

Machine Learning (DLMD SML01)

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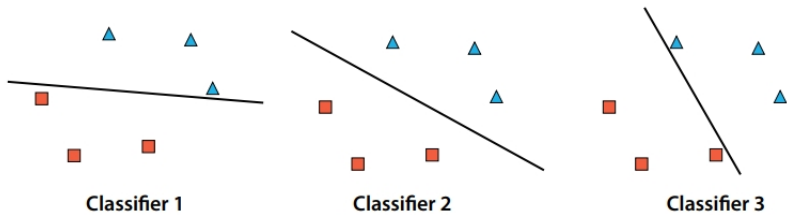


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Section 4: Support Vector Machine (SVM)

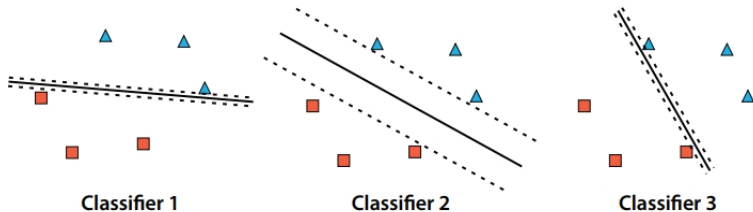
- ▶ Textbook: check it in MyCampus
- ▶ Basic concepts
- ▶ Hyperplane
- ▶ Error function
- ▶ C parameter
- ▶ RBF kernel
- ▶ Gamma parameter

Basic concepts



Parallel lines

- ▶ An SVM classifier uses two parallel lines instead of one line
- ▶ The goal of the SVM is twofold
 - ▶ it tries to classify the data correctly and
 - ▶ also tries to space the lines as much as possible

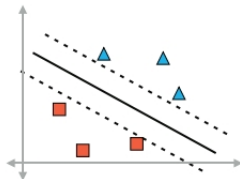


Hyperplane

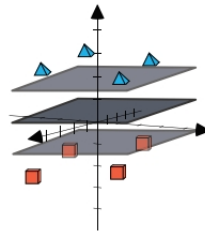
- ▶ SVMs work equally well in datasets of higher dimensions
- ▶ The linear boundaries in one dimension are points and in two dimensions are lines
- ▶ Likewise, the linear boundaries in three dimensions are planes, and in higher dimensions, they are hyperplanes of one dimension less than the space in which the points live
- ▶ In each of these cases, we try to find the boundary that is the farthest from the points



One dimension



Two dimensions



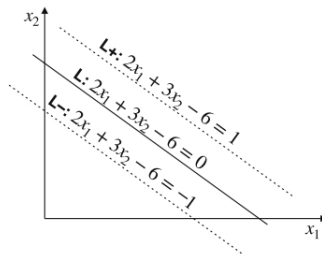
Three dimensions

Error function of SVMs

- ▶ The Error function of SVMs tries to maximize two things at the same time: the classification of the points and the distance between the lines
- ▶ The following are the two things we want to achieve
 - ▶ Each of the two lines should classify the points as best as possible
 - ▶ The two lines should be as far away from each other as possible
- ▶ Therefore, our error function can look like this:
$$\text{Error} = \text{Classification Error} + \text{Distance Error}$$

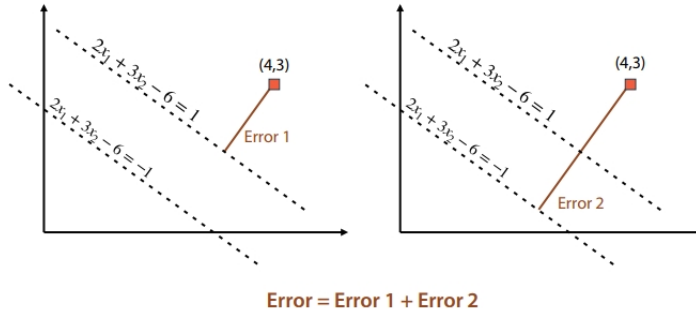
Classification error function

- ▶ The SVM uses two parallel lines that have similar equations; they have the same weights but a different bias
- ▶ We use the central line as a frame of reference L with equation $w_1x_1 + w_2x_2 + b = 0$, and construct two lines
 - ▶ $L+ : w_1x_1 + w_2x_2 + b = 1$
 - ▶ $L- : w_1x_1 + w_2x_2 + b = -1$



