

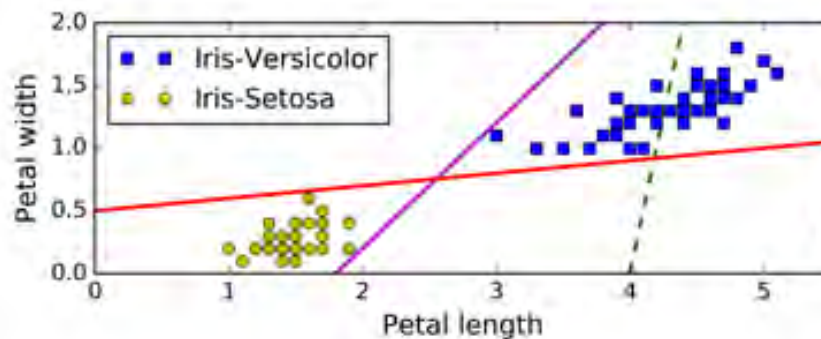
Advanced Data Analysis

DATA 71200

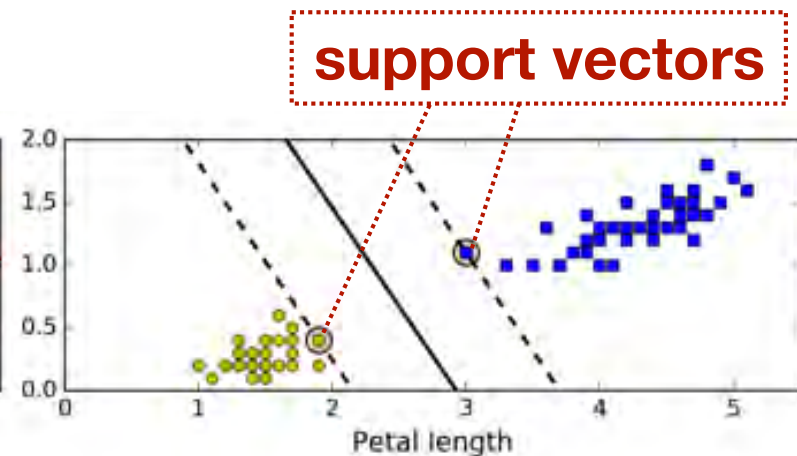
Class 10: Support Vector Machines and
Uncertainty Estimates from Classifiers

Linear Support Vector Classifier

- ▶ Find the linear classifier with the best separation (margin) between the two classes
- Operationally the data points used to make this calculation are the support vectors



**Three possible
linear classifiers**



**Linear classifier with
the widest margin**

Support Vector Machines

- ▶ **Linear models are limited to separating classes with lines (hyperplanes in higher dimensions)**

