

SVM – Support Vector Machine

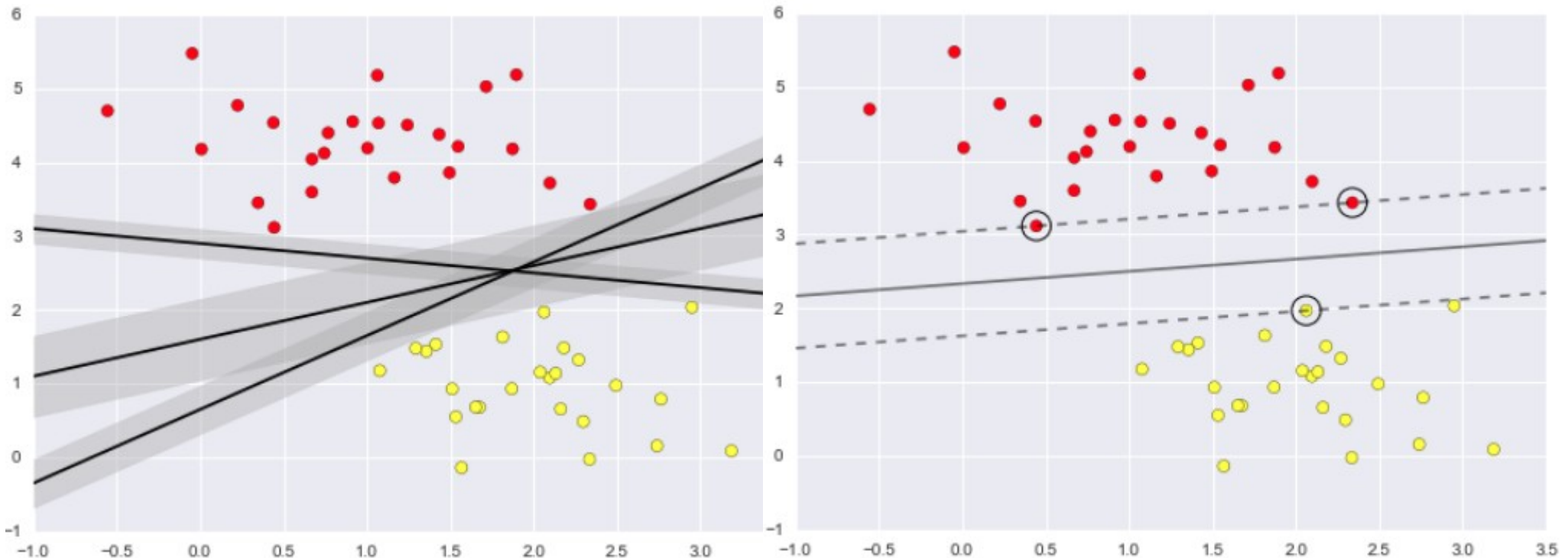
- SVM
- supervised classification and regression
discriminative (line or curve separating classes)

- Application to Indoor Localization
(MLP x LVQ x SVM)

SVM Master

GitHub, Colab: [05.07-Support-Vector-Machines.ipynb](#)

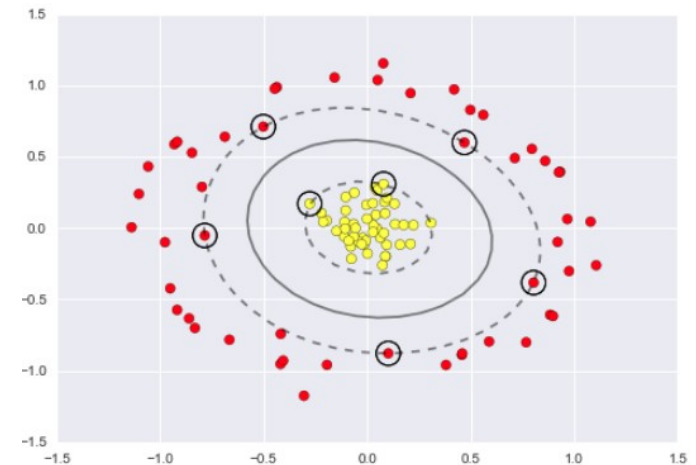
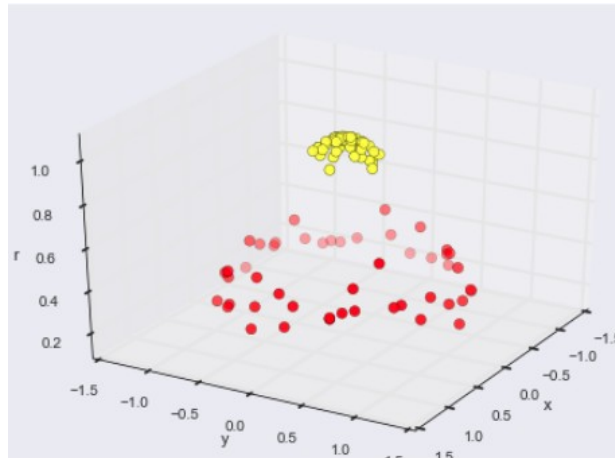
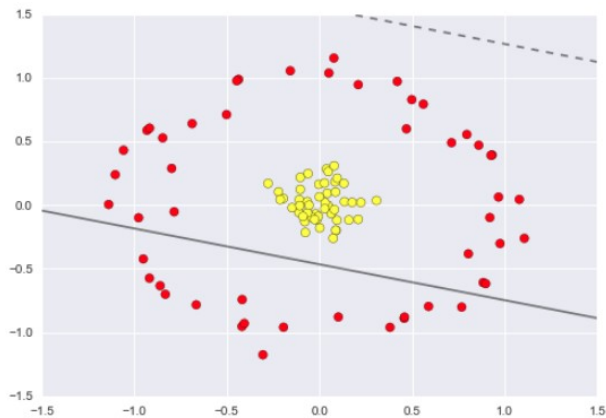
Python Data Science Handbook by Jake VanderPlas, 2018



SVM Master

GitHub, Colab: [05.07-Support-Vector-Machines.ipynb](#)

Python Data Science Handbook by Jake VanderPlas, 2018

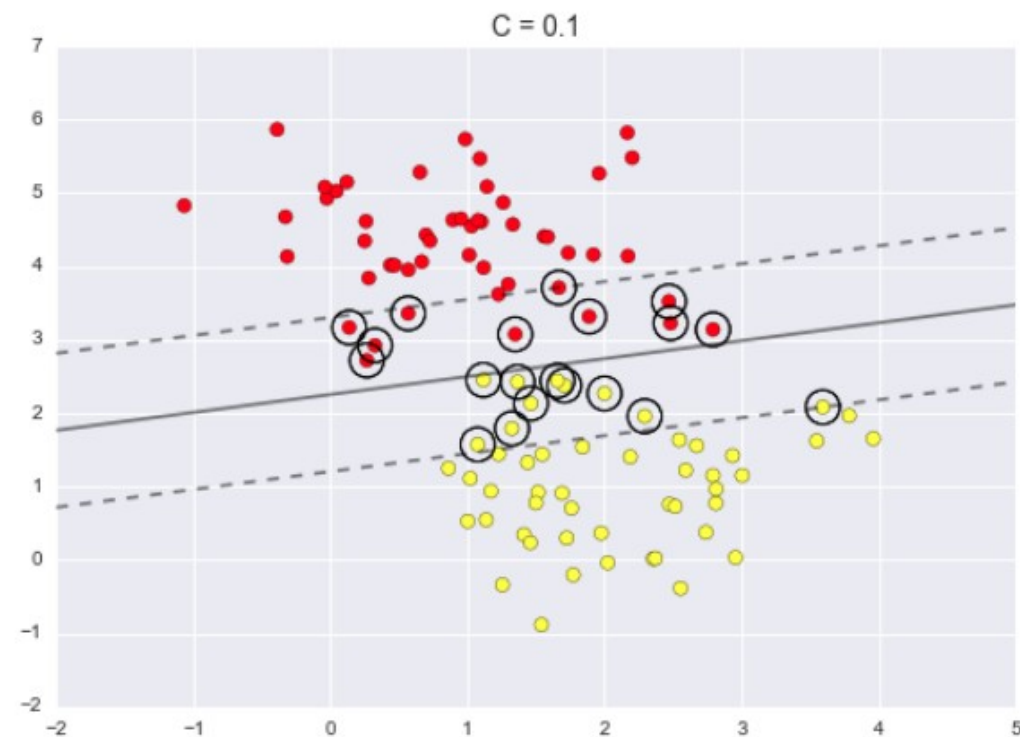
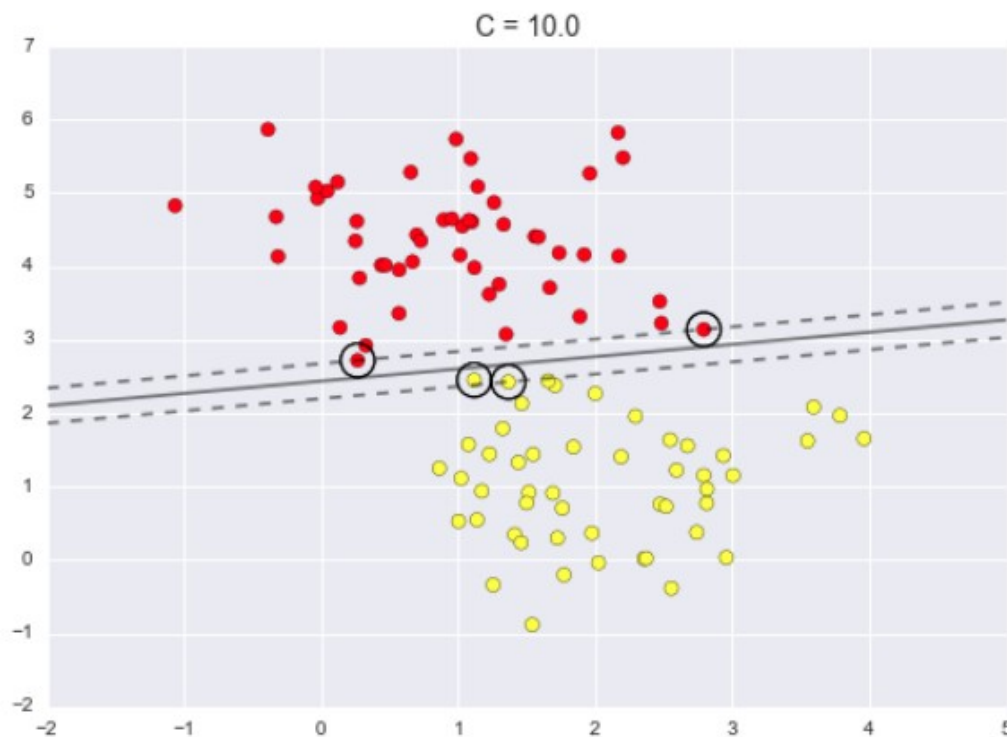


SVM Master

GitHub, Colab: [05.07-Support-Vector-Machines.ipynb](#)

Python Data Science Handbook by Jake VanderPlas, 2018

Softening Margins: `model = SVC(kernel='linear', C=C).fit(X, y)`

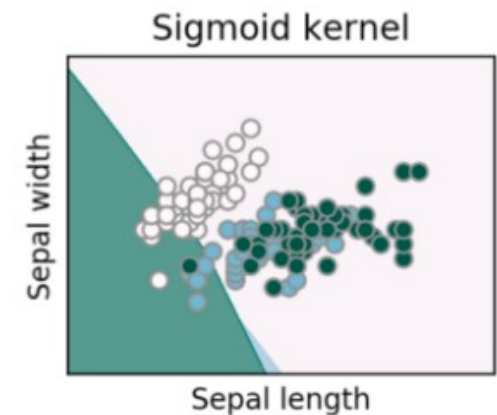
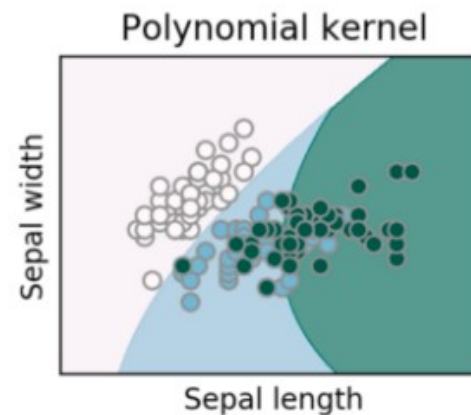
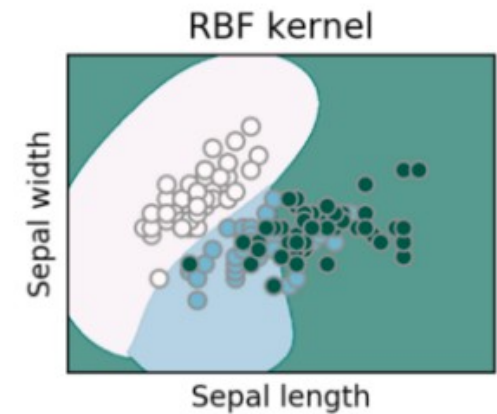
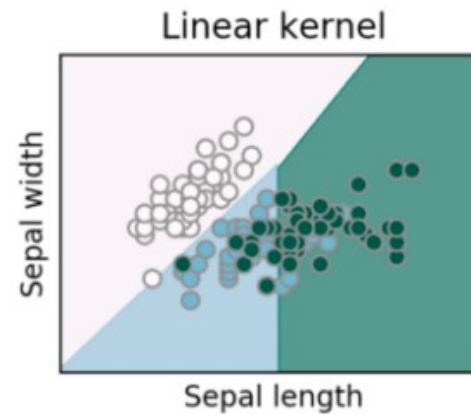


Multiclass SVM

[Multiclass Classification with Support Vector Machines \(SVM\), Dual Problem and Kernel Functions](#)

Towards data science, Hucker Marius. Jun. 8. 2020

```
linear = svm.SVC(kernel='linear', C=1,  
decision_function_shape='ovo').fit(X_train, y_train)  
rbf = svm.SVC(kernel='rbf', gamma=1, C=1,  
decision_function_shape='ovo').fit(X_train, y_train)  
poly = svm.SVC(kernel='poly', degree=3, C=1,  
decision_function_shape='ovo').fit(X_train, y_train)  
sig = svm.SVC(kernel='sigmoid', C=1,  
decision_function_shape='ovo').fit(X_train, y_train)
```



SVM – Kernel Trick

[What is the kernel trick? Why is it important?](#)

Medium.com, Grace Zhang, Nov 11, 2018

$$\phi(\mathbf{x}) = (x_1^2, x_1x_2, x_1x_3, x_2x_1, x_2^2, x_2x_3, x_3x_1, x_3x_2, x_3^2)^T$$

$$\phi(\mathbf{y}) = (y_1^2, y_1y_2, y_1y_3, y_2y_1, y_2^2, y_2y_3, y_3y_1, y_3y_2, y_3^2)^T$$

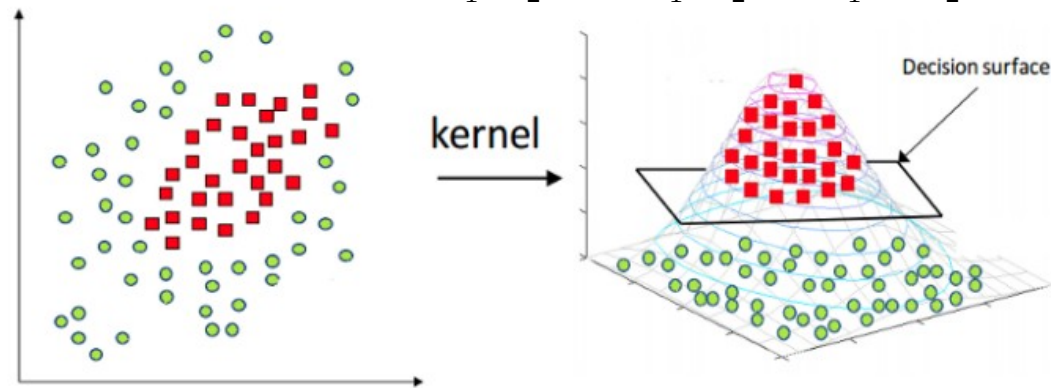
$$\phi(\mathbf{x})^T \phi(\mathbf{y}) = \sum_{i,j=1}^3 x_i x_j y_i y_j$$

$$\begin{aligned} k(\mathbf{x}, \mathbf{y}) &= (\mathbf{x}^T \mathbf{y})^2 \\ &= (x_1 y_1 + x_2 y_2 + x_3 y_3)^2 \\ &= \sum_{i,j=1}^3 x_i x_j y_i y_j \end{aligned}$$

$O(n^2)$

$$(x_1, x_2) \rightarrow (x_1, x_2, \phi(x_1, x_2))$$

$$\text{e.g., } (x_1, x_2) \rightarrow (x_1, x_2, 1/(x_1^2 + x_2^2))$$



$O(n)$.