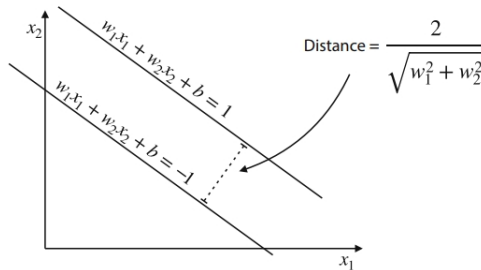
Classification error function

- Our classifier consists of the lines L_+ and L_- as two independent classifiers

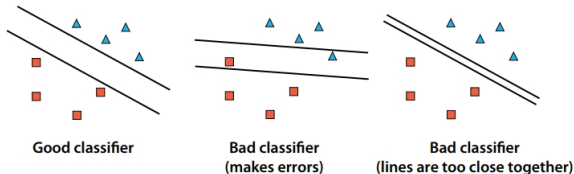
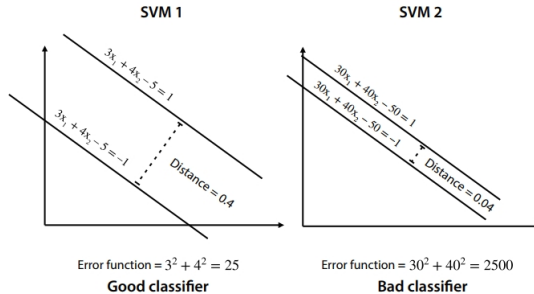


Distance error function

- Now that we have created an error function that measures classification errors, we need to build one that looks at the distance between the two lines and raises an alarm if this distance is small
- An error function that is large when the two lines are close and small when they are far

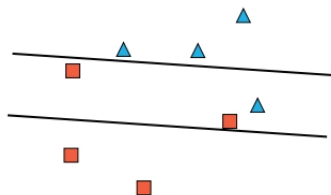


Distance error function

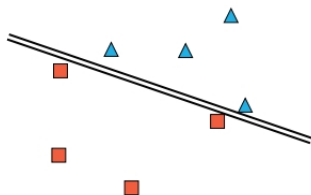


The C parameter

- ▶ The C parameter is used in cases where we want to train an SVM that pays more attention to classification than to distance (or the other way around)
 - ▶ Error formula = $C \cdot (\text{Classification Error}) + (\text{Distance Error})$



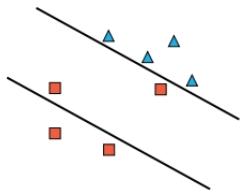
Lines are far apart (good).
Makes errors (bad).



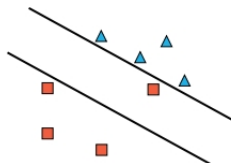
Lines are too close (bad).
Doesn't make errors (good).

The C parameter

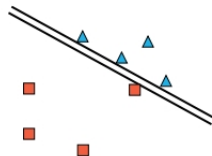
- ▶ If C is large, then the error formula is dominated by the classification error, so our classifier focuses more on classifying the points correctly
- ▶ If C is small, then the formula is dominated by the distance error, so our classifier focuses more on keeping the lines far apart



$C = 0.01$



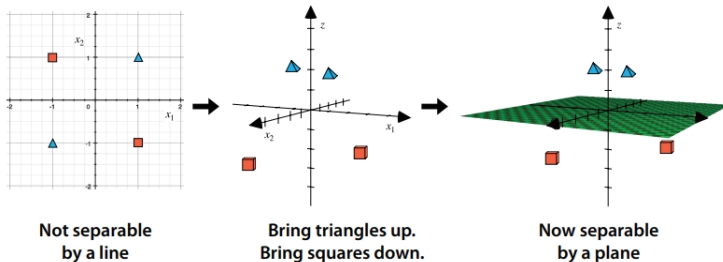
$C = 1$



$C = 100$

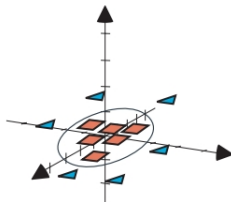
Training SVMs with nonlinear boundaries

- ▶ The kernel method
 - ▶ If we have a dataset and find that we can't separate it with a linear classifier
 - ▶ One idea is to add more columns to this dataset and hope that the richer dataset is linearly separable
 - ▶ The kernel method consists of adding more columns in a clever way, building a linear classifier on this new dataset and later removing the columns we added while keeping track of the (now nonlinear) classifier

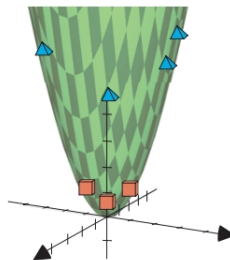


The kernel method

- ▶ The kernel method as a way of adding columns to our dataset to make the points separable
 - ▶ For example, the dataset has two columns, x_1 and x_2 , and we have added the third column with the value $x_1 x_2$.



