

PH-227

AI and Data Science

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Another Example (SVM)

- Consider the following set of data points
- $(2,2); (10,6); (6,6); (6,10);$ ➔ (+1 labelled)
- $(1,1); (1,-1); (-1,-1); (-1,1)$ ➔ (-1 labelled)

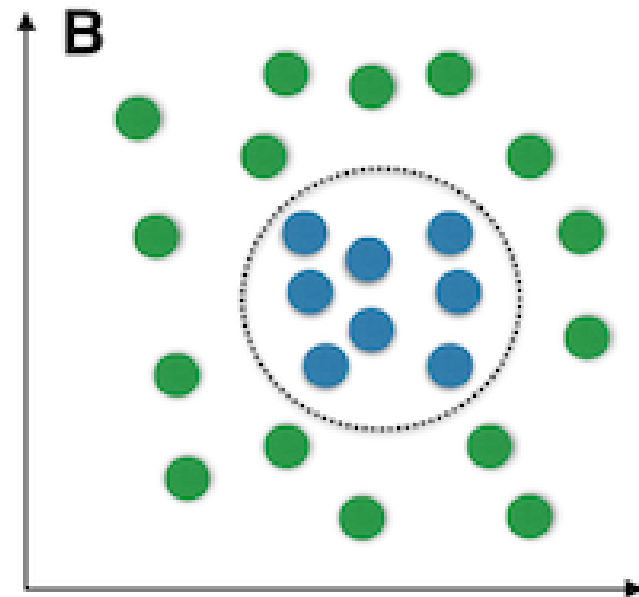
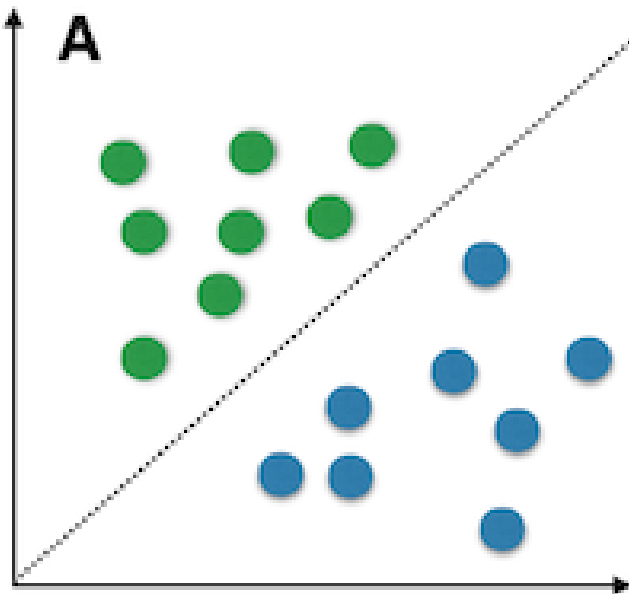
Construct the optimal hyperplane corresponding to these data points

- Consider the following set of data points
- $(3,1); (3,-1); (6,1); (6,-1);$ ➔ (+1 labelled)
- $(1,0); (0,1); (0,-1); (-1,0)$ ➔ (-1 labelled)

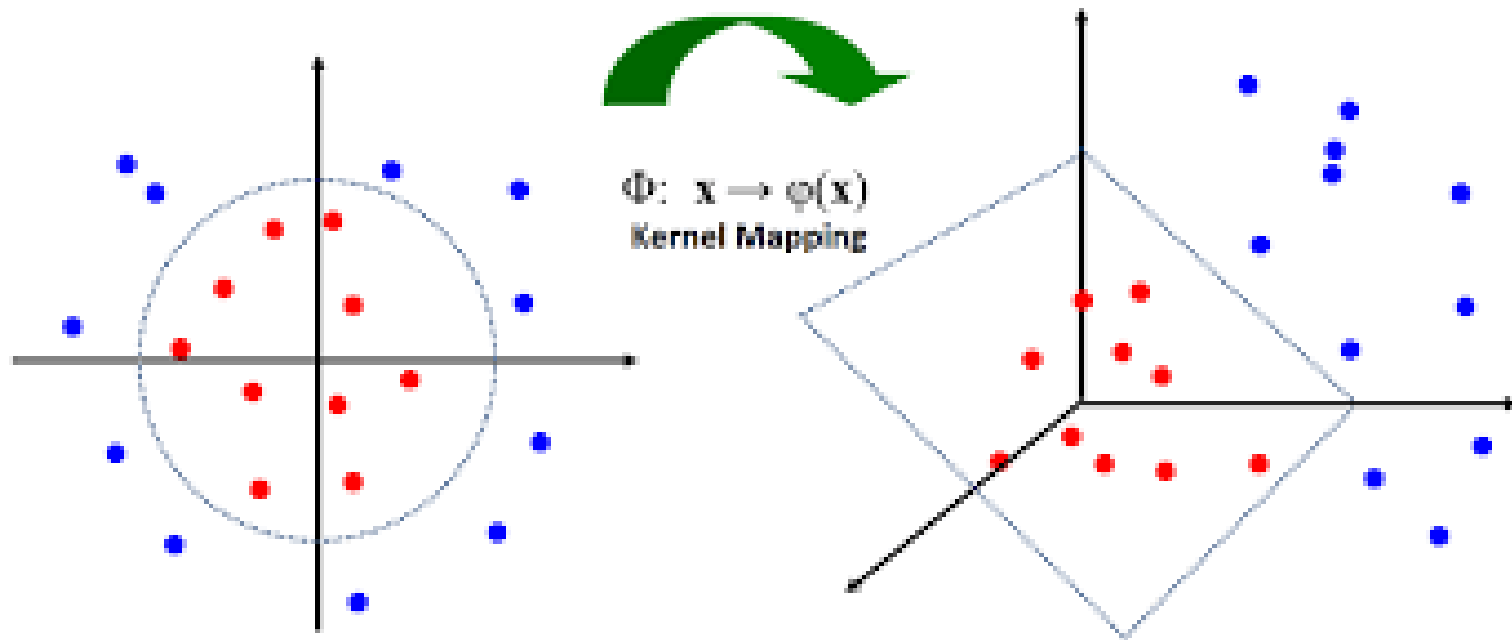
Construct the optimal hyperplane corresponding to these data points