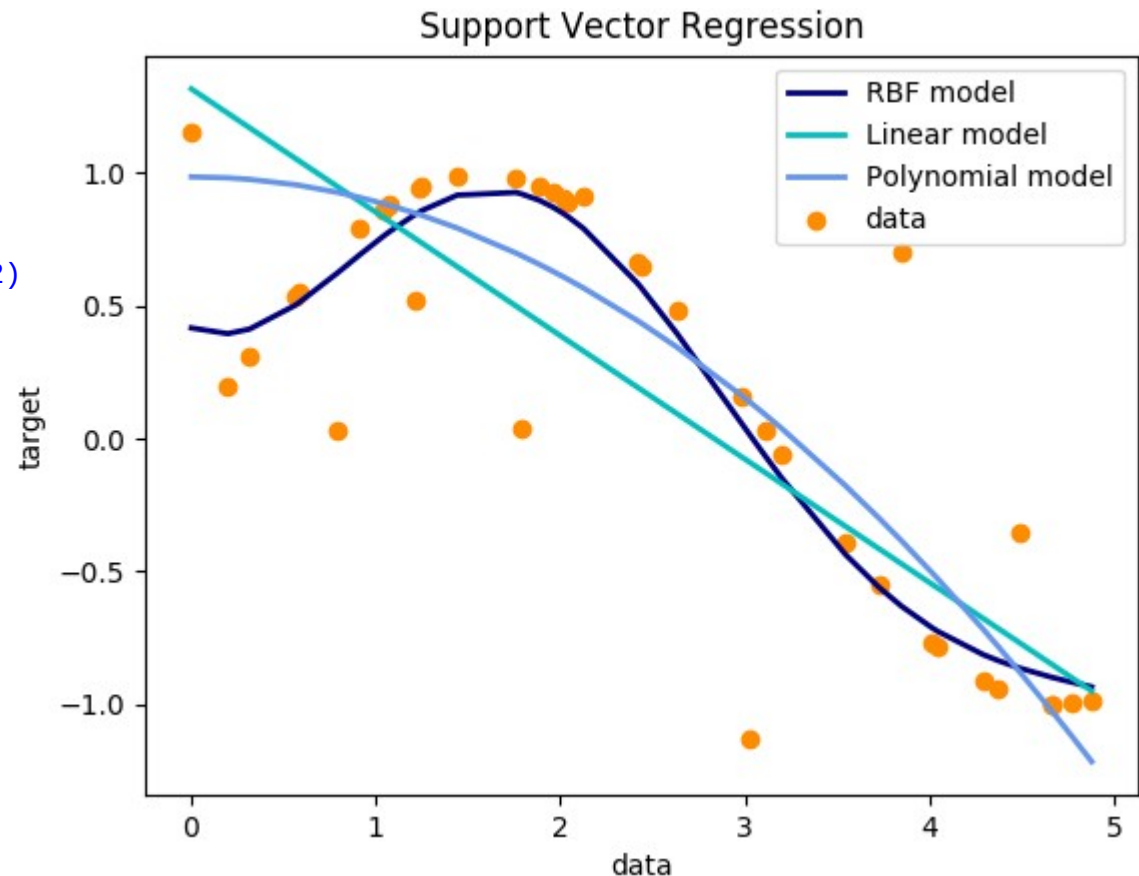
SVR – Support Vector Regression

[Support Vector Regression \(SVR\) using linear and non-linear kernel](#)
[S](#)

Scikit-learn v0.20.20

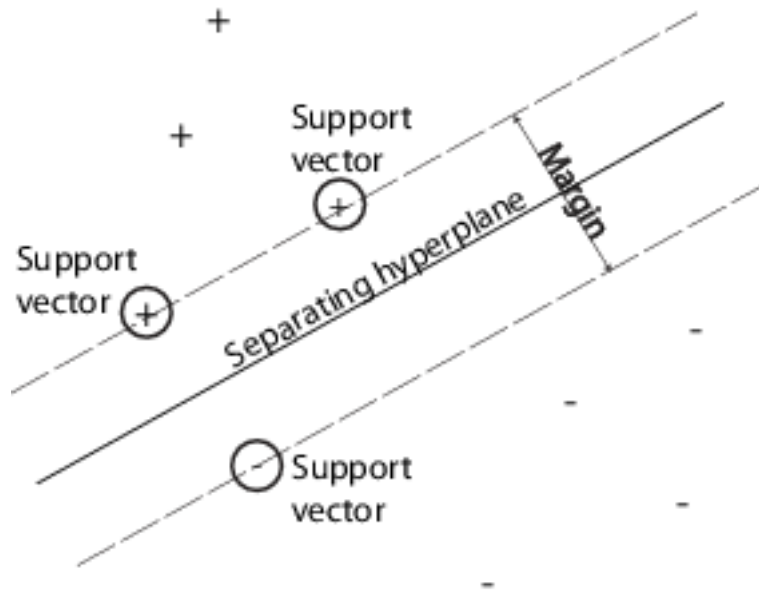
```
svr_rbf = SVR(kernel='rbf', C=1e3, gamma=0.1)
svr_lin = SVR(kernel='linear', C=1e3)
svr_poly = SVR(kernel='poly', C=1e3, degree=2)

y_rbf = svr_rbf.fit(X, y).predict(X)
y_lin = svr_lin.fit(X, y).predict(X)
y_poly = svr_poly.fit(X, y).predict(X)
```



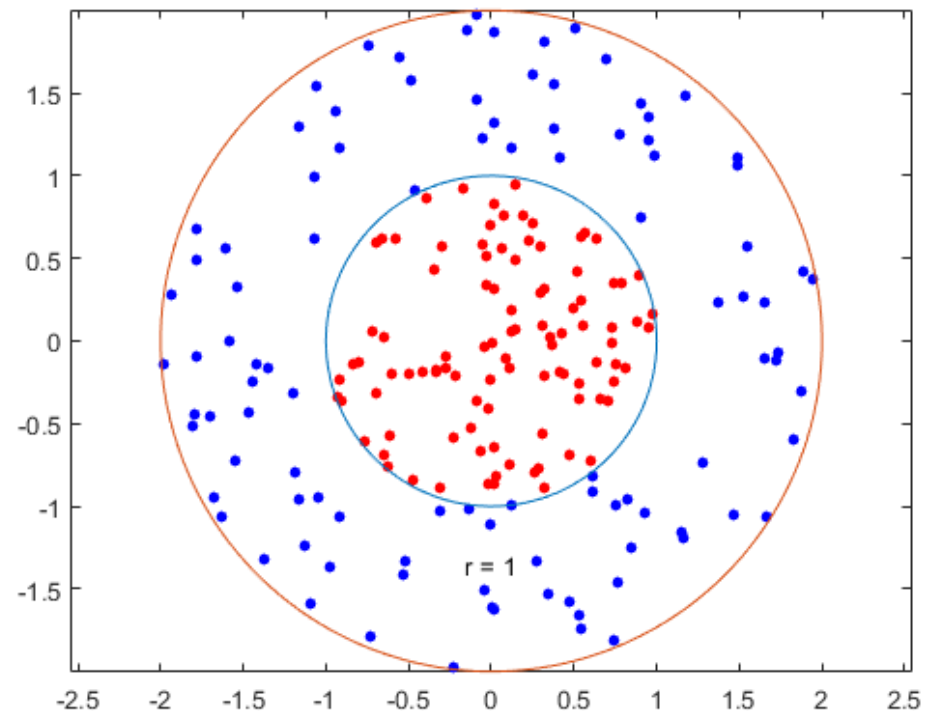
SVM – Support Vector Machine

Linear Separable Classes



Optimality –
Maximum margin to the Separating Hyperplane

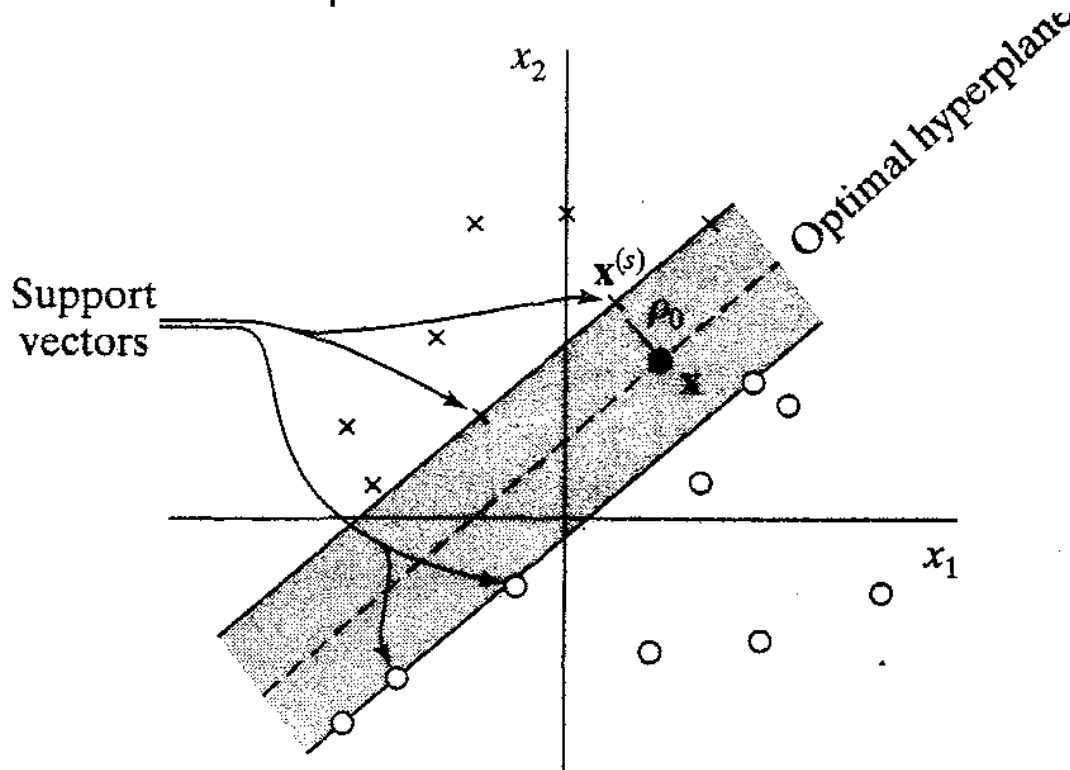
Non Linear Separable Classes



Features transformation – $K(x,y) = \langle \phi(x), \phi(y) \rangle$
Linear in the output space!

SVM – Support Vector Machine

Linear Separable Classes



Classes

$$\mathbf{w}^T \mathbf{x}_i + b \geq 0 \quad \text{for } d_i = +1$$

$$\mathbf{w}^T \mathbf{x}_i + b < 0 \quad \text{for } d_i = -1$$

Optimal hyperplane

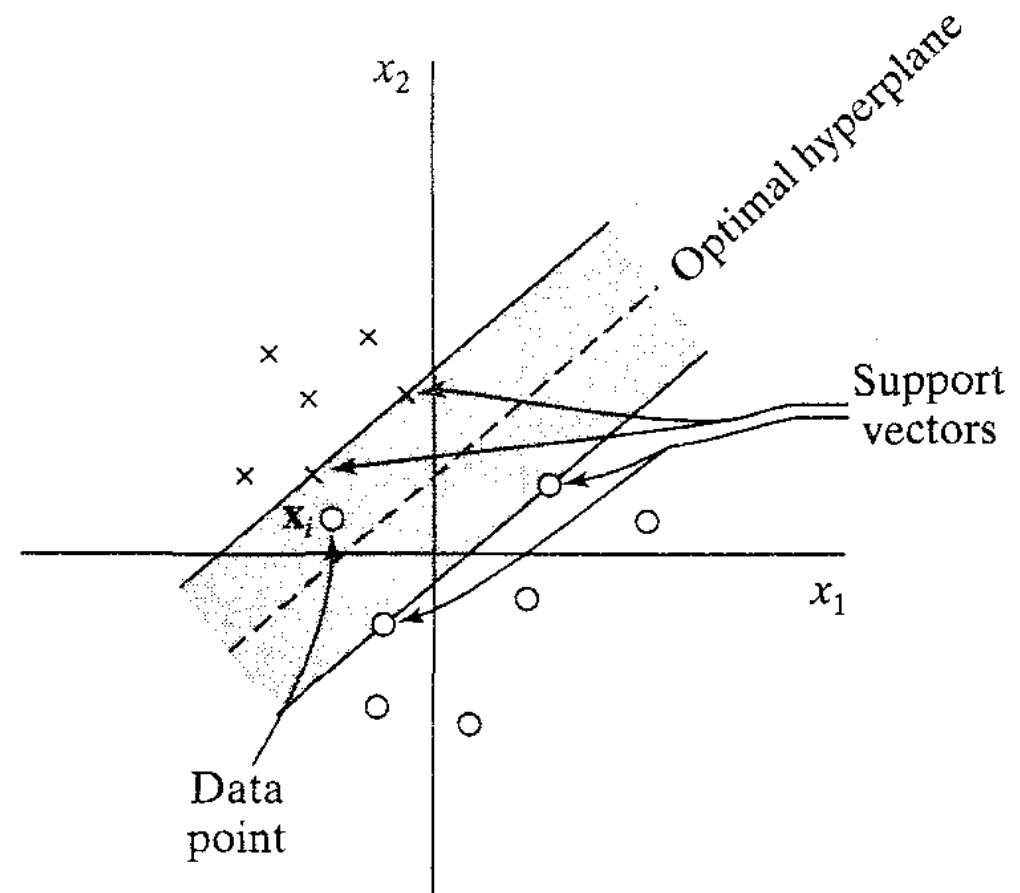
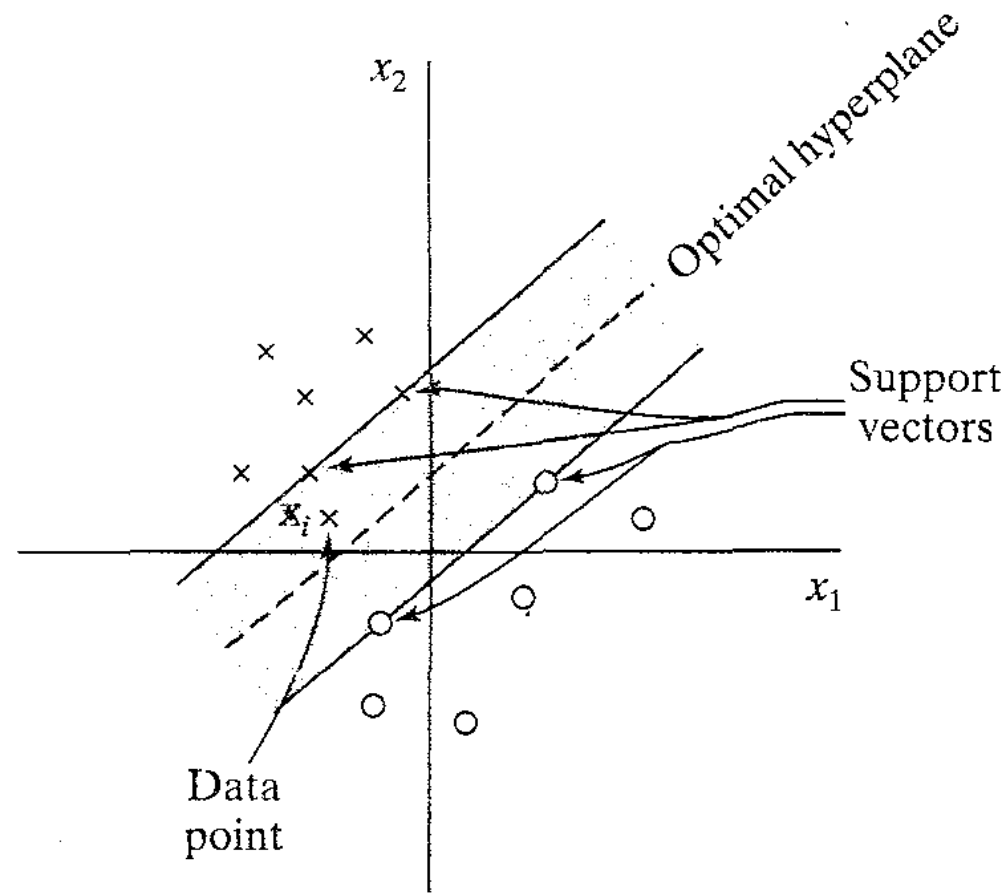
$$\mathbf{w}_0^T \mathbf{x} + b_0 = 0$$

Distance to the optimal hyperplane

$$g(\mathbf{x}) = \mathbf{w}_0^T \mathbf{x} + b_0$$

Optimality –
Maximum margin to the Separating Hyperplane

SVM for non separable patterns



SVM for pattern recognition – feature space

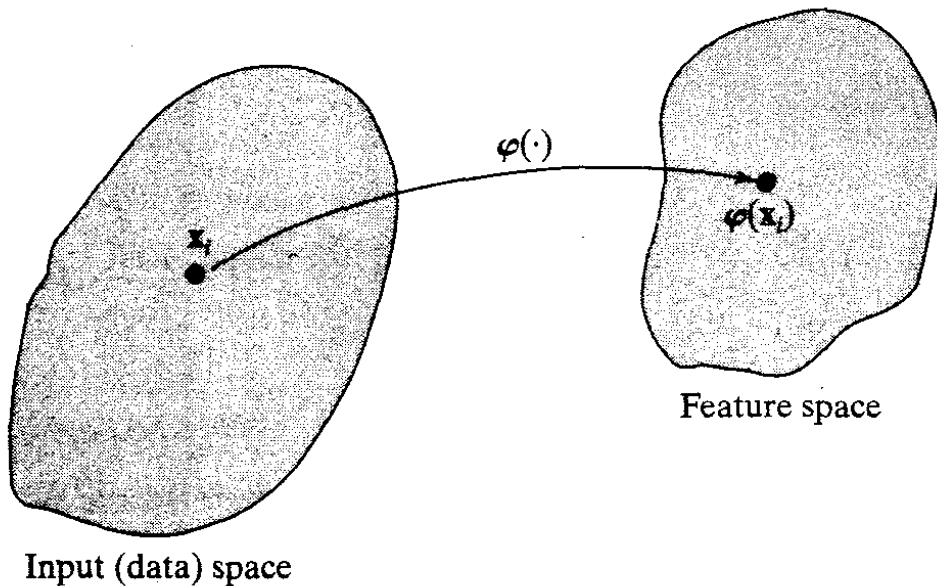
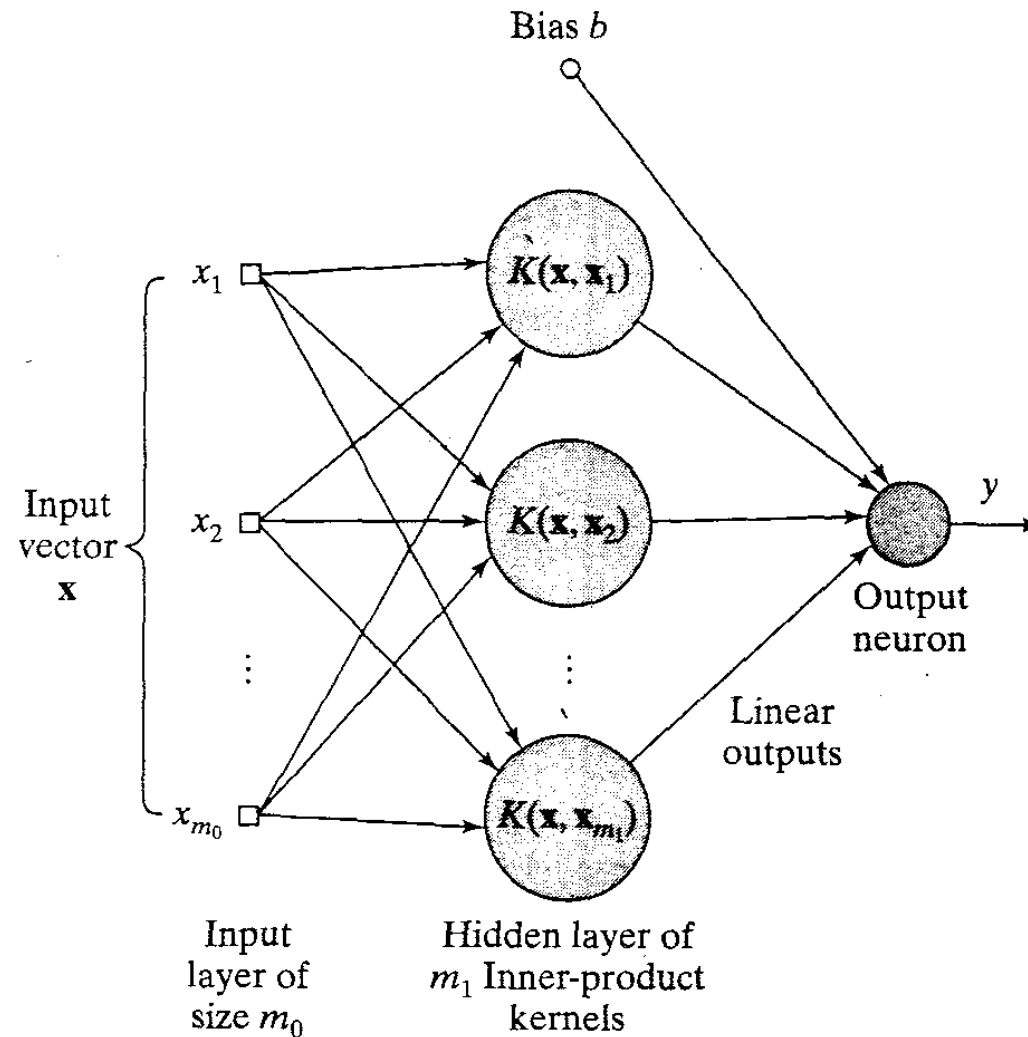