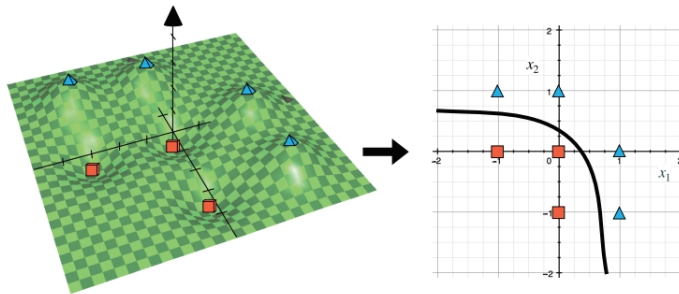
Not linearly separable



Raise each point of coordinates (x_1, x_2)
to a height of $x_1^2 + x_2^2$

Going beyond quadratic equations: Polynomial kernel

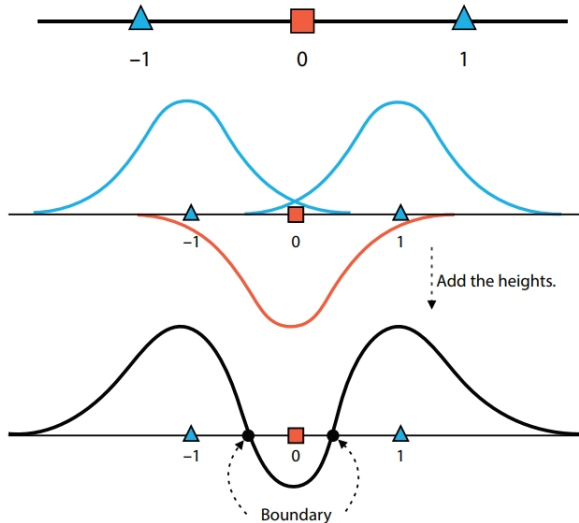
- ▶ The polynomial kernel of degree 2: $(x_1, x_2, x_1^2, x_1 x_2, x_2^2)$
- ▶ The polynomial kernel of degree 3: $(x_1, x_2, x_1^2, x_1 x_2, x_2^2, x_1^3, x_1^2 x_2, x_1 x_2^2, x_2^3)$



The radial basis function (RBF) kernel

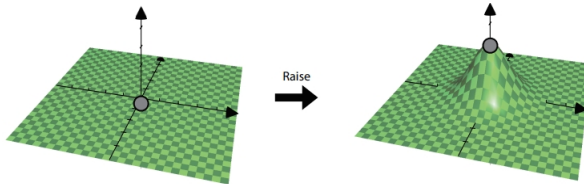


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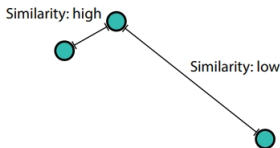


RBF kernel

- ▶ To build the mountains and valleys on the plane, imagine the plane as a blanket
 - ▶ If we pinch the blanket at that point and raise it, we get the mountain
 - ▶ If we push it down, we get the valley
 - ▶ These mountains and valleys are radial basis functions
 - ▶ They are called radial basis functions because the value of the function at a point is dependent only on the distance between the point and the center
 - ▶ We can raise the blanket at any point we like, and that gives us one different radial basis function for each point



- ▶ To build an SVM using the RBF kernel, we need one notion: the notion of similarity
- ▶ We say that two points are similar if they are close to each other, and not similar if they are far away
 - ▶ the similarity between two points is high if they are close to each other and low if they are far away from each other
 - ▶ If the pair of points are the same point, then the similarity is 1
 - ▶ In theory, the similarity between two points that are an infinite distance apart is 0
 - ▶ $\text{similarity}(p, q) = e^{-\text{distance}(p, q)^2}$