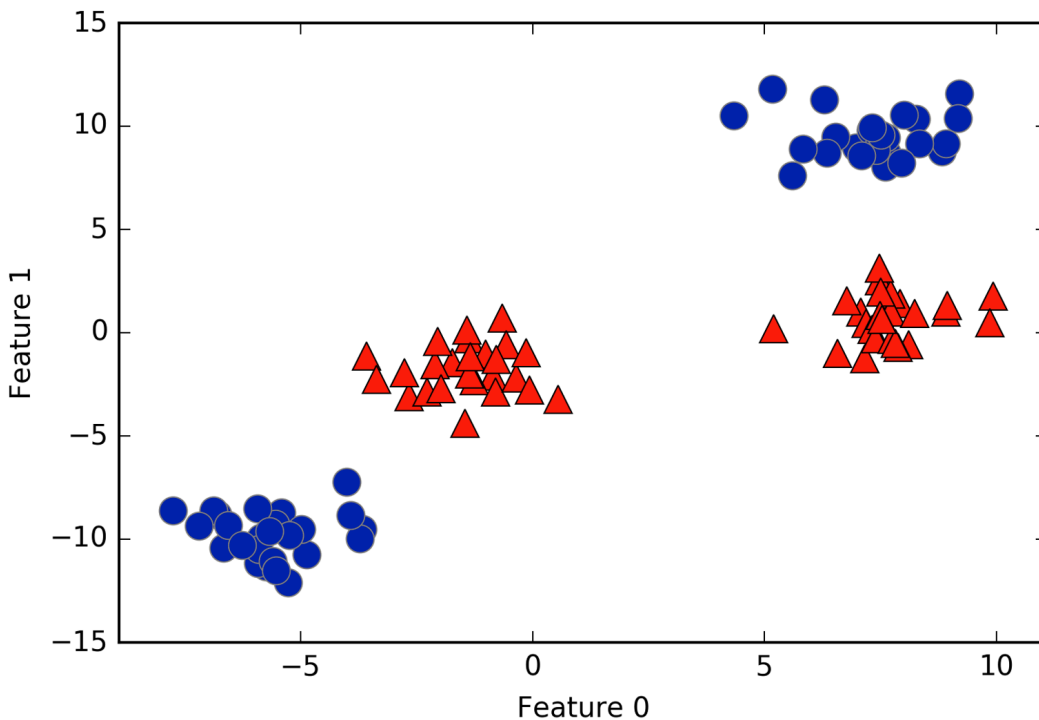


Figure 2-36. Two-class classification dataset in which classes are not linearly separable

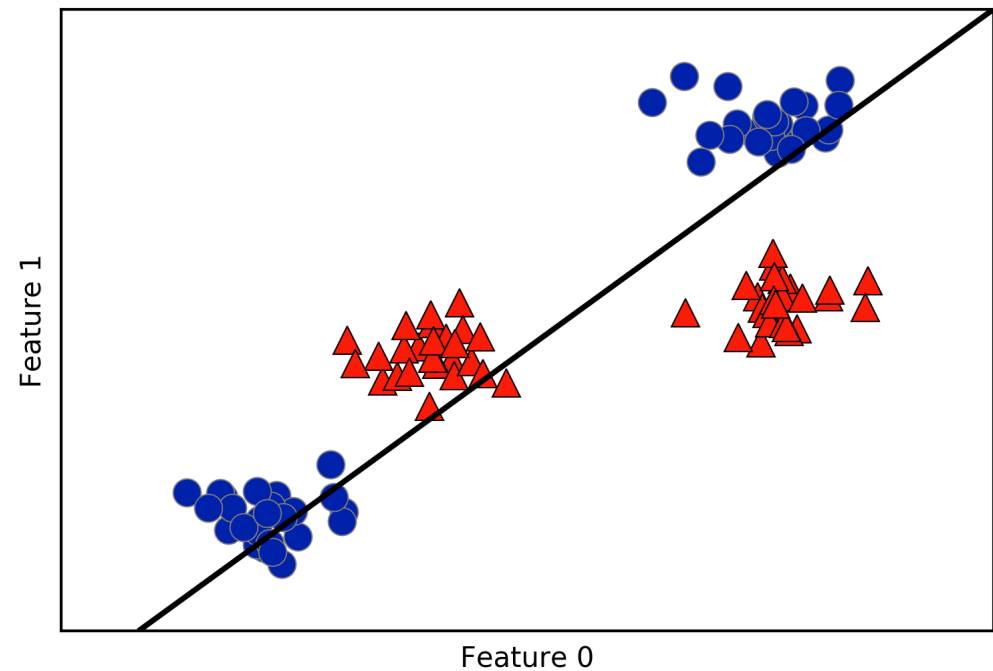


Figure 2-37. Decision boundary found by a linear SVM

Support Vector Machines

- ▶ Data can be transformed into a higher dimension
- ▶ Where an effective linear hyperplane can be fit to separate the data classes