TABLE 6.1 Summary of Inner-Product Kernels

Type of support vector machine	Inner product kernel $K(\mathbf{x}, \mathbf{x}_i), i = 1, 2, \dots, N$
Polynomial learning machine	$(\mathbf{x}^T \mathbf{x}_i + 1)^p$
Radial-basis function network	$\exp\left(-\frac{1}{2\sigma^2} \ \mathbf{x} - \mathbf{x}_i\ ^2\right)$
Two-layer perceptron	$\tanh(\beta_0 \mathbf{x}^T \mathbf{x}_i + \beta_1)$

Architecture of a SVM



X-Or using SVM

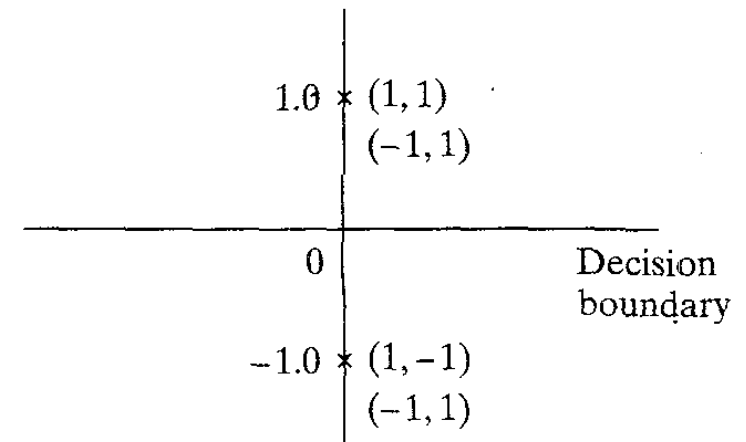
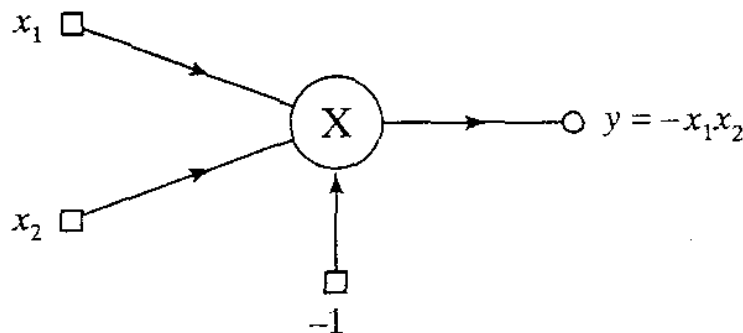
TABLE 6.2 XOR Problem

Input vector, \mathbf{x}	Desired response, d
$(-1, -1)$	-1
$(-1, +1)$	$+1$
$(+1, -1)$	$+1$
$(+1, +1)$	-1

$$K(\mathbf{x}, \mathbf{x}_i) = (1 + \mathbf{x}^T \mathbf{x}_i)^2$$

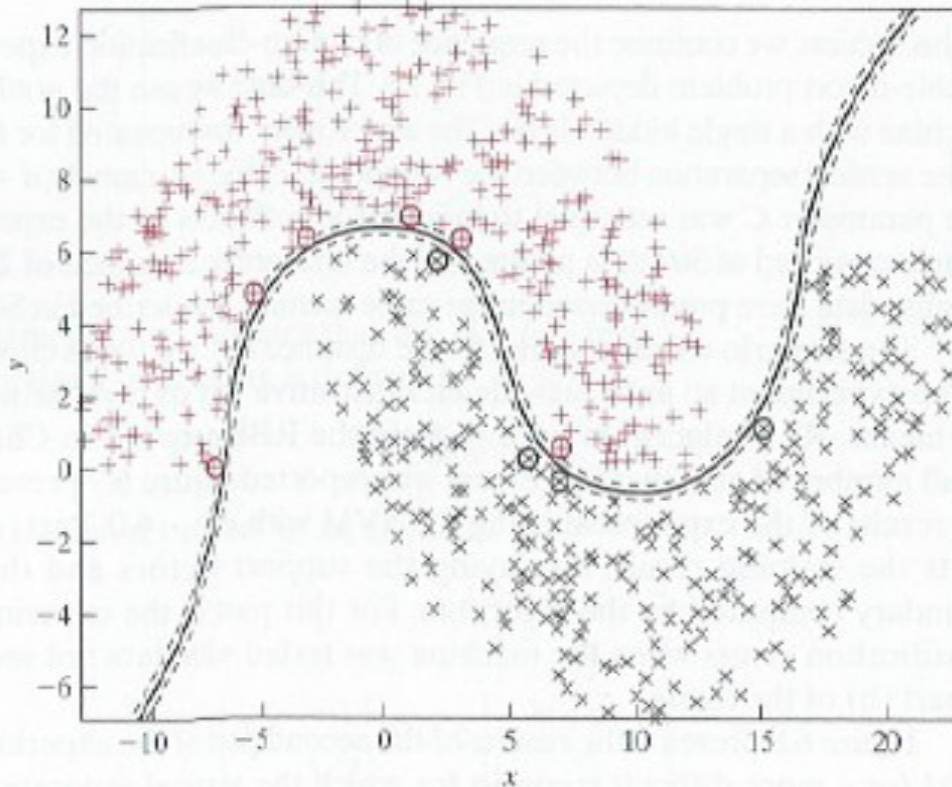
$$K(\mathbf{x}, \mathbf{x}_i) = 1 + x_1^2 x_{i1}^2 + 2x_1 x_2 x_{i1} x_{i2} + x_2^2 x_{i2}^2 + 2x_1 x_{i1} + 2x_2 x_{i2}$$

$$\varphi(\mathbf{x}) = [1, x_1^2, \sqrt{2}x_1 x_2, x_2^2, \sqrt{2}x_1, \sqrt{2}x_2]^T$$



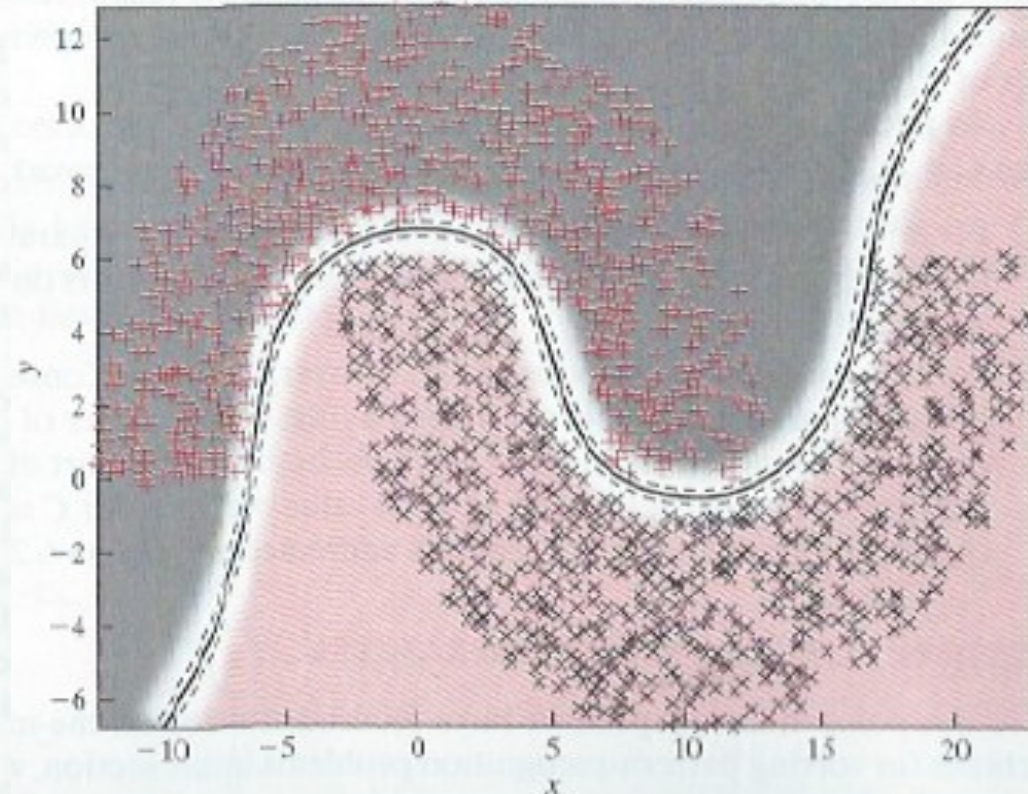
SVM 'Double Moon' classification

Classification using SVM with distance = -6, radius = 10, and width = 6



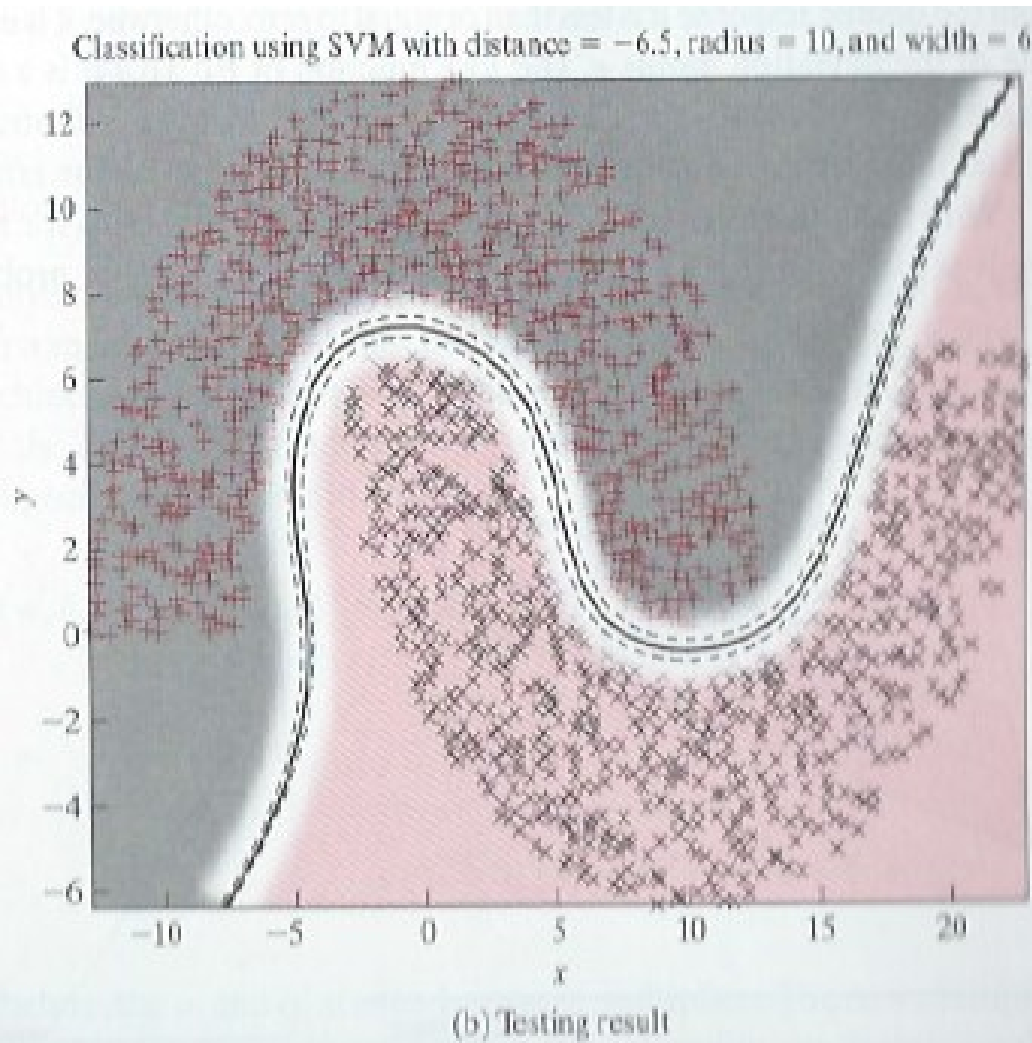
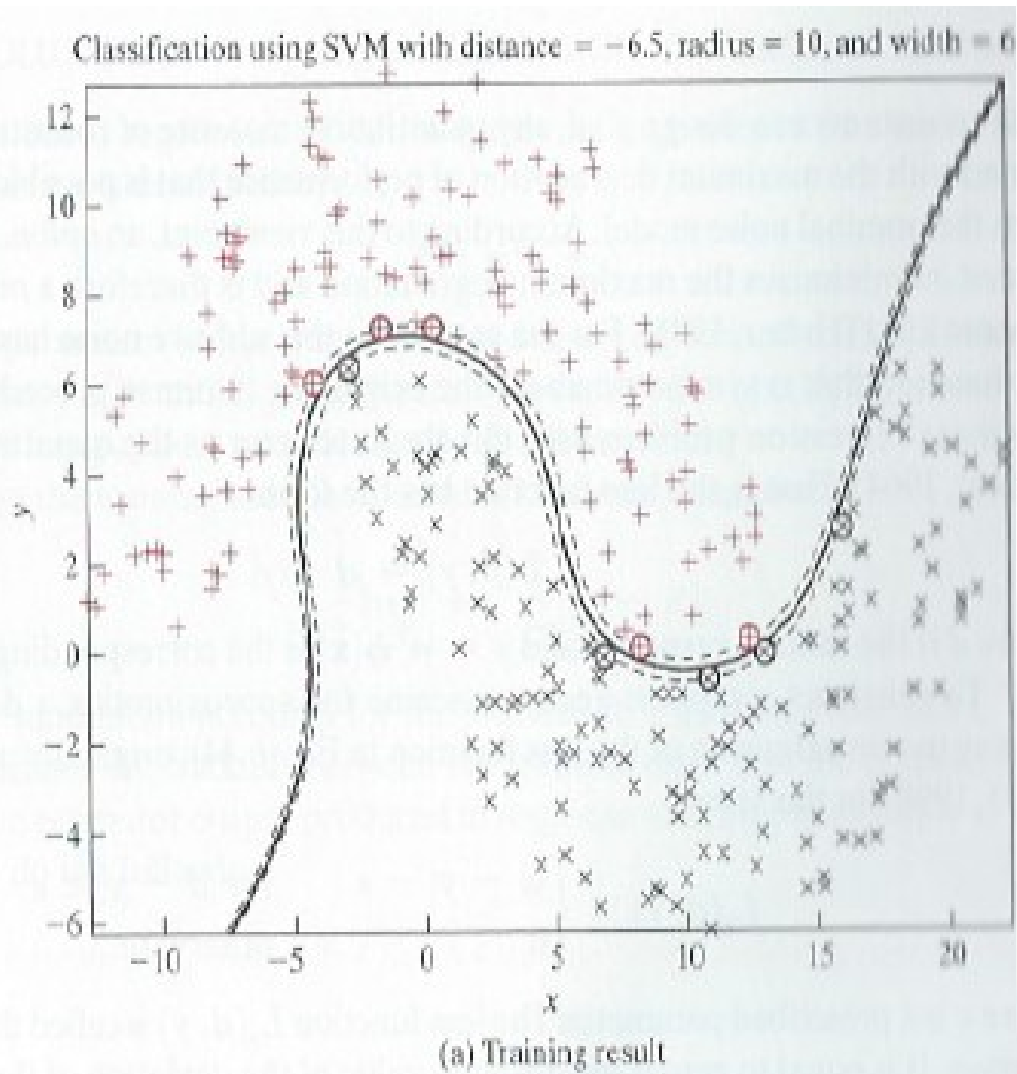
(a) Training result

