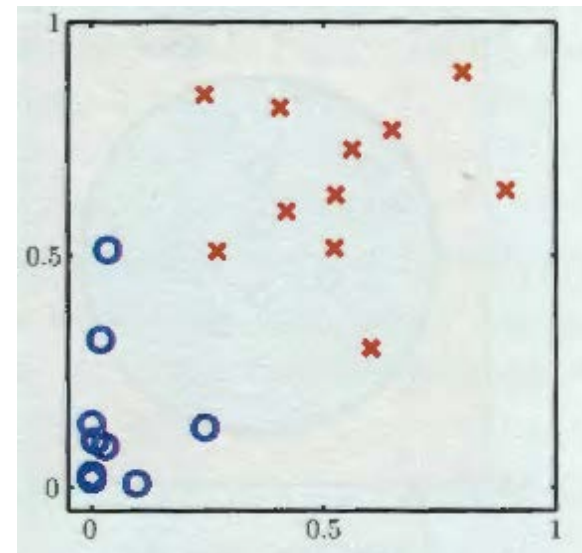
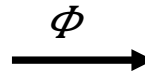
Transform the data from X -space to Z -space

$$z^{(i)} = \Phi\left(1, x_1^{(i)}, x_2^{(i)}\right) = \left(1, \left(x_1^{(i)}\right)^2, \left(x_2^{(i)}\right)^2\right)$$