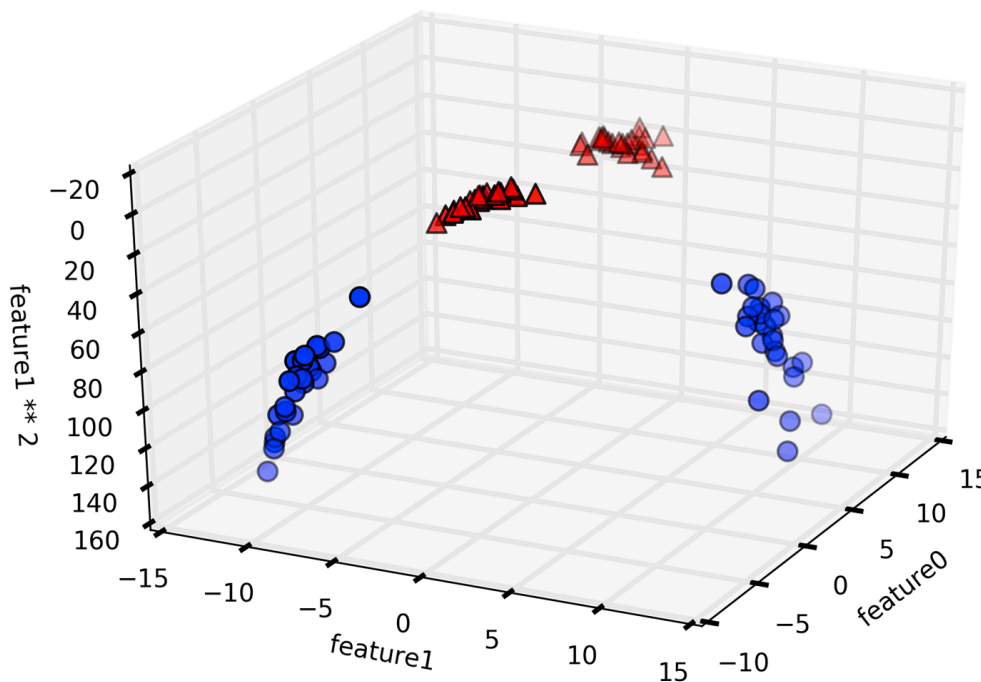


Figure 2-38. Expansion of the dataset shown in Figure 2-37, created by adding a third feature derived from feature1

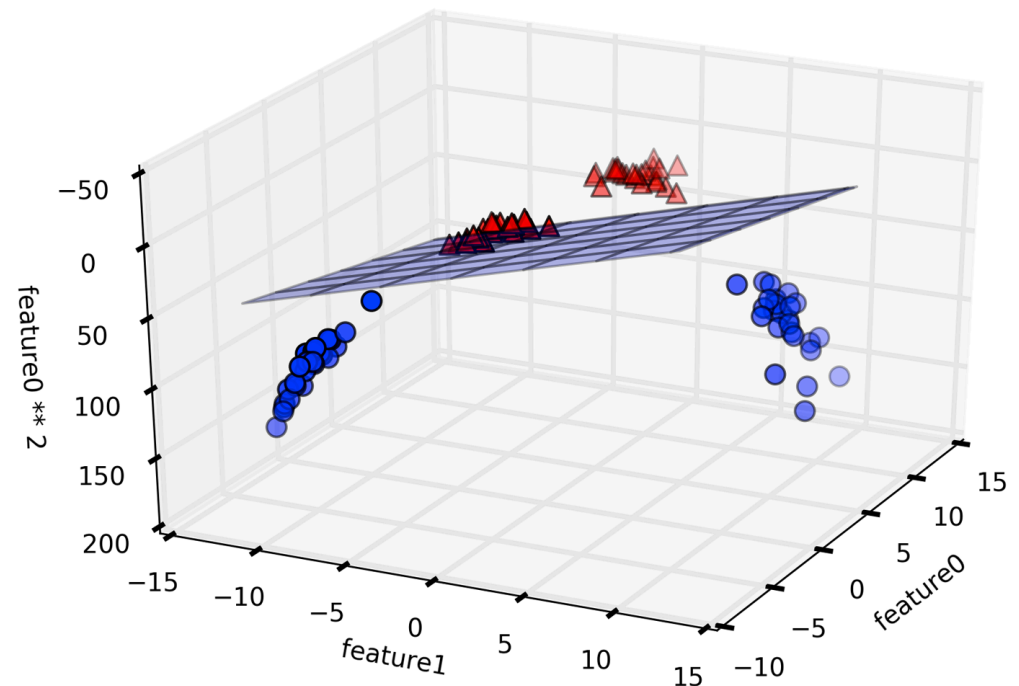


Figure 2-39. Decision boundary found by a linear SVM on the expanded three-dimensional dataset