Classification using SVM with distance = -6, radius = 10, and width = 6



(b) Testing result

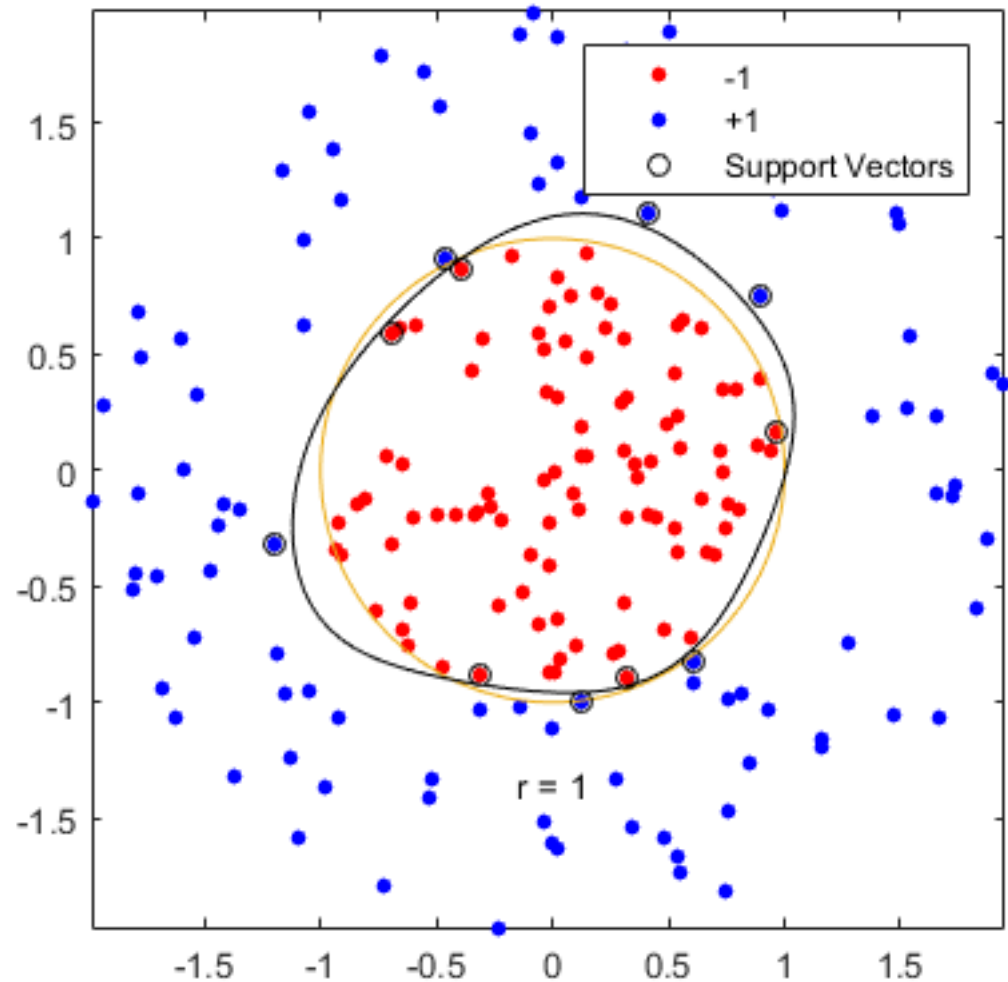
SVM 'Double Moon' classification



Train the SVM Classifier

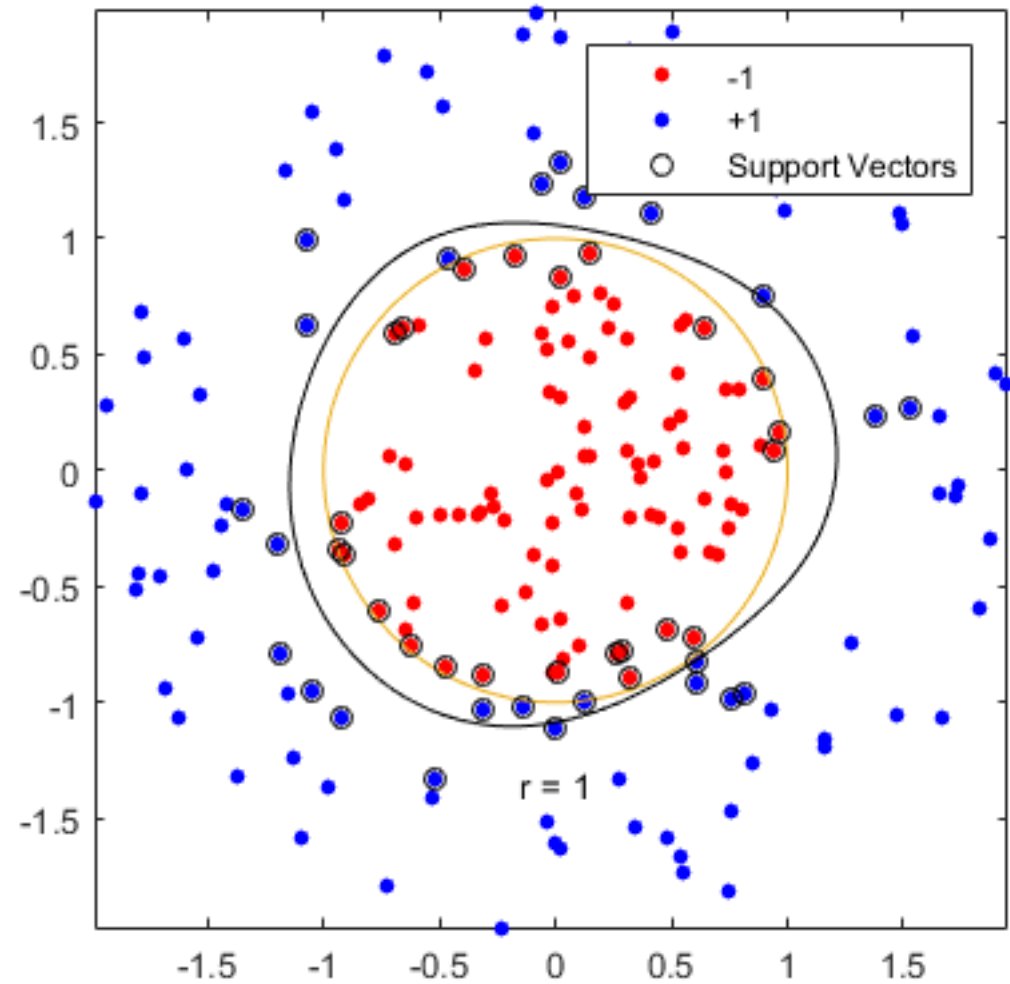
```
cl = fitcsvm(data3,theclass,'KernelFunction','rbf',...  
            'BoxConstraint',Inf,'ClassNames',[-1,1]);
```

```
data3 = [data1;data2];  
theclasse = ones(200,1);  
theclasse(1:100) = -1;
```



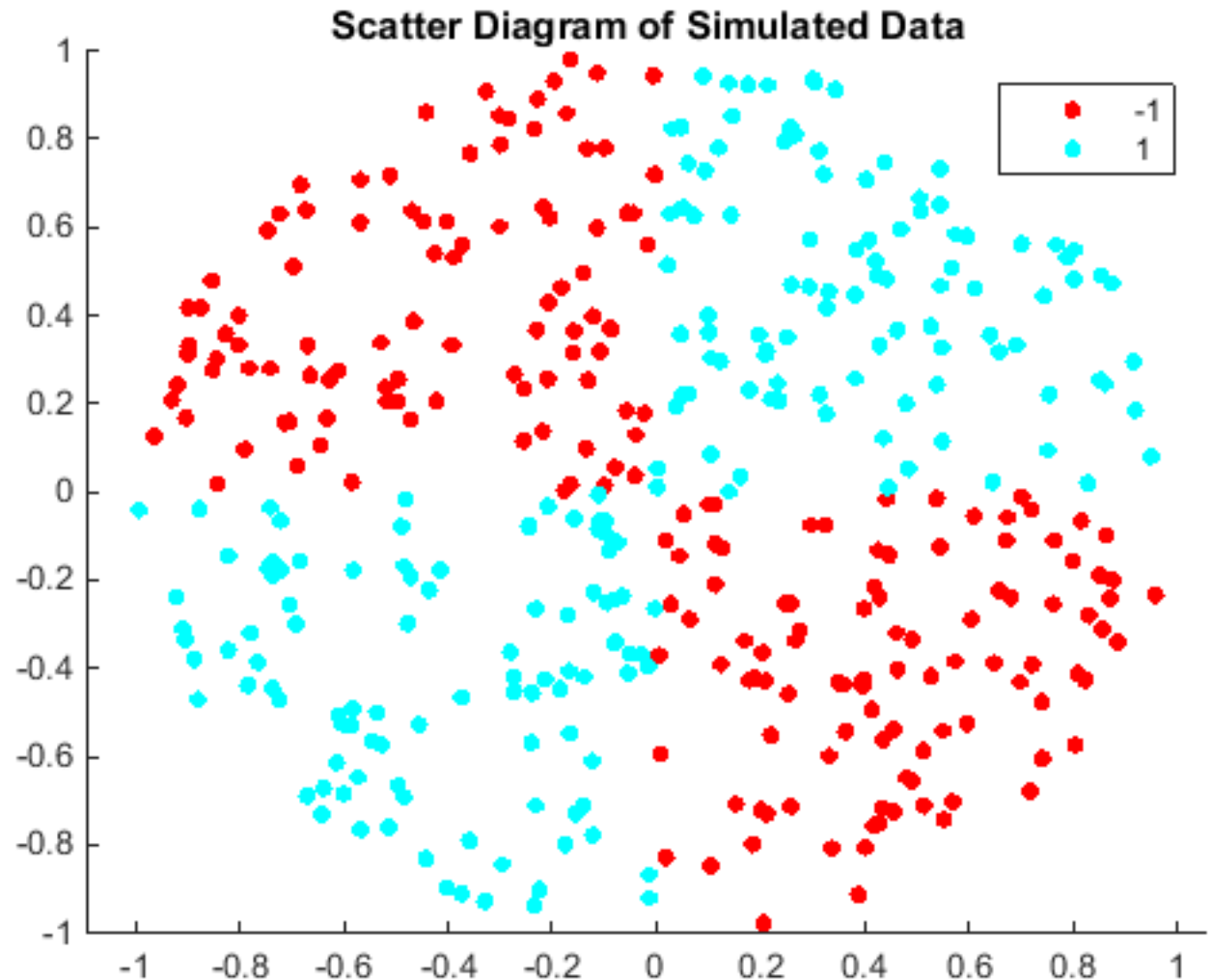
SVM

Training with the default parameters makes a more nearly circular classification boundary, but one that misclassifies some training data. Also, the default value of BoxConstraint is 1, and, therefore, there are more support vectors.

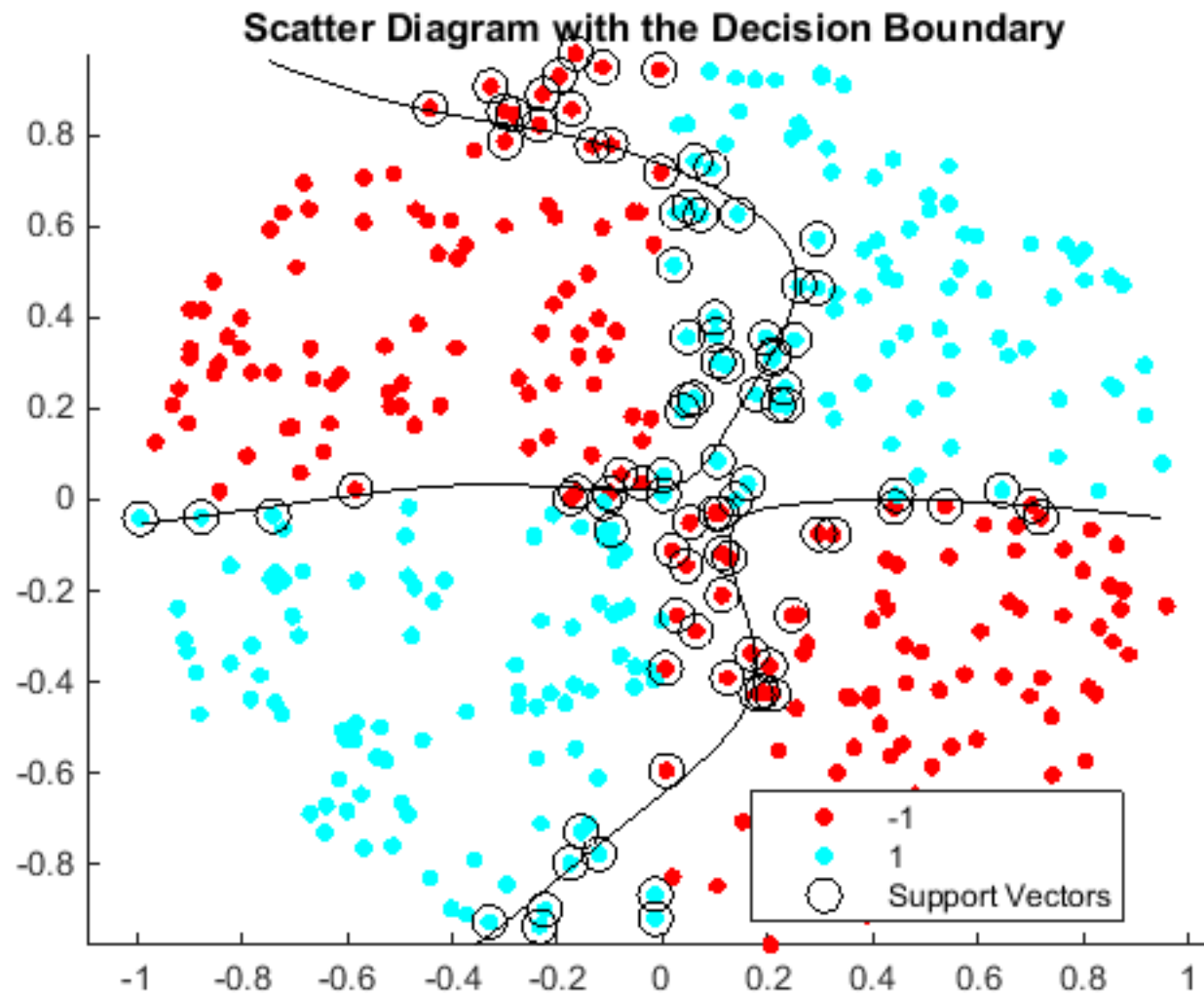


SVM

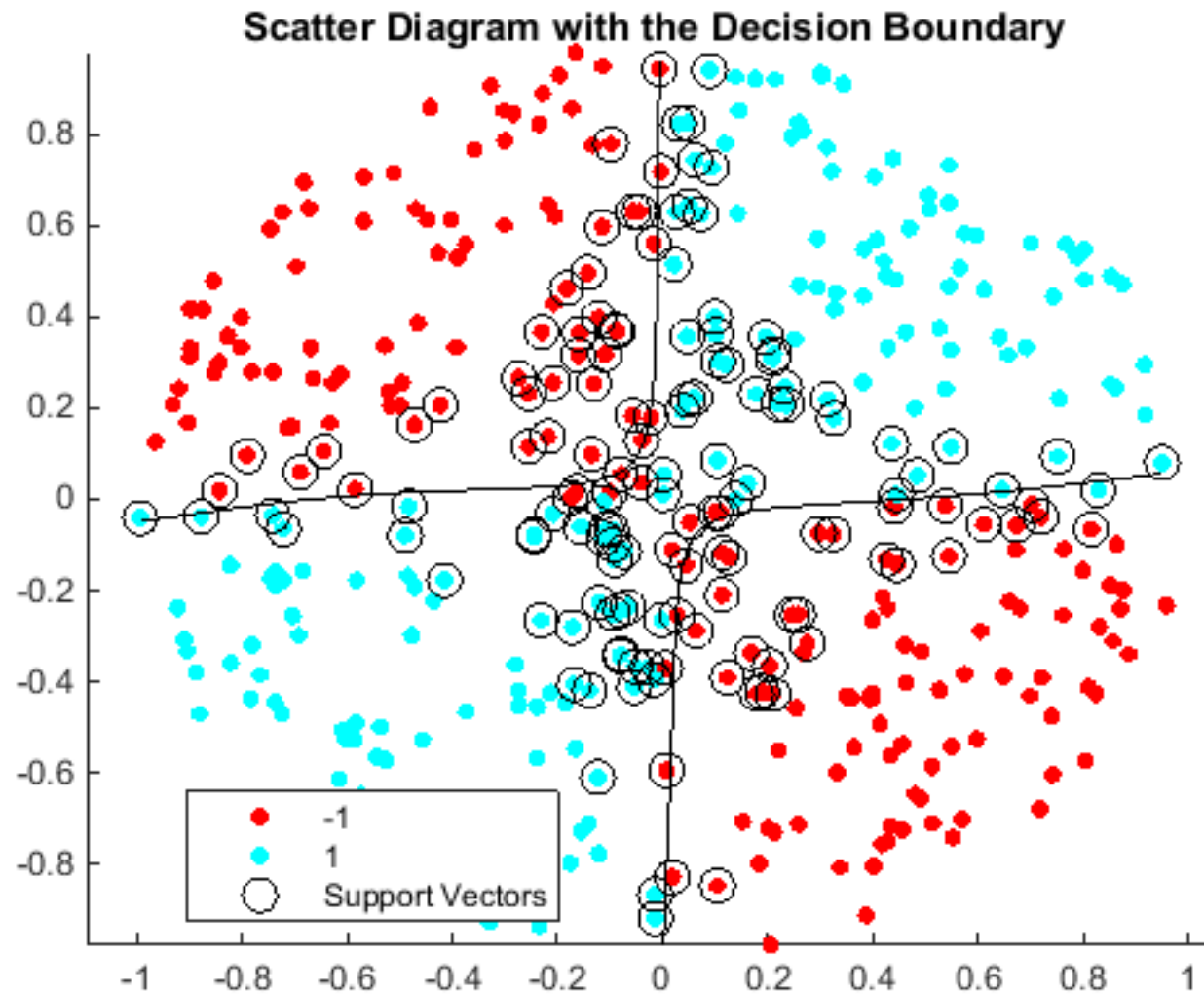
This example shows how to use a custom kernel function, such as the sigmoid kernel, to train SVM classifiers, and adjust custom kernel function parameters.