Non-linear SVM Method

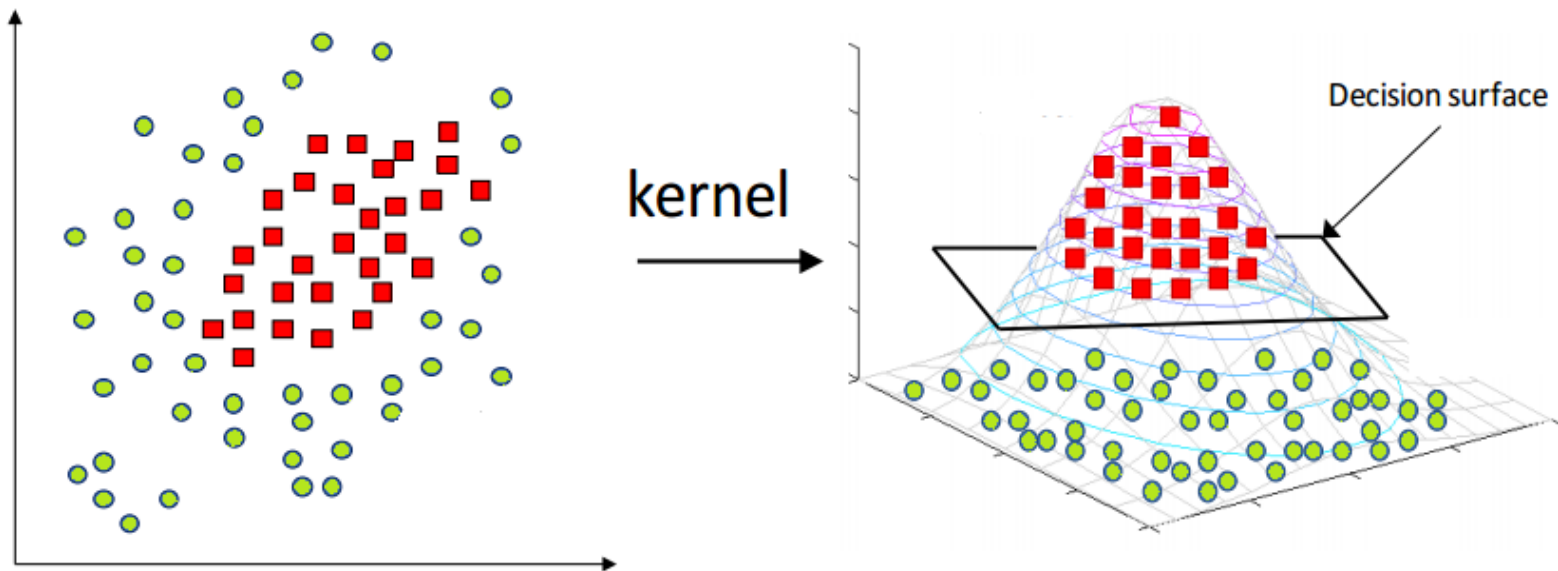
Linear vs. nonlinear problems



Non-linear SVM Method



Non-linear SVM Method



Non-linear SVM Method Example

➤ We are given the following positively labelled data points
 $(2,2); (2,-2); (-2,-2); (-2,2); \rightarrow (+1 \text{ labelled})$

And following negatively labelled data points,
 $(1,1); (1,-1); (-1,-1); (-1,1) \rightarrow (-1 \text{ labelled})$

Construct the optimal hyperplane corresponding to these data points

➤ After Kernel transformation, one gets
 $(2,2); (10,6); (6,6); (6,10); \rightarrow (+1 \text{ labelled})$
 $(1,1); (1,-1); (-1,-1); (-1,1) \rightarrow (-1 \text{ labelled})$

Construct the optimal hyperplane corresponding to these data points

Non-linear SVM Method Example

- Convert the original data from one feature space to other

$$\text{Phi}(x_1, x_2) = (4 - x_2 + |x_1 - x_2|, 4 - x_1 + |x_1 - x_2|), \quad \text{if } \sqrt{x_1 * x_1 + x_2 * x_2} > 2$$
$$= (x_1, x_2) \quad \text{otherwise}$$

Advantages of SVM

- The main strength of SVM is that they work well even when the number of SVM features is much larger than the number of instances
- It can work on datasets with huge feature space, such as the case in spam filtering, where number of words are the potential signifiers of a message being spam
- Even when the optimal decision boundary is a nonlinear curve, the SVM transforms the variables to create new dimensions such that the representation of the classifier is a function of those transformed dimensions of the data
- SVMs are conceptually easier to understand. They create an easy-to-understand linear classifier
- SVMs are now available with almost all data analytics toolsets.

Applications of SVM

- Classification problems
- Regression problems
- Pattern recognition
- Outliers detection
- Relevance based applications.