Support Vector Machines

- ▶ When projected back to the two original features (2D) the resultant decision boundary is not linear

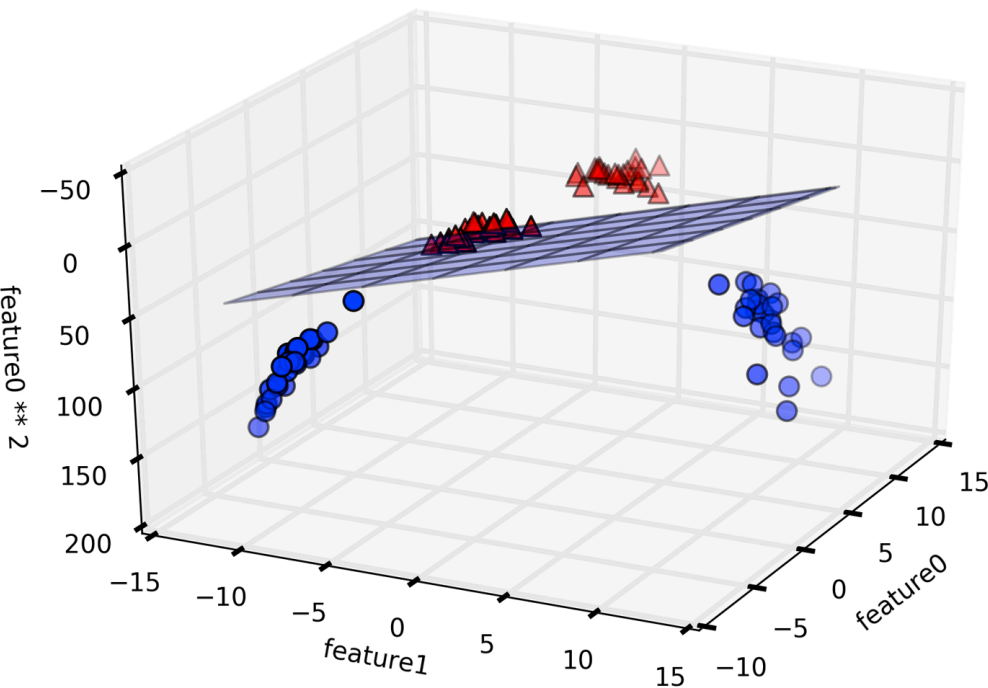


Figure 2-39. Decision boundary found by a linear SVM on the expanded three-dimensional dataset