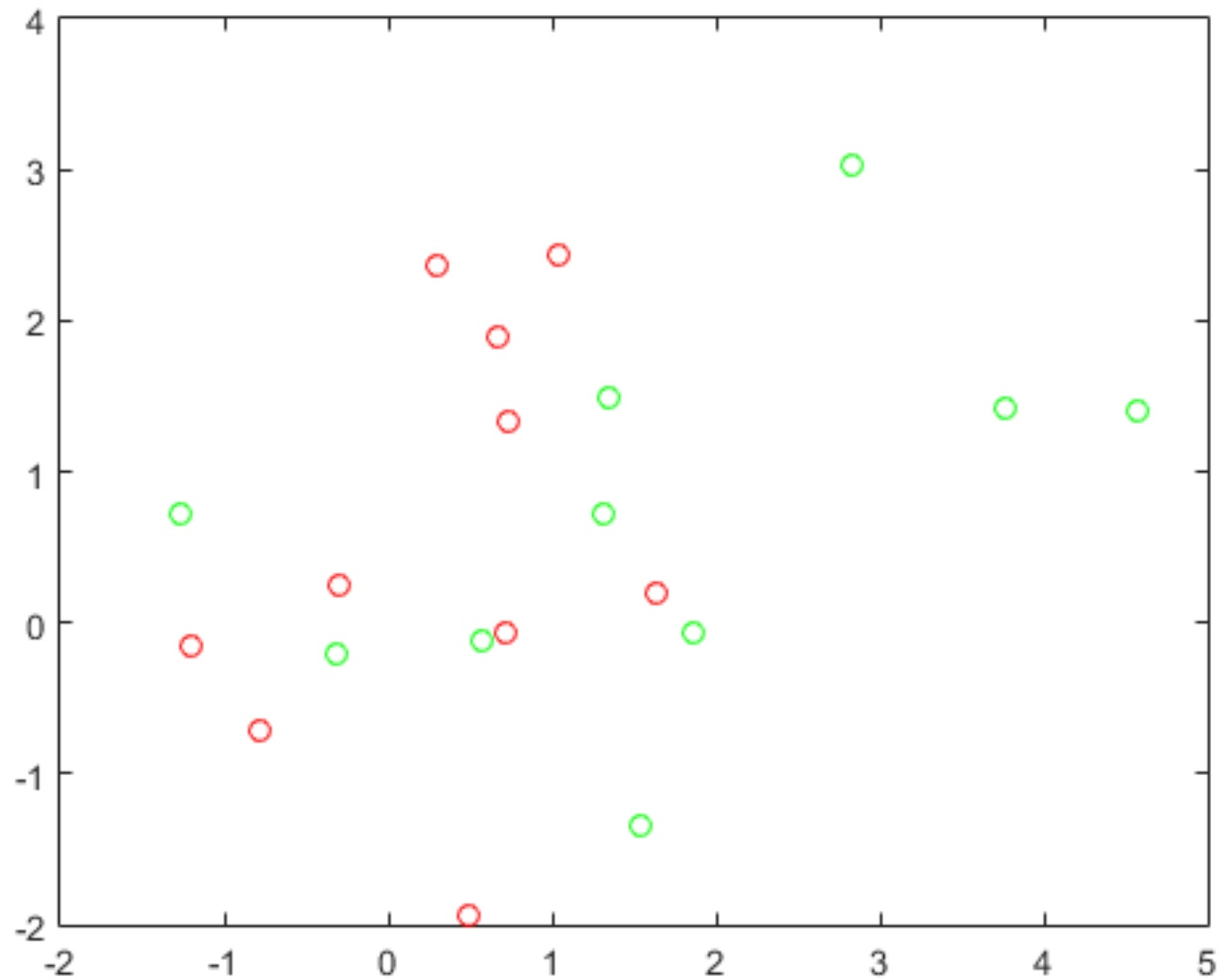
SVM



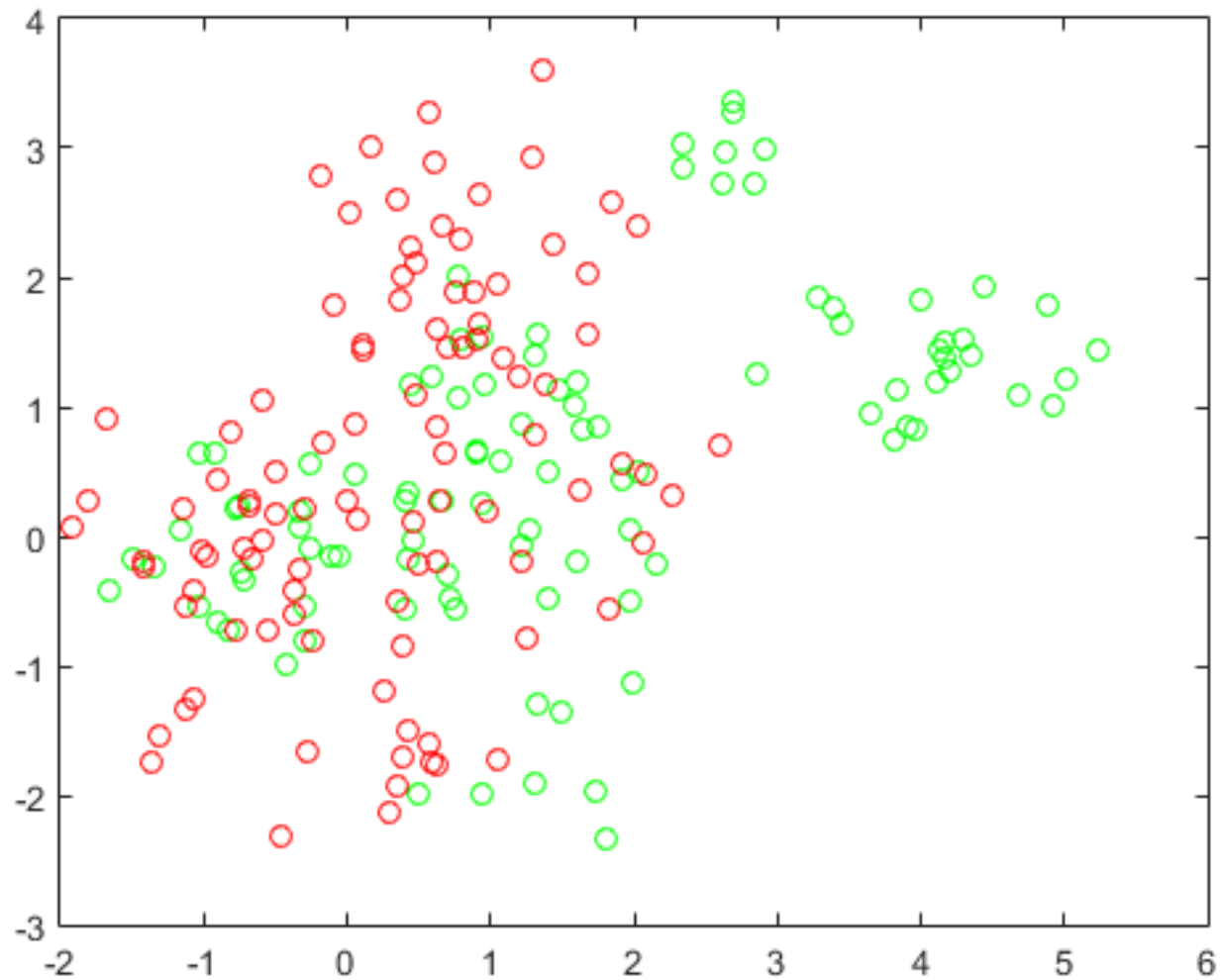
SVM



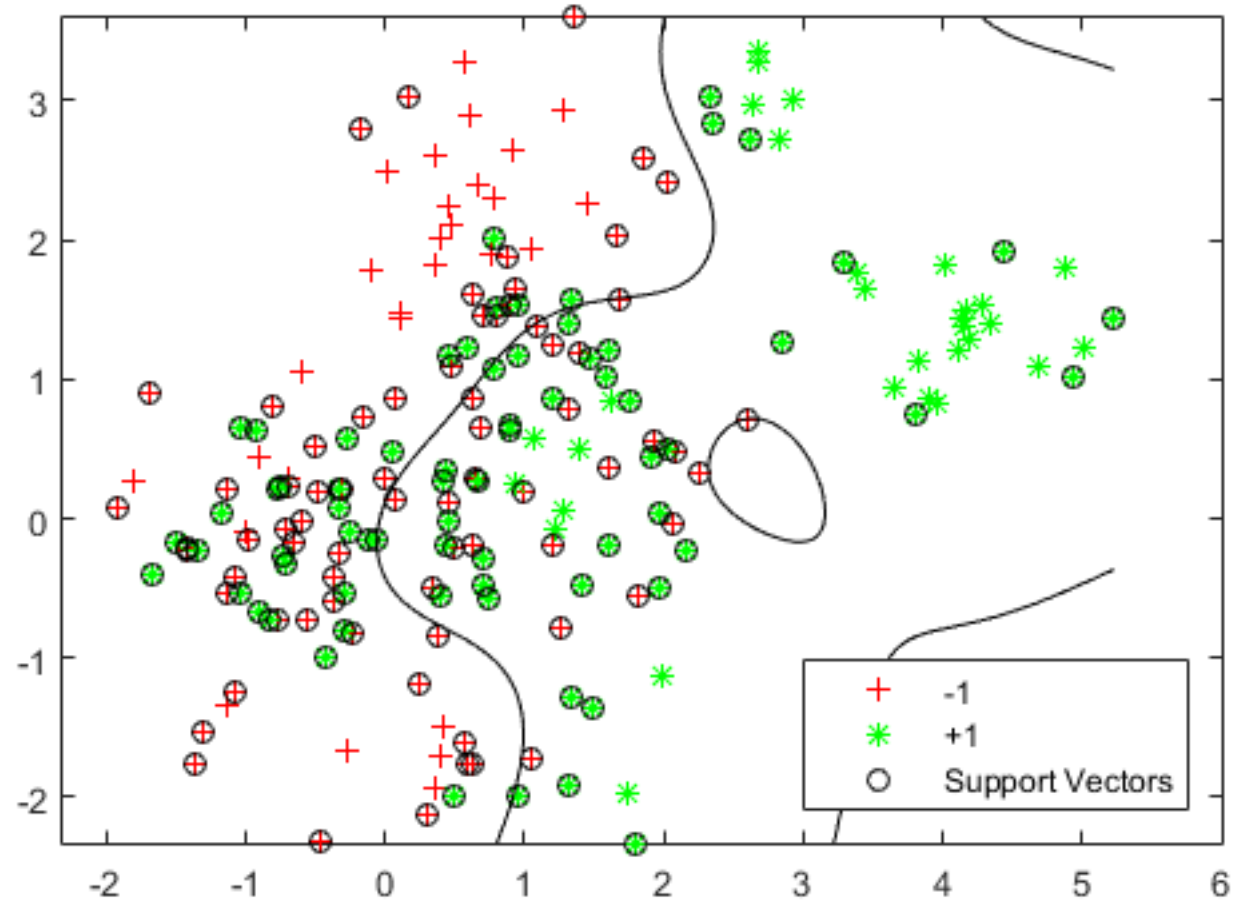
Train and Cross Validate SVM Classifiers



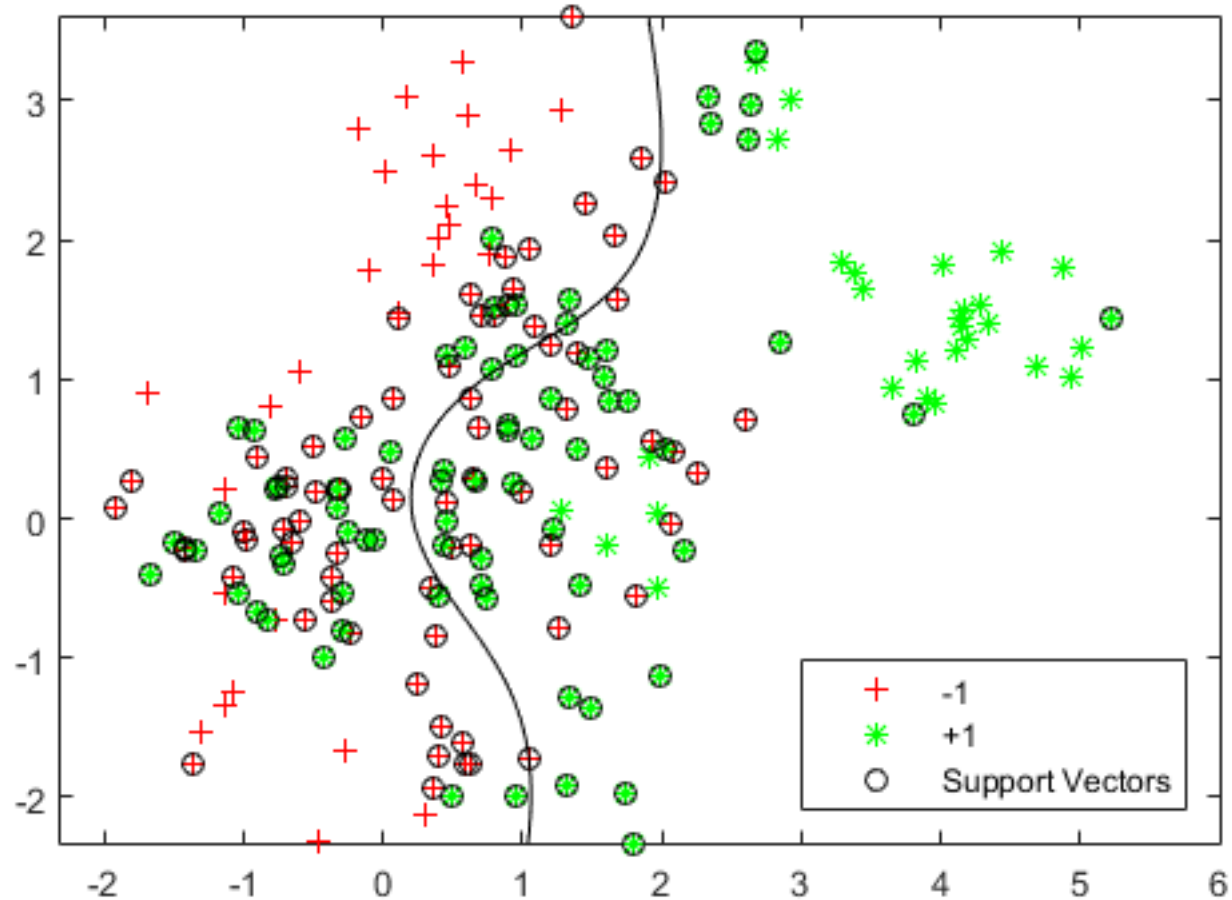
Train and Cross Validate SVM Classifiers



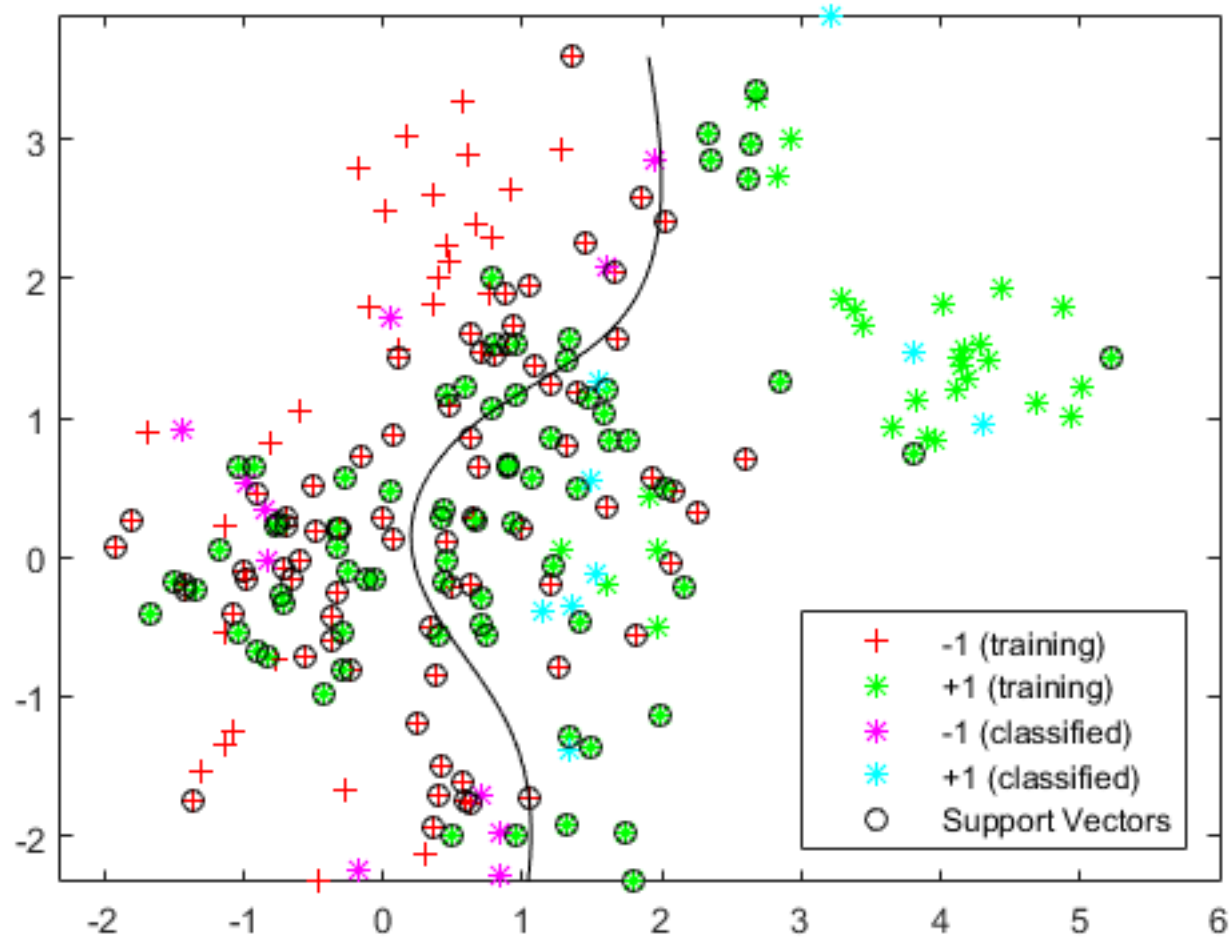
Train and Cross Validate SVM Classifiers