Original Data

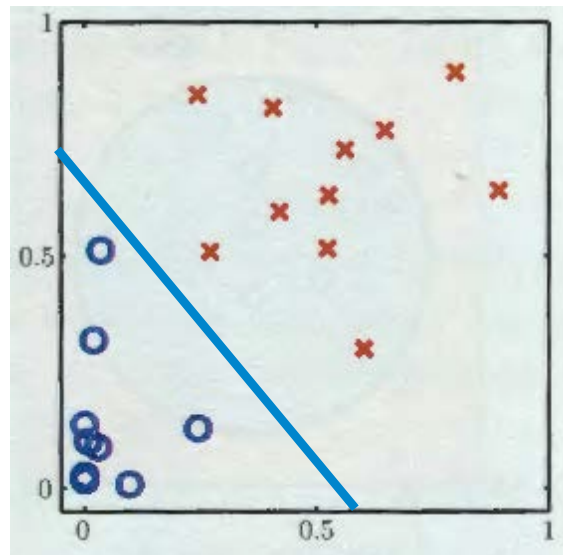
$$\mathbf{x}^{(i)} \in X$$



Transformed Data

$$\mathbf{z}^{(i)} = \Phi\left(\mathbf{x}^{(i)}\right) \in Z$$

Possible linear decision boundary in Z -space

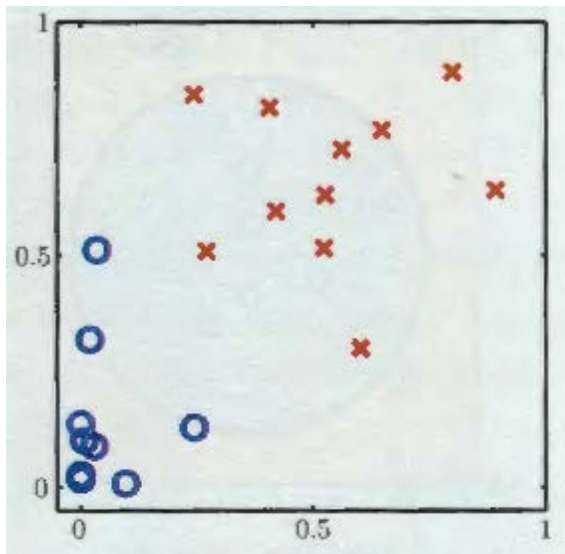


Transformed Data

$$z^{(i)} \in Z$$

with Potential Decision Boundary

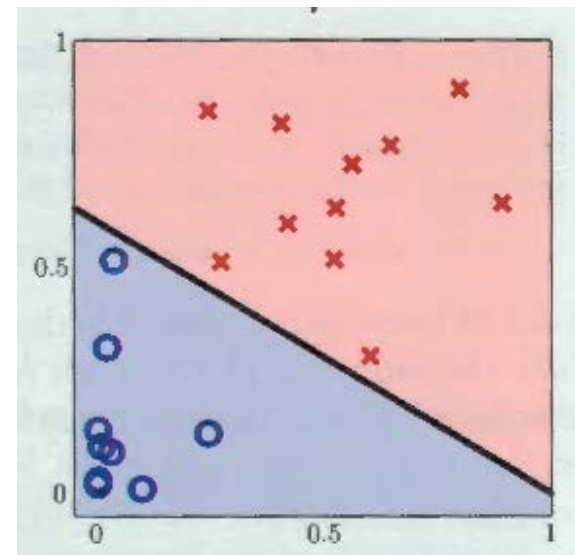
Find the decision boundary



Transformed Data

$$z^{(i)} = \Phi(x^{(i)}) \in Z$$

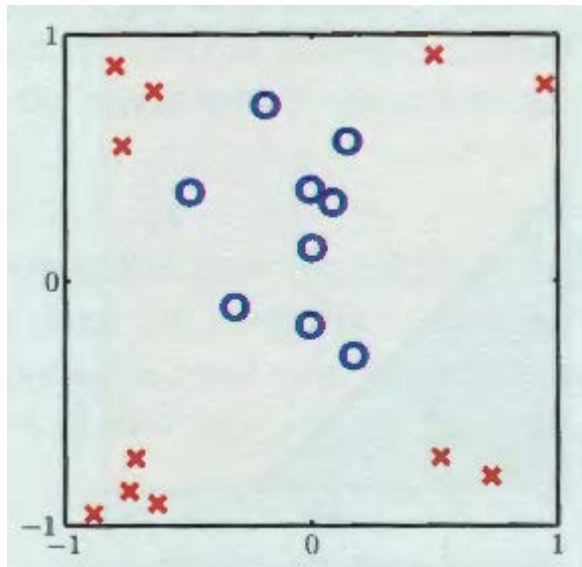
$\frac{SV}{M}$ \rightarrow



Transformed Data

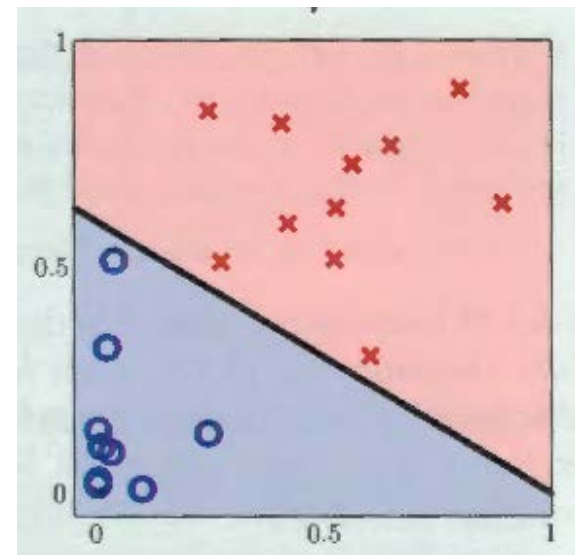
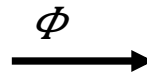
$$z^{(i)} = \Phi(x^{(i)}) \in Z$$