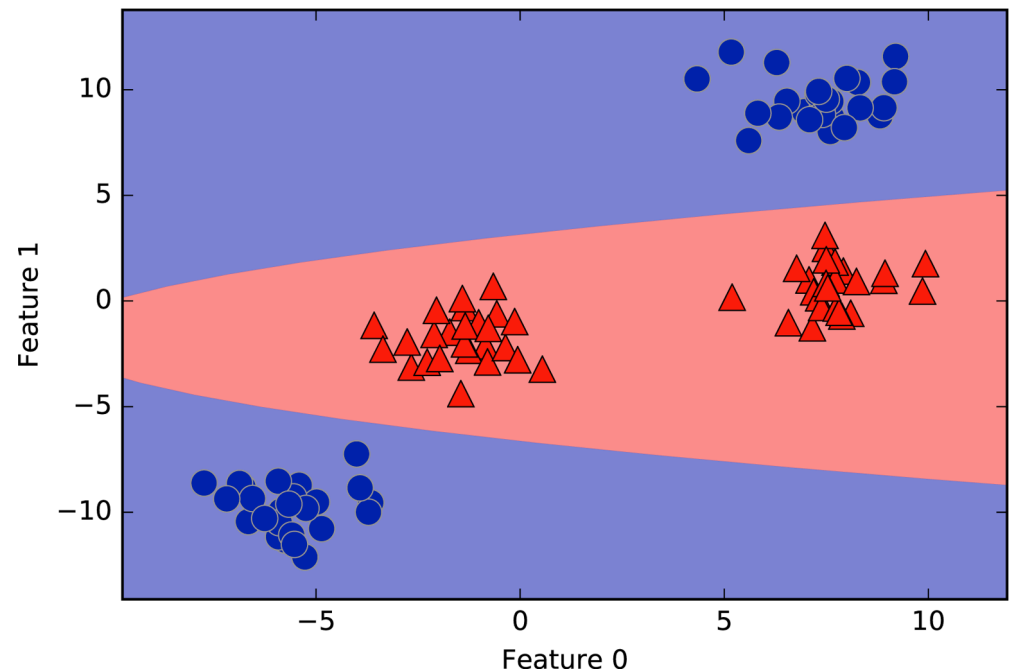


Figure 2-40. The decision boundary from Figure 2-39 as a function of the original two features

Support Vector Machines

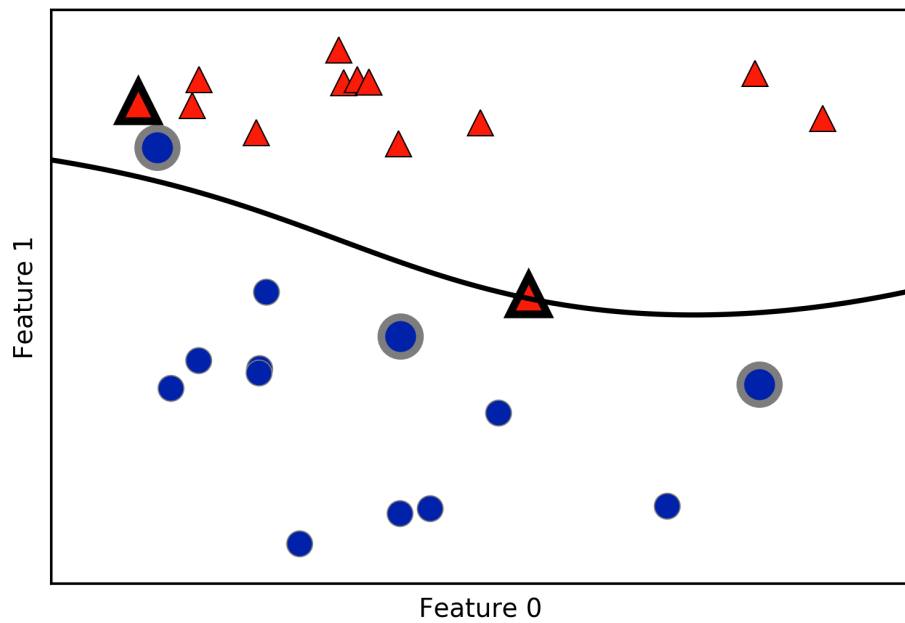
- ▶ **Adding nonlinear features to the data can be useful**
- ▶ **Kernel trick - computes the distances (scalar products) between the nonlinear features (rather than having to calculate the full representation)**
 - ▶ **Polynomial kernel - all possible polynomials up to a specified degree**
 - ▶ **Radial basis function (RBF) - Gaussian weighting of all possible polynomials**

Support Vector Machines

- Distance for the RBF is measured with the equation

$$k_{\text{rbf}}(x_1, x_2) = \exp(-\gamma \|x_1 - x_2\|^2)$$

- x_1 and x_2 are the data points
- gamma sets the width of the Gaussian kernel
 - width of influence each data point



- As in linear models, the regularization is set by the C parameter
 - low values: algorithm adjusts to the majority of the data points
 - high value: algorithm attempts to correctly classify as many data points as possible