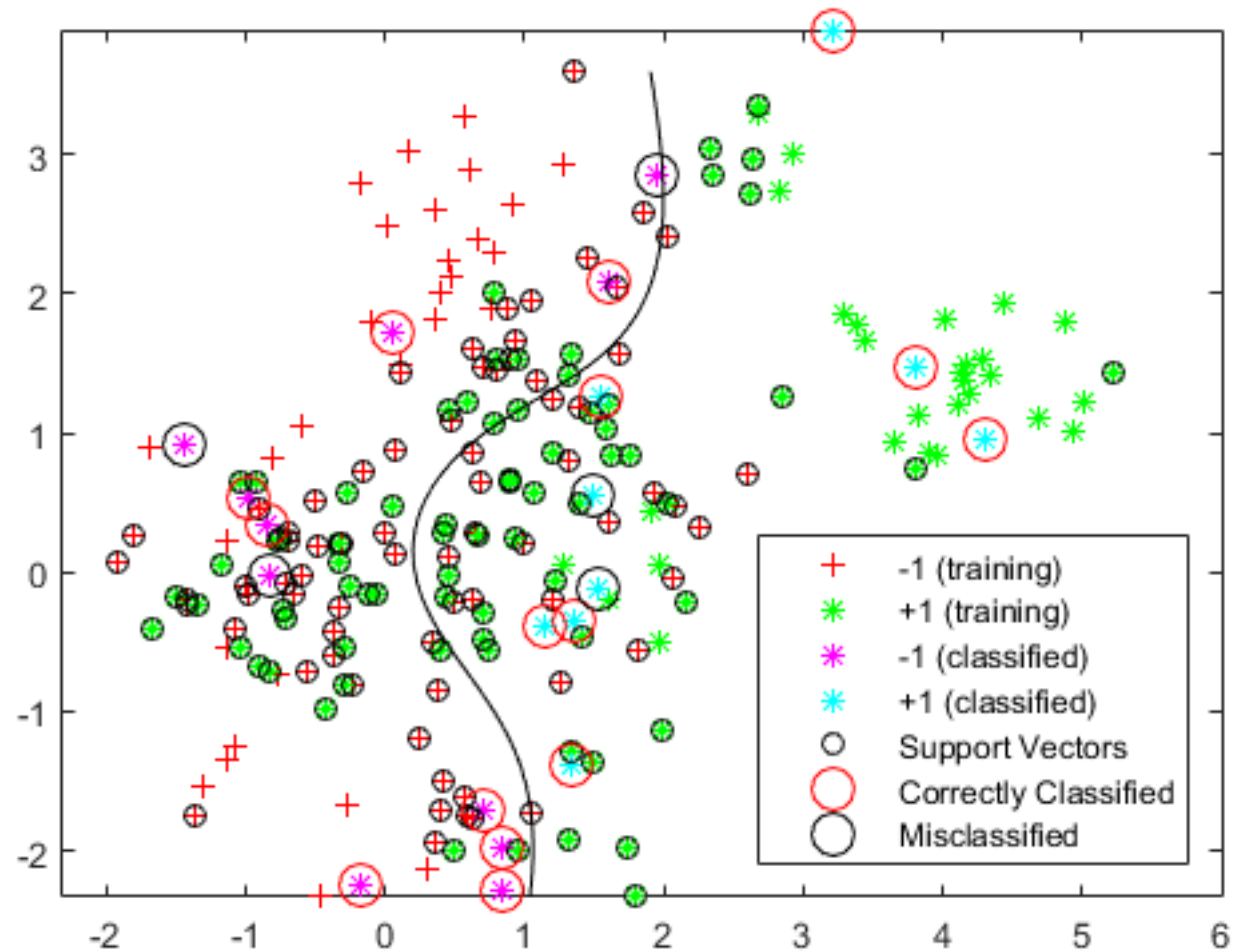
Train and Cross Validate SVM Classifiers



Train and Cross Validate SVM Classifiers



Train and Cross Validate SVM Classifiers



Indoor Localization

- **Indoor Localization**
- **Ambient Intelligence (Occupancy dependent services)**
- **Thermal Load Estimation**

Energy Efficiency

(mainly Air conditioning)

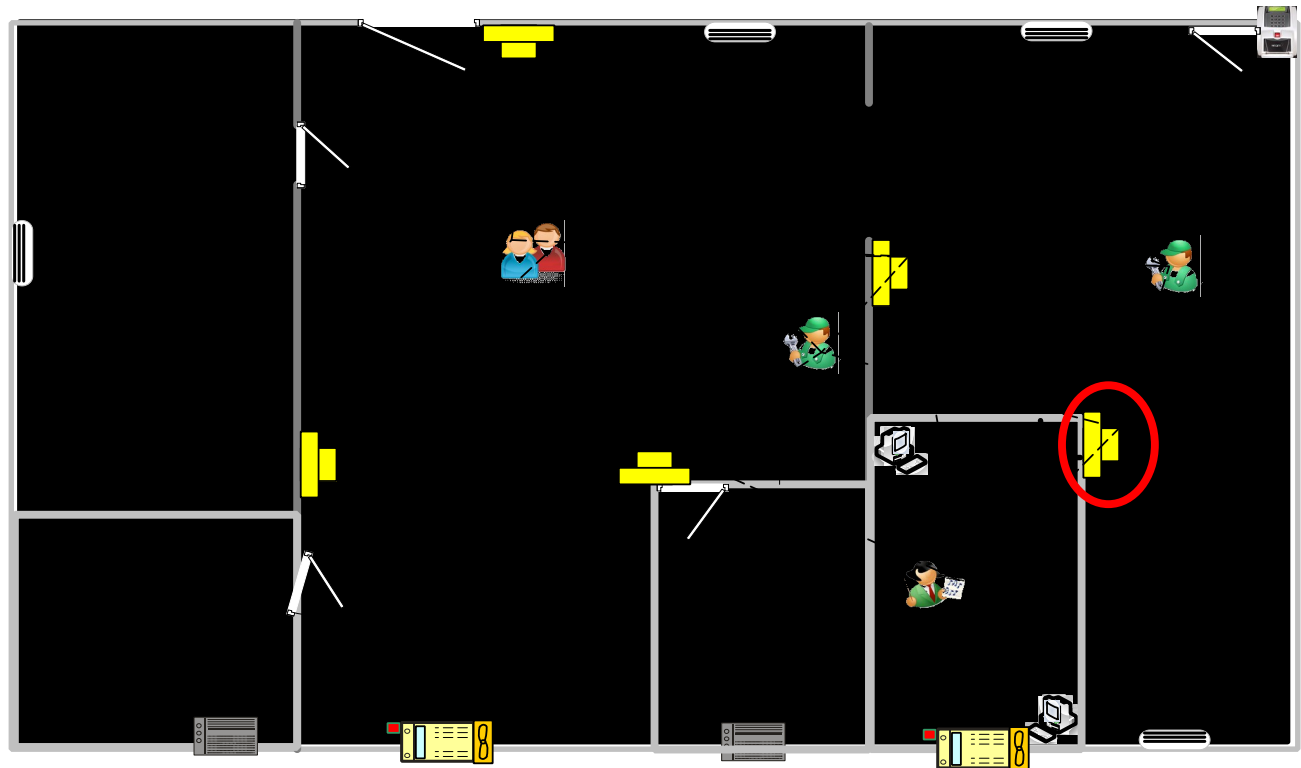
Credits:

Next slides are mainly based on:

- Lucas O. Fonseca, 2011, Sistema de Identificação de Usuários utilizando RFID para Racionalização de Energia em Ambientes Inteligentes.
- Gabriel Figueiró Oliveir e André Luiz Gama de Souza, 2011, Sistema de Localização para Robótica Móvel com RFID.
- Cristovam A. Silva Jr., 2012, Classificação de Ambientes Prediais para usuários utilizand tags RFID ativas e Filtro de Kalman.

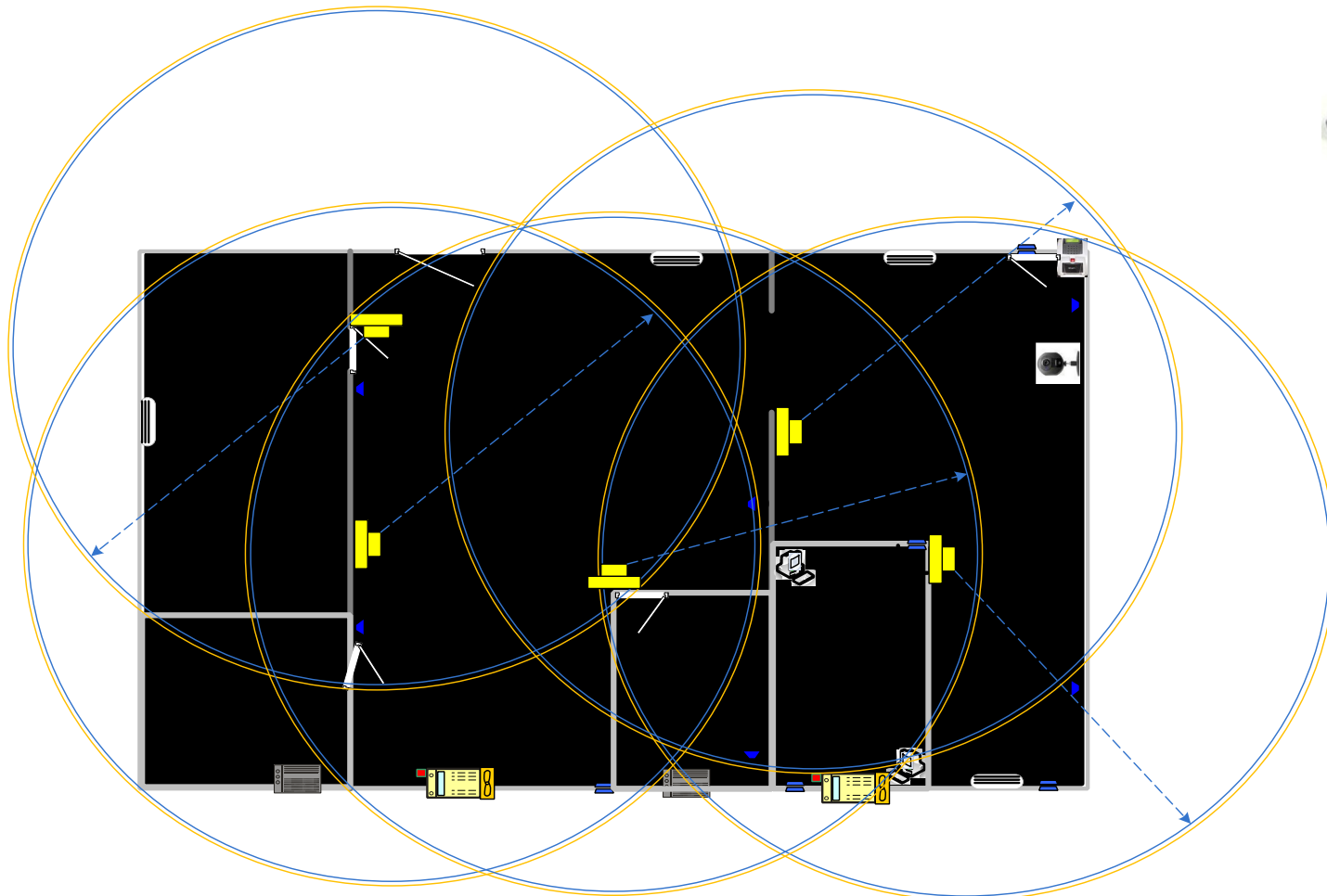
RFID occupancy identification

(GPS indoor) for thermal load estimation



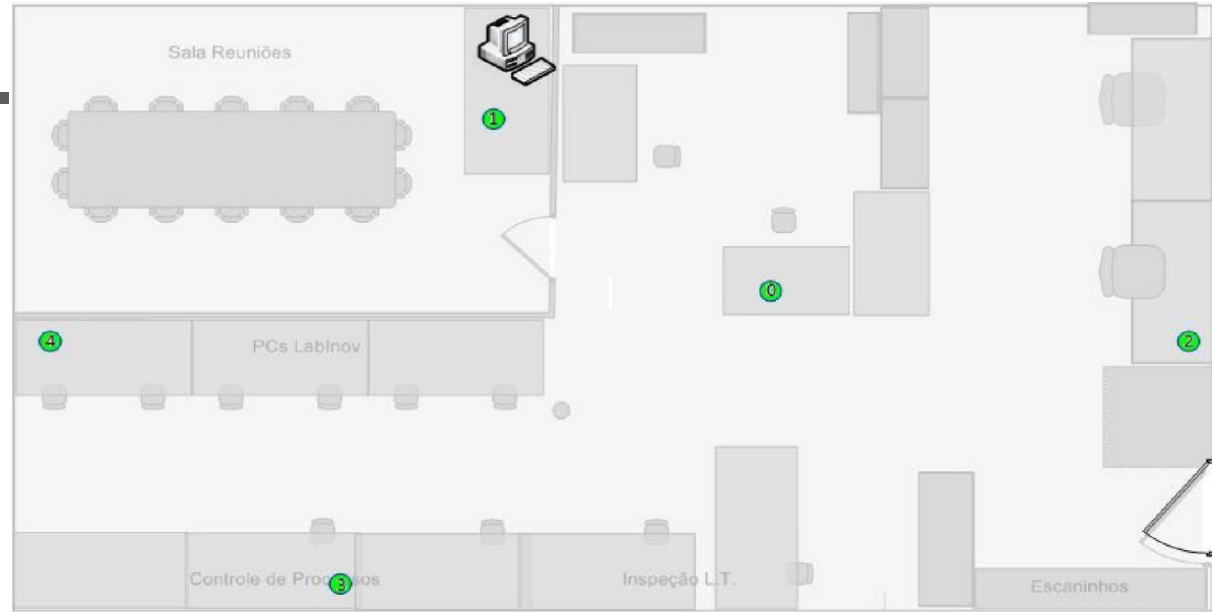
RFID occupancy identification

for thermal load estimation



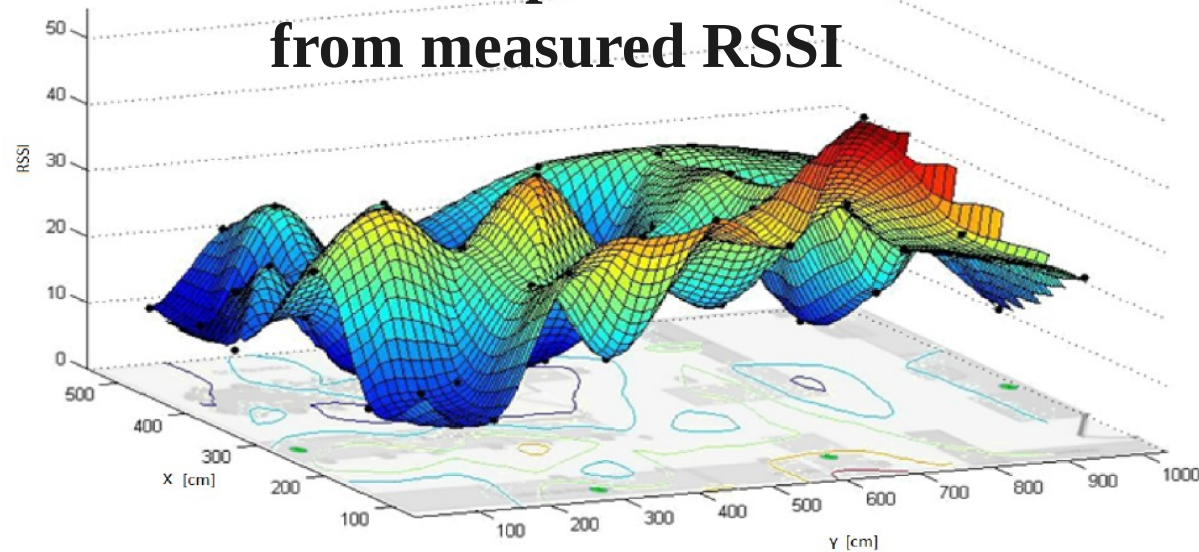
RFID

occupancy
identification
for thermal load
estimation



(Lucas Fonseca, 2011)

Interpolated
from measured RSSI

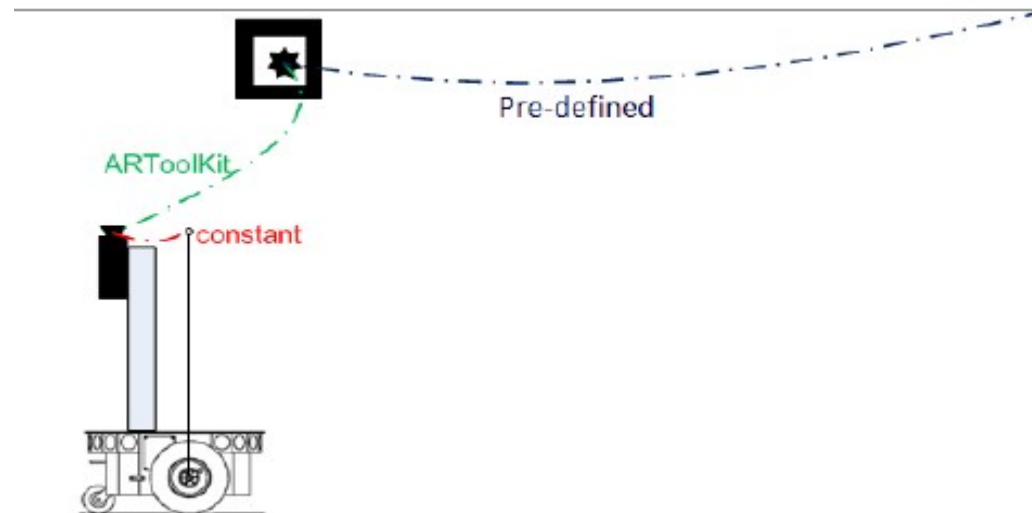


Indoor RFID Localization

in the Context of Mobile Robotics
with Application in Ambient
Intelligence



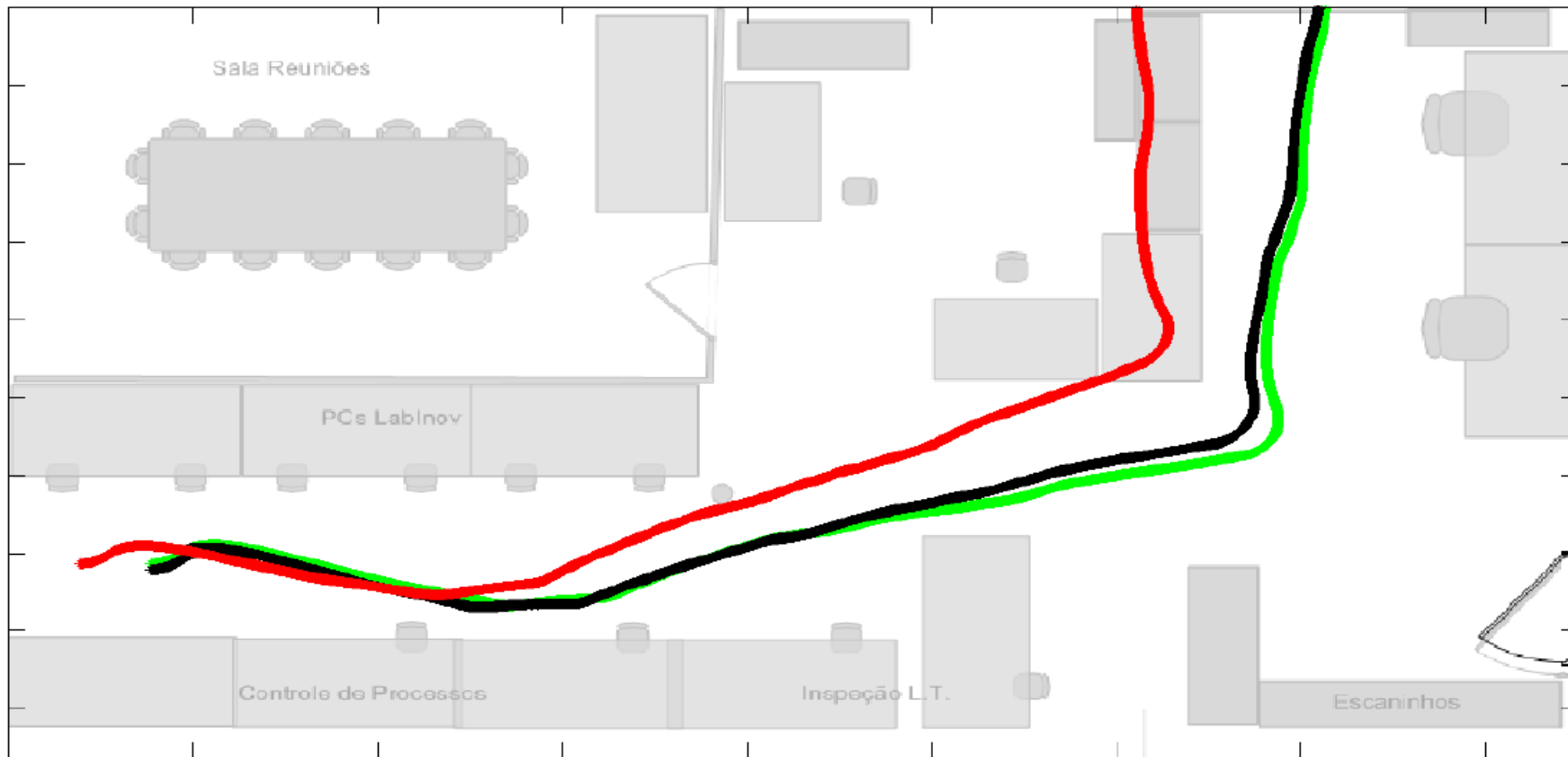
**Augmented Reality
Localization**



(Gabriel Figueiró e André Luiz Gama, 2011)