Option 1: Classify New Data in Z-Space



New Data

$$\mathbf{x}^{(i)} \in X$$

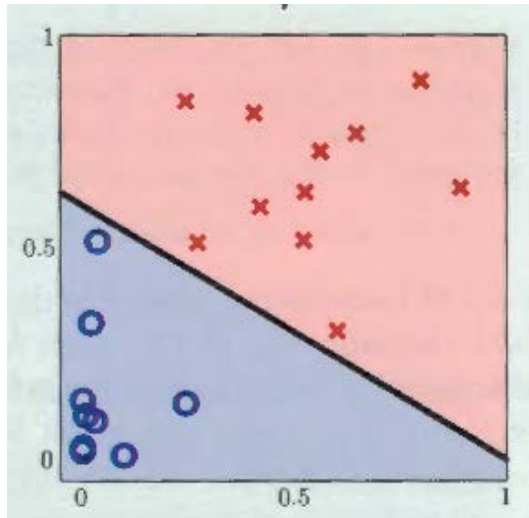


Transformed New Data

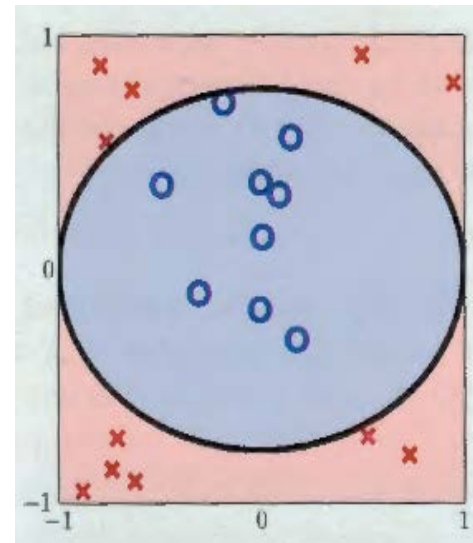
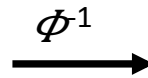
$$\mathbf{z}^{(i)} = \Phi(\mathbf{x}^{(i)}) \in Z$$

Option 2: Transform the decision boundary from Z -space to X -space

$$x^{DB} = \Phi^{-1}\left(1, z_1^{DB}, z_2^{DB}\right) = \left(1, \pm\sqrt{\left(z_1^{DB}\right)}, \pm\sqrt{\left(z_1^{DB}\right)}\right)$$

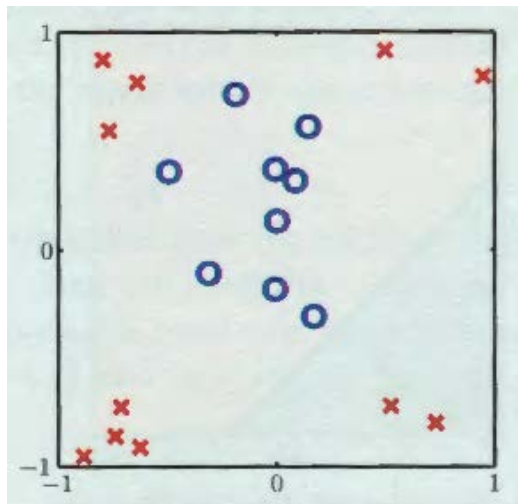


Non-linear decision boundary
in Z -Space



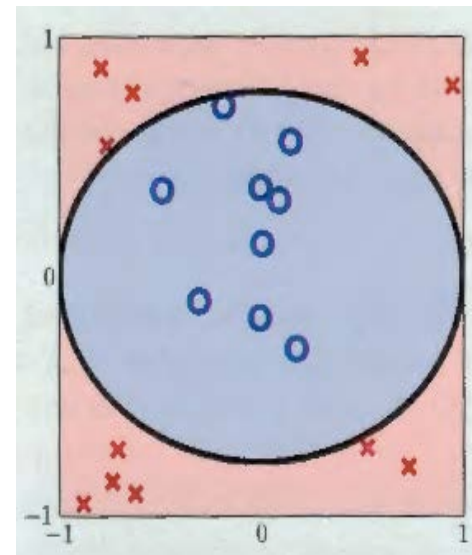
Non-linear decision boundary
in X -Space

Option 2: Classify new data in X -space using the transformed decision boundary



New Data

$$\mathbf{x}^{(i)} \in X$$



New Data

$$\mathbf{x}^{(i)} \in X$$

STOP