Figure 2-41. Decision boundary and support vectors found by an SVM with RBF kernel

Support Vector Machines

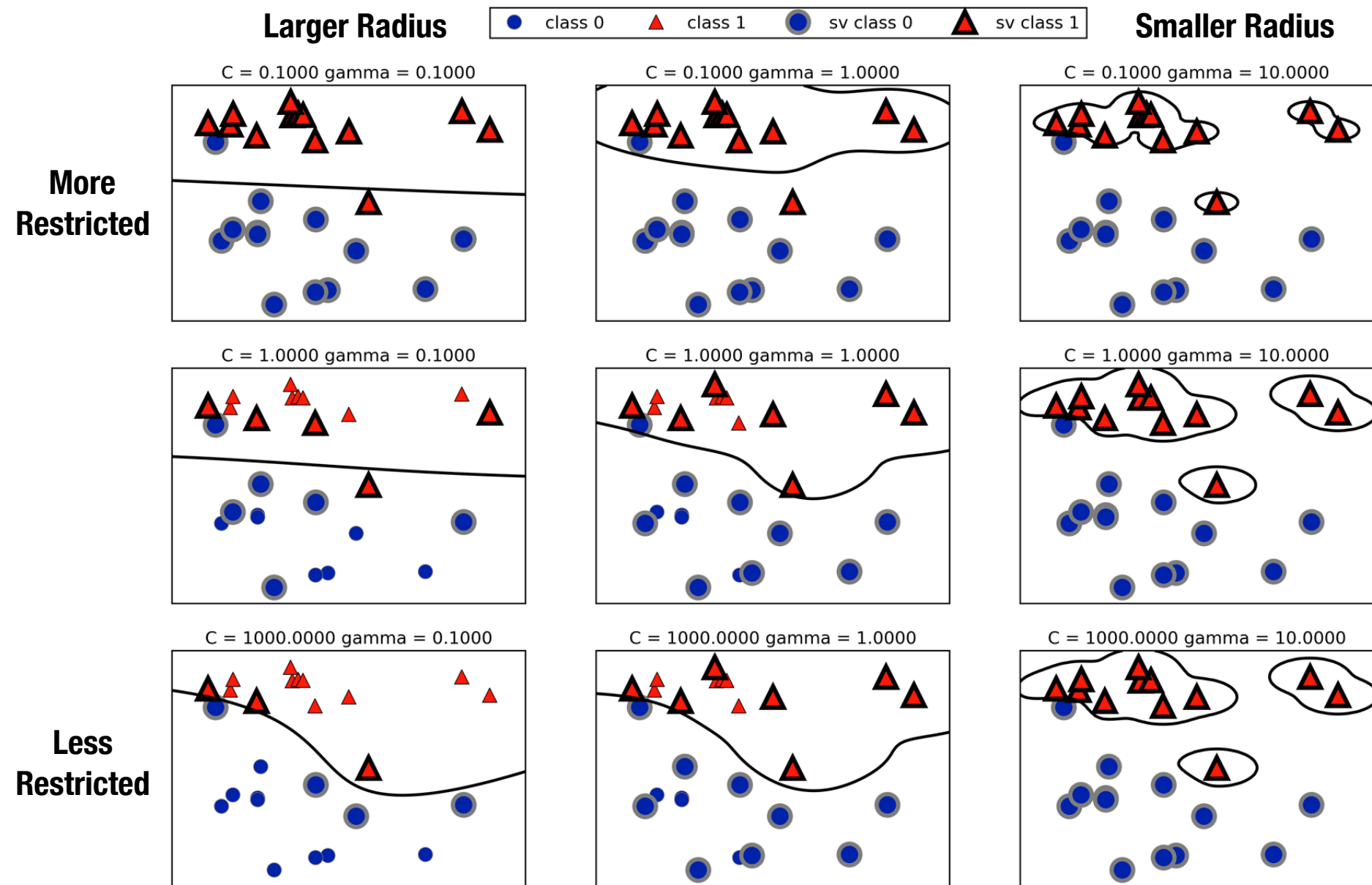


Figure 2-42. Decision boundaries and support vectors for different settings of the parameters C and γ