Indoor Localization

(Gabriel Figueiró e André Luiz Gama, 2011)

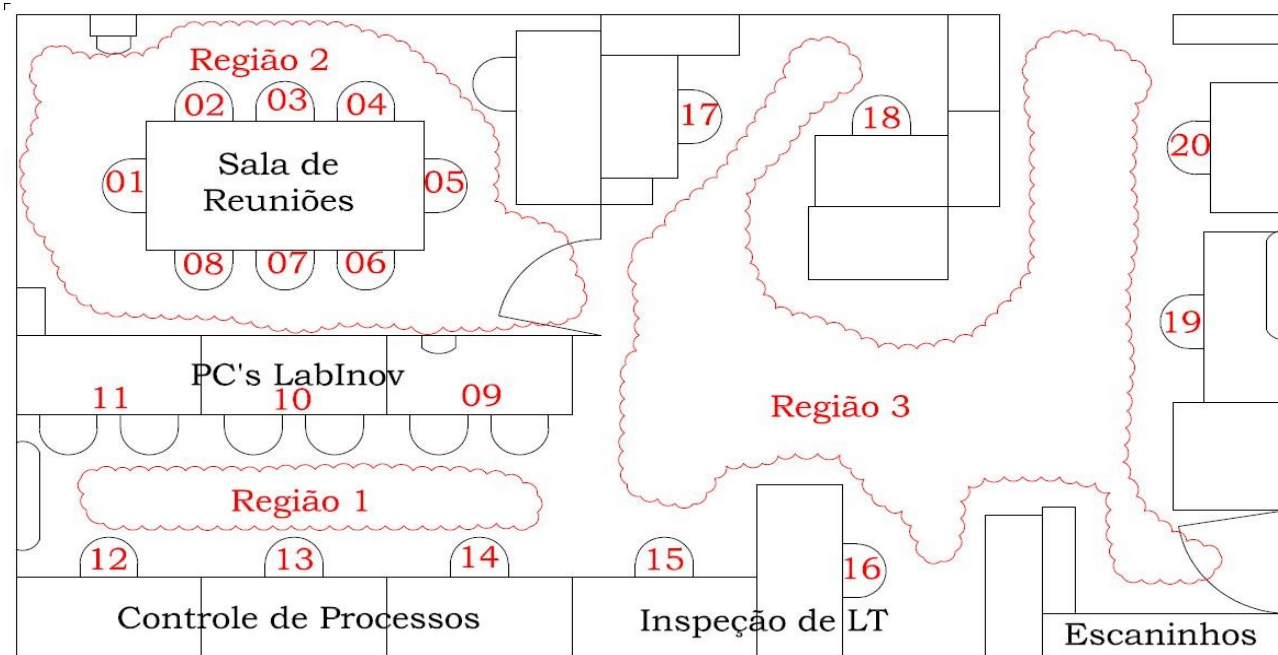


Red – odometry

Black – odometry + vision (augmented reality)

Green – odometry + vision + ANN RFID RSSI

Thermal Load Influence Areas



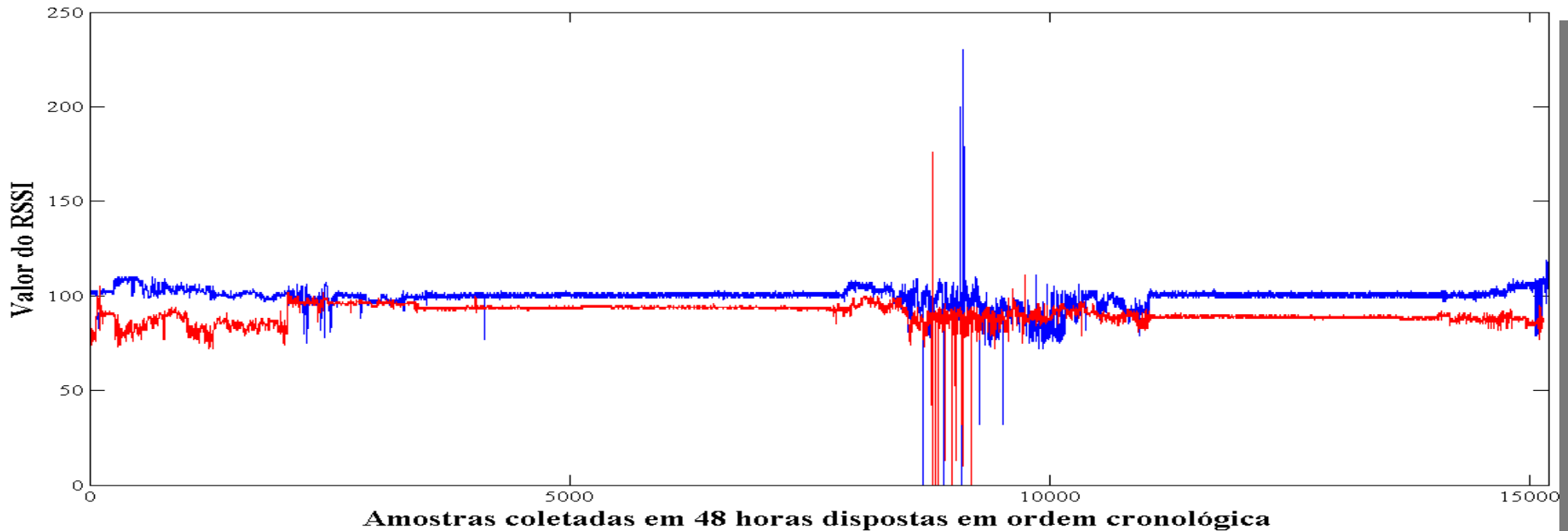
Identification of users in areas by
RFID – RSSI classifiers

(Cristovam Silva Jr., 2012)

Sistemas de Localização Indoor

RSSI – Received Signal Strength Indicator

- valor adimensional
- influenciado pelo efeito de Caminhos Múltiplos



Sistemas de Localização Indoor

OUTROS SISTEMAS DE LOCALIZAÇÃO

- GPS-Indoor
 - A-GPS
 - Repetidores
 - LOCATA
- UWB – Princípio de funcionamento de um radar
- WIFI – Localização baseada em RSSI
- WSN – Localização baseada em RSSI
- Bluetooth – Localização baseada em RSSI

Classificação

MULTI LAYER PERCEPTRON - MLP

- Reconhecedor de padrões de ampla aplicação;
- Sua arquitetura permite atuar em problemas não lineares e complexos;

Classificação

LEARNING VECTOR QUANTIZATION - LVQ

- Rede do tipo Mapa Auto Organizável com aprendizagem supervisionada;
- Possui uma camada competitiva e outra linear;
- Quantidade de saídas igual a quantidade de classes do problema;

Classificação

SUPPORT VECTOR MACHINE - SVM

- Classificador de padrões binários;
- Vetores de Suporte definem hiperplano que separa as classes;
- Definição de classe vem da comparação com os vetores de suporte;
- Conseguir fazer multiclassificação dividindo o problema em várias classificações.

Materiais e Métodos Aplicados

Hardware do Sistema RFID Ativo



Materiais e Métodos Aplicados

MIDDLEWARE DO SISTEMA RFID

The screenshot shows a software interface for an RFID system. The window title is "Form1". At the top left, there is a logo for "Universidade de Brasília" and the name "Lucas Fonseca" with the ID "06/36011". On the top right, there are buttons for "Ver saídas", "Mapa", and "Salvar", along with a checkbox for "Salvar automaticamente" and a text input field containing "log". The LARNA logo is also present in the top right corner.

The main area contains two large text input fields. The left one is labeled "Memo1" and the right one is empty. Below the left field is a button labeled "Conectar todas as Leitoras". Below the right field is a button labeled "Apagar" and a text input field containing "991643". To the right of this field are five small numeric input fields, each containing "0". Below the "Apagar" field is a checkbox for "Monitorar automaticamente" and a button labeled "Monitorar".

At the bottom left, there are buttons for "Ativar MatLab" and "Desativa MatLab". Below these is a text input field containing the file path "C:\Users\Public\Documents\My Dropbox\Dados TG\net.mat" and a button labeled "Carregar rede". Below that is a text input field containing the formula "round(sim(net, + DADOS + ,2)))" and a button labeled "Calcular". At the very bottom left is a text input field containing "Edit6".

At the bottom right, there is a text input field labeled "Memo3".

Materiais e Métodos Aplicados

NEURAL NETWORK TOOLBOX DO MATLAB

- Ferramenta completa para Redes Neurais;
- Interfaces gráficas facilitam o acompanhamento dos processos de treinamento e teste das redes neurais;



Materiais e Métodos Aplicados

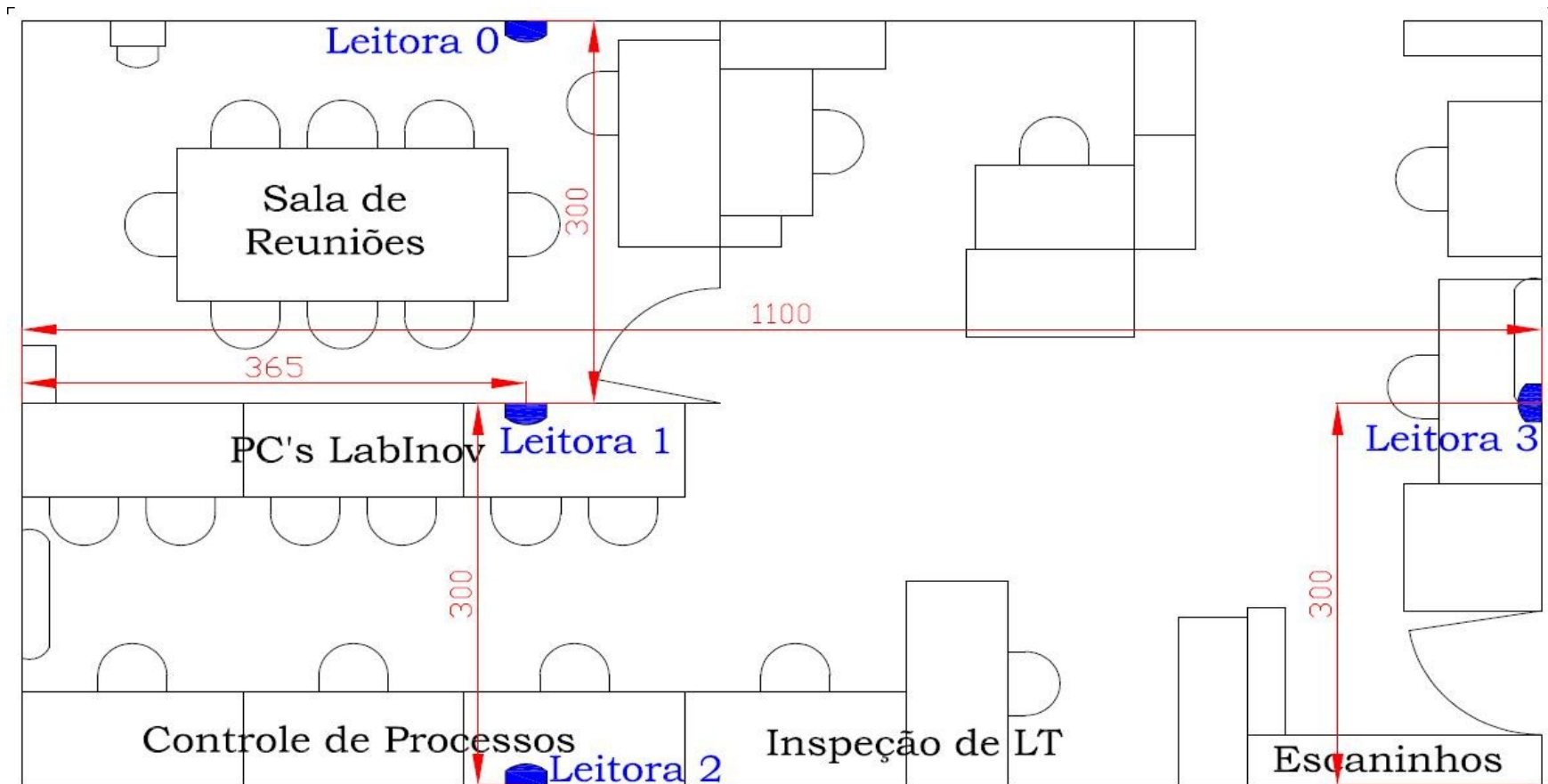
PACOTE DE APLICATIVOS LIBSVM

- Biblioteca de Software Livre;
- Aplicativos de treinamento gera conjunto de Vetores de Suporte;
- Permite várias configurações de função de núcleo da SVM (Linear, RBF, Polinomial, Sigmoides)

Materiais e Métodos Aplicados

CONFIGURAÇÃO FÍSICA DOS EXPERIMENTOS

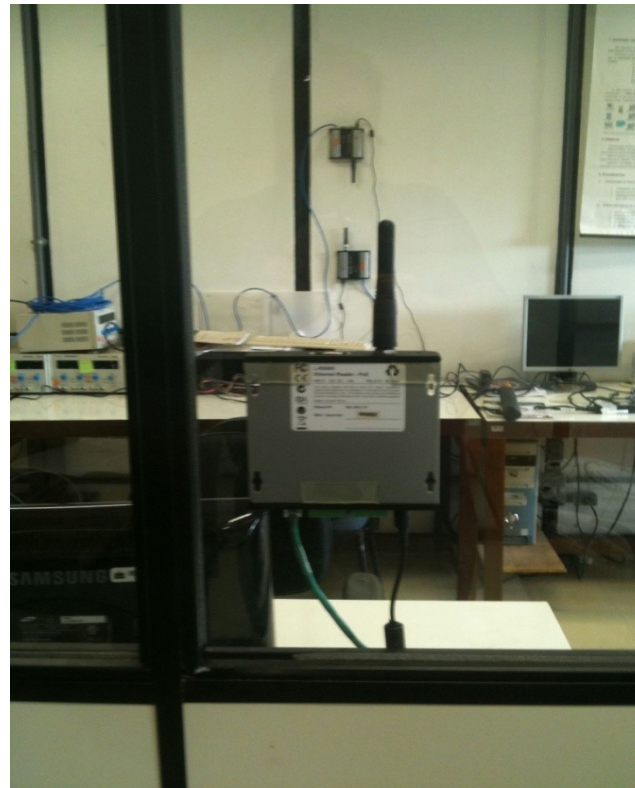
Localização das leitoras nos ambientes delimitados