Training an SVM with the RBF kernel



Point	x	y (label)
1	-1	1
2	0	0
3	1	1

Point	x	Sim1	Sim2	Sim3	y
1	-1	1	0.368	0.018	1
2	0	0.368	1	0.368	0
3	1	0.018	0.368	1	1

Training an SVM with the RBF kernel

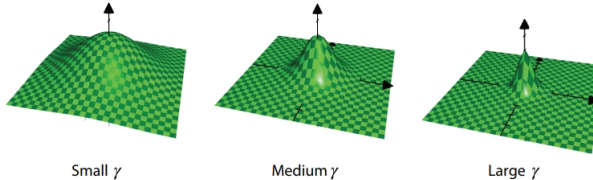


Point	x_1	x_2	y
1	0	0	0
2	-1	0	0
3	0	-1	0
4	0	1	1
5	1	0	1
6	-1	1	1
7	1	-1	1

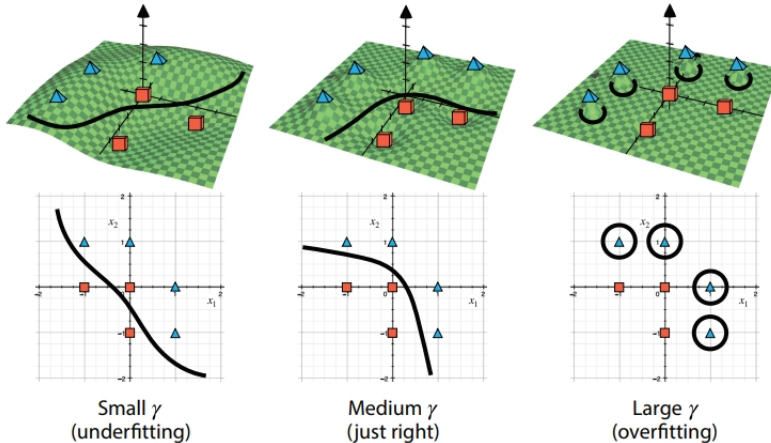
Point	x_1	x_2	Sim1	Sim2	Sim3	Sim4	Sim5	Sim6	Sim7	y
1	0	0	1	0.368	0.368	0.368	0.368	0.135	0.135	0
2	-1	0	0.368	1	0.135	0.135	0.018	0.368	0.007	0
3	0	-1	0.368	0.135	1	0.018	0.135	0.007	0.368	0
4	0	1	0.368	0.135	0.018	1	0.135	0.368	0.007	1
5	1	0	0.368	0.018	0.135	0.135	1	0.007	0.368	1
6	-1	1	0.135	0.368	0.007	0.367	0.007	1	0	1
7	1	-1	0.135	0.007	0.368	0.007	0.368	0	1	1

Overfitting and underfitting with the RBF kernel

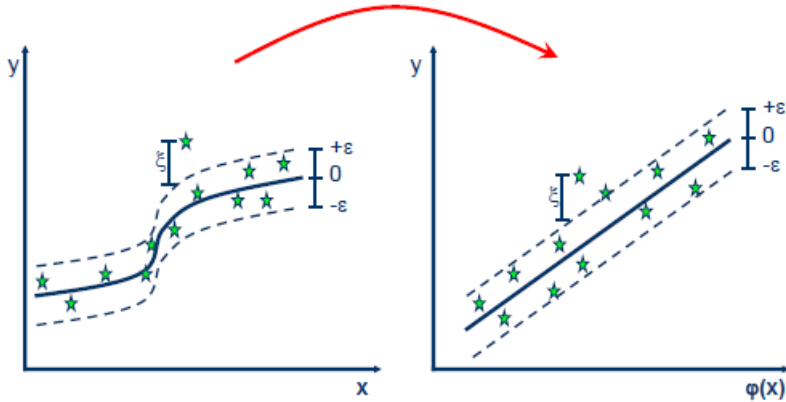
- The gamma parameter: $\text{similarity}(p, q) = e^{-\gamma \text{distance}(p, q)^2}$



Overfitting and underfitting with the RBF kernel



SVR



- ▶ Serrano, L. (2021). Grokking Machine Learning. Simon and Schuster.
- ▶ <https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html>
- ▶ <https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVR.html>
- ▶ <https://www.datacamp.com/tutorial/svm-classification-scikit-learn-python>
- ▶ https://www.tutorialspoint.com/scikit_learn/scikit_learn_support_vector_machines.htm

Questions?