Support Vector Machines

▸ **Best Practices**

- Features should be scaled to have 0 mean and unit variance

▸ **Parameters**

- Choice of kernel (polynomial, radial basis function, etc.)
- C - regularization parameter
- gamma - inverse of width of Gaussian kernel (RBF)

▸ **Strengths**

- Works well with only a few data points
- Works on both low- and high-dimensional data

▸ **Weaknesses**

- Doesn't scale very well to a large number of samples
- Data often needs to be pre-processed

Uncertainty Estimates from Classifiers

- **Decision Functions** encode how strongly the model believes a given datapoint belongs to a given class

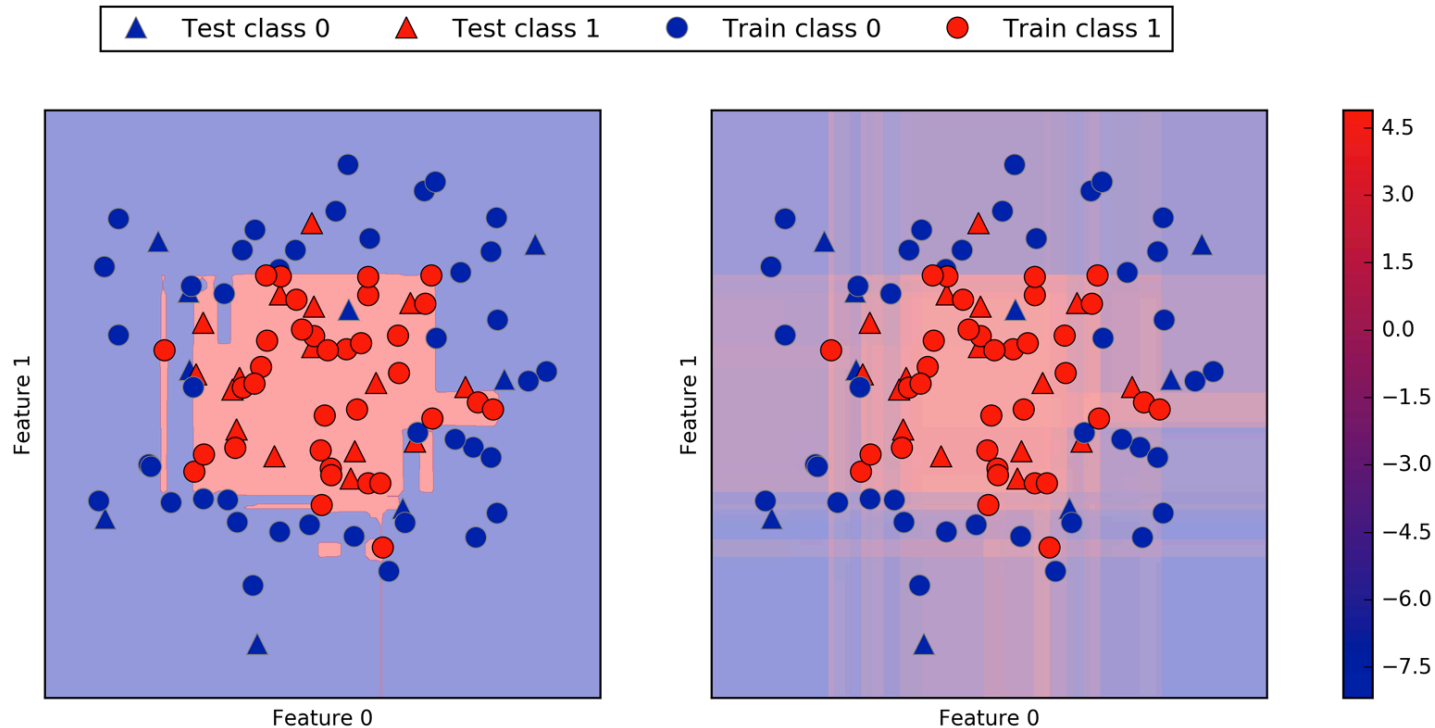


Figure 2-55. Decision boundary (left) and decision function (right) for a gradient boosting model on a two-dimensional toy dataset