Materiais e Métodos Aplicados

CONFIGURAÇÃO FÍSICA DOS EXPERIMENTOS

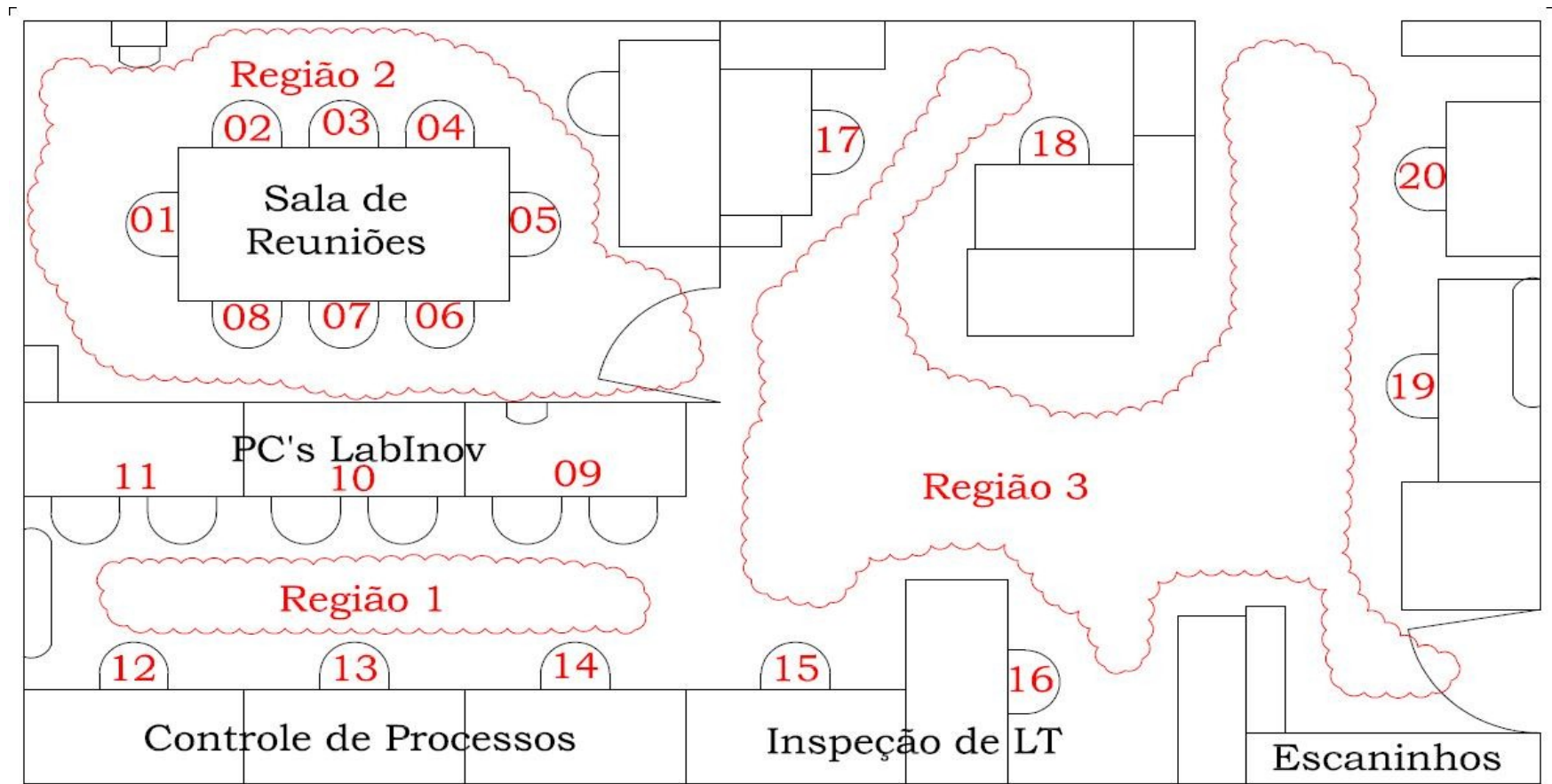
Leitoras instaladas nos ambientes delimitados



Materiais e Métodos Aplicados

CONFIGURAÇÃO FÍSICA DOS EXPERIMENTOS

Pontos de coleta de dados nos ambientes delimitados



Materiais e Métodos Aplicados

PROCEDIMENTOS DE LEITURA DOS DADOS

- Tempo de coleta de 30 minutos por ponto;
- Usuário portando a *Tag* como crachá;
- Liberdade de movimento em torno do eixo vertical;
- Dados armazenados em planilhas eletrônicas;
- Correção manual de erros de registro do middleware.

Pré-Tratamento e Filtragem dos Dados

(Como lidar com a ausência de alguma leitura das antenas)

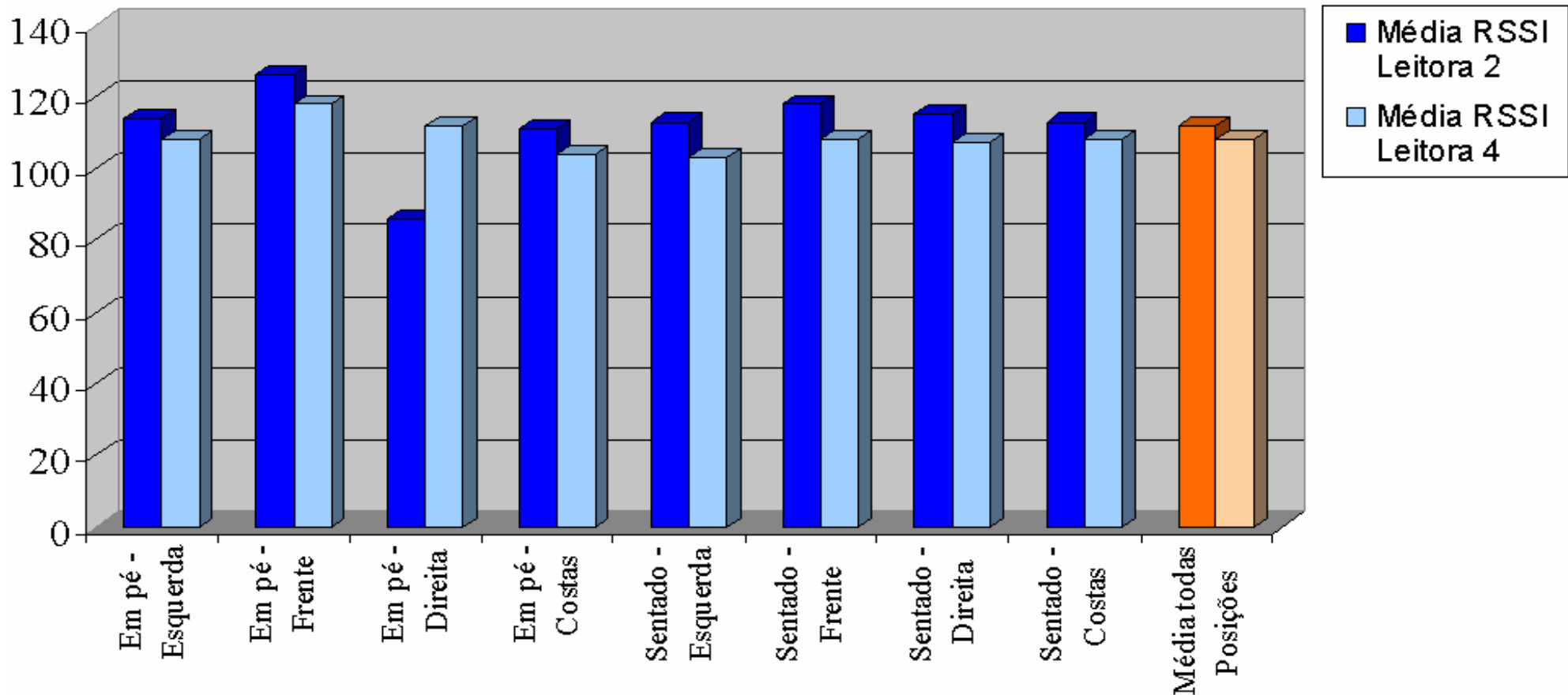
Metodologia	Formulação
Método_1	Sem alteração (Dados conforme coleta)
Método_1E	Método_1 + Filtragem EKF
Método_2	RSSI nulo = 71
Método_2E	Método_2 + Filtragem EKF
Método_3	RSSI nulo = RSSI anterior
Método_3E	Método_3 + Filtragem EKF

Arquivos de Treinamento dos Classificadores

- Rotulação das amostras quanto aos ambientes;
- Aglutinação das amostras em uma única planilha;
- Embaralhamento das amostras;
- Separação de amostras para teste e validação;

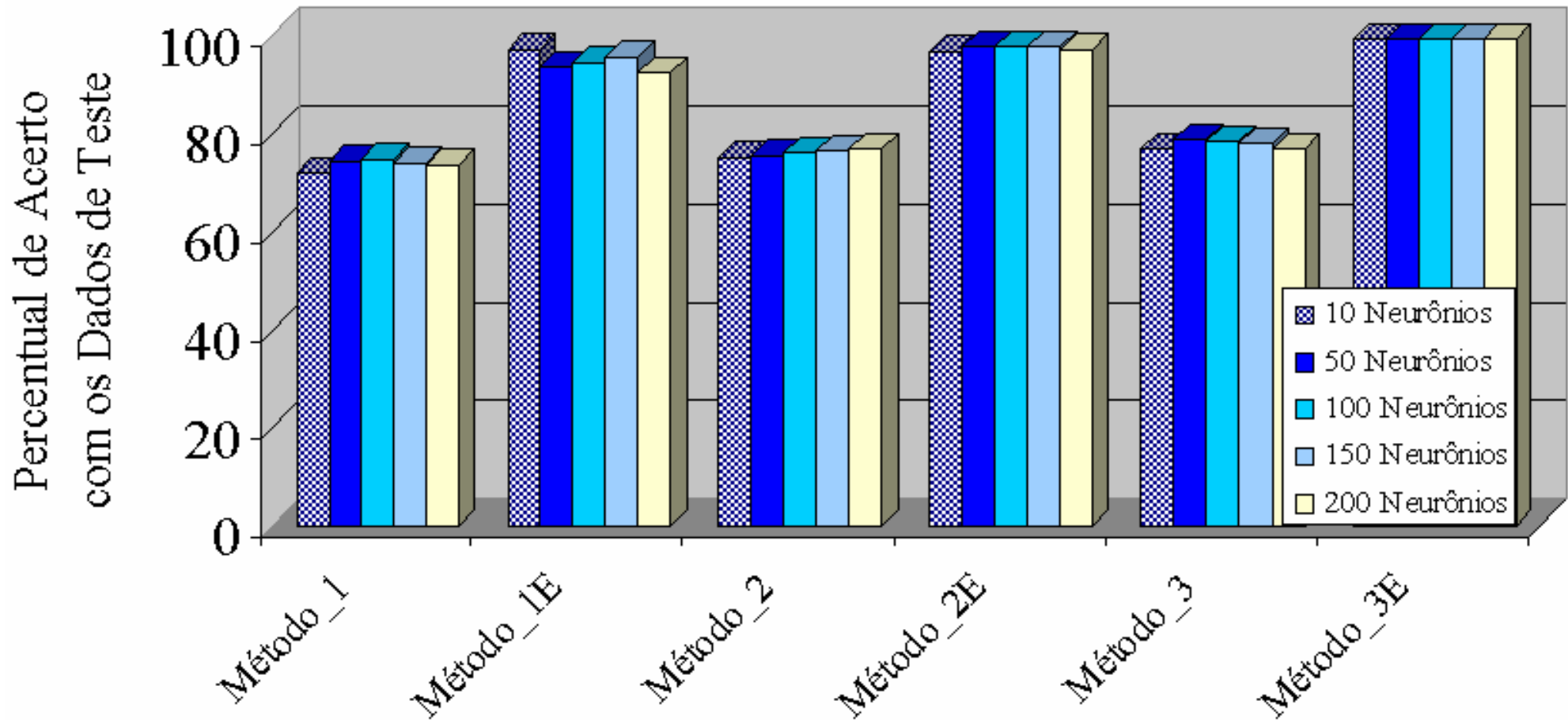
Resultados

Testes em relação à Orientação das Antenas



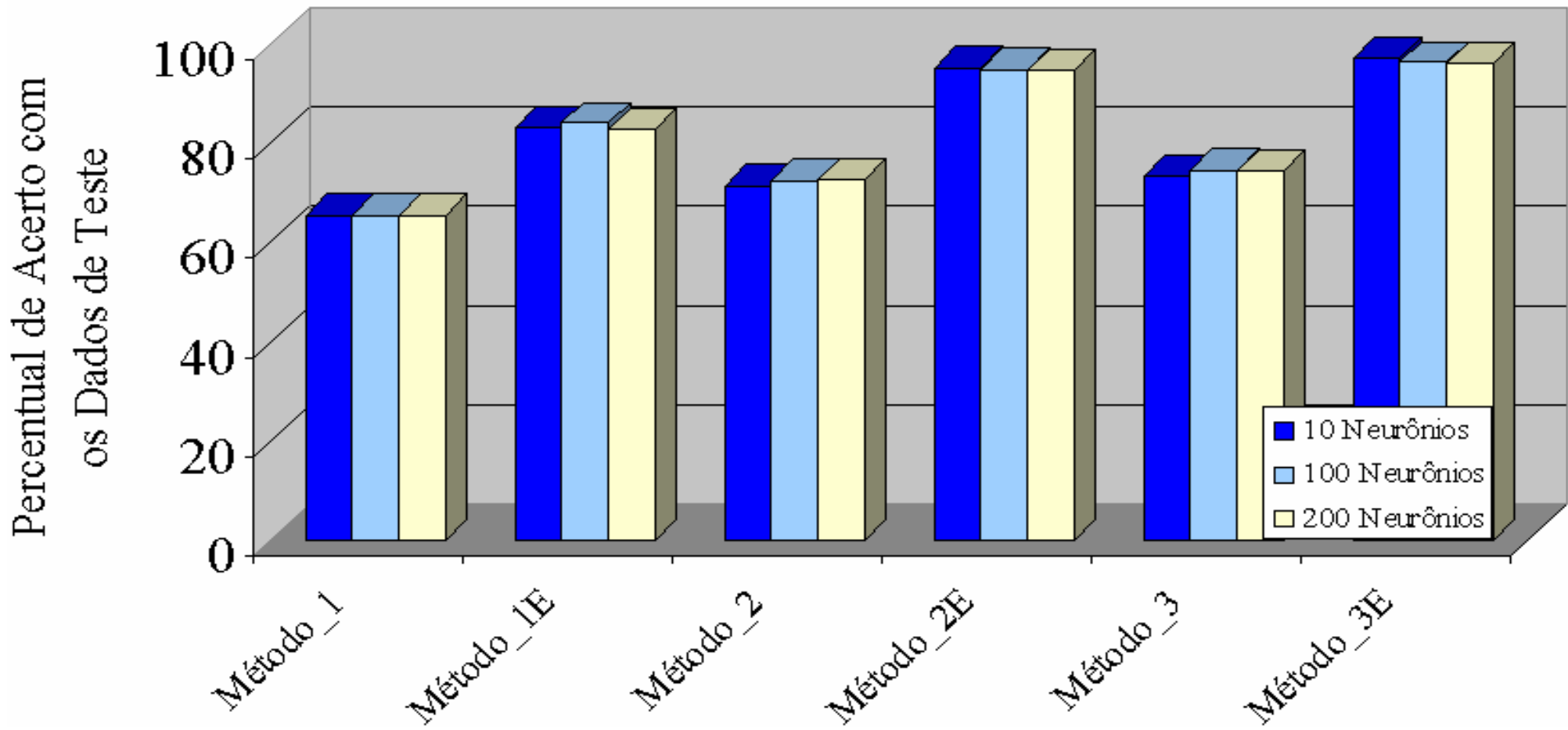
Resultados

DESEMPENHO DO TREINAMENTO DAS REDES MLP



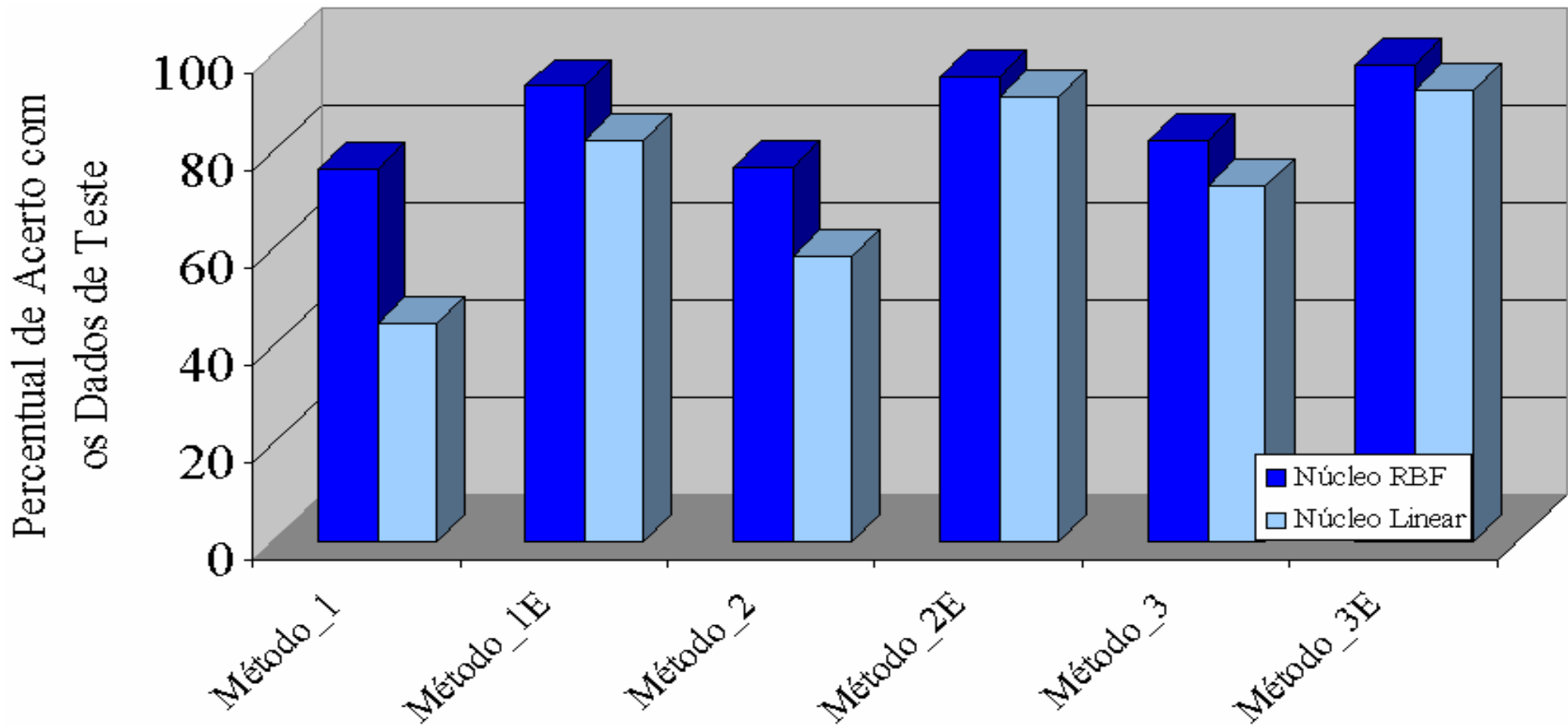
Resultados

DESEMPENHO DO TREINAMENTO DAS REDES LVQ



Resultados

DESEMPENHO DO TREINAMENTO DAS SVM



Resultados

MELHOR DESEMPENHO DENTRE OS CLASSIFICADORES PARA CADA BASE DE DADOS