Uncertainty Estimates from Classifiers

- **Prediction Probabilities** indicate the probability (between 0 and 1) that the a given data point belongs to a given class

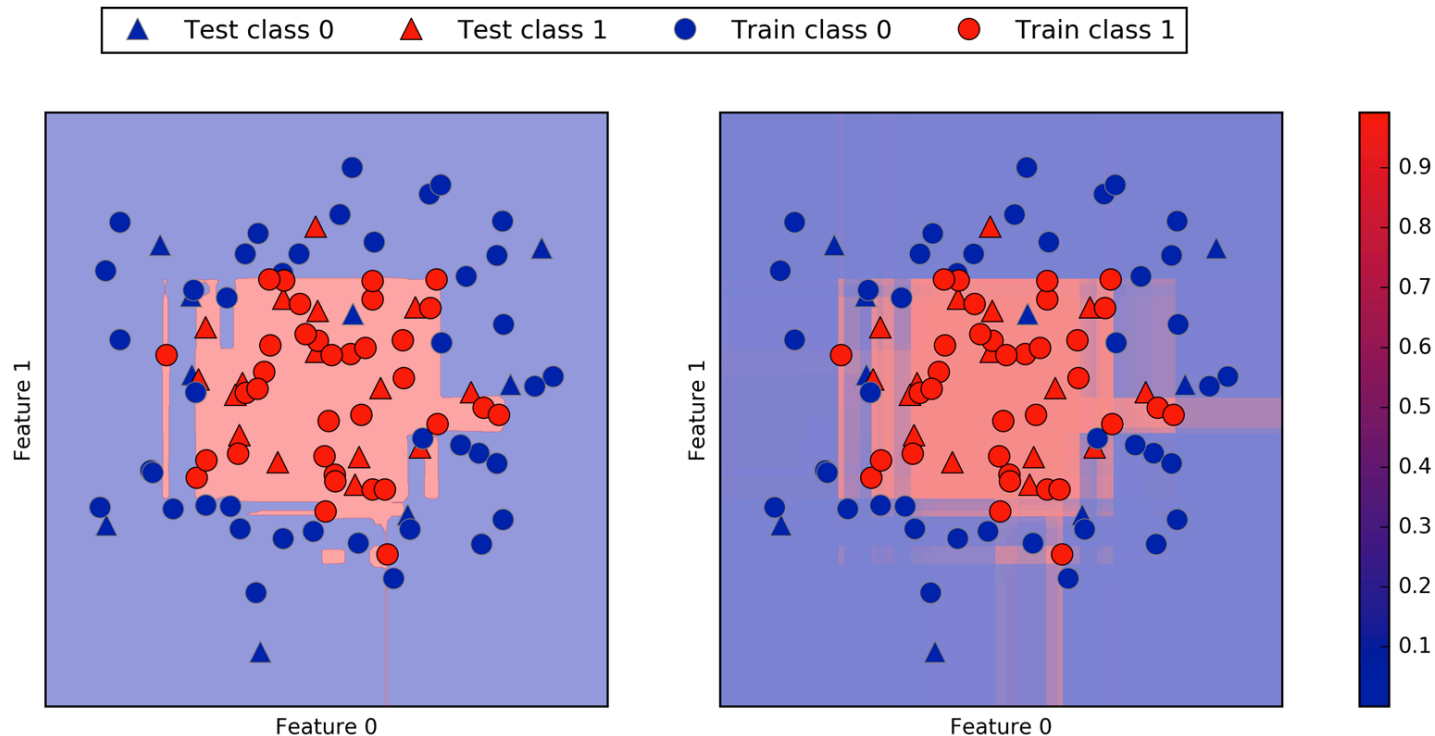


Figure 2-56. Decision boundary (left) and predicted probabilities for the gradient boosting model shown in Figure 2-55