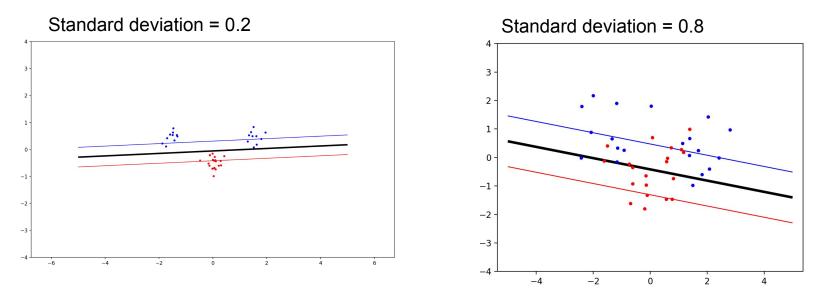
DD2421 - Machine Learning

Lab 2: Support Vector Machines

Pablo Laso, Antonia Schroff

Move the **clusters** around and change their sizes to make it easier or harder for the classifier to find a decent **boundary**. Pay attention to when the optimizer (minimize function) is not able to find a solution at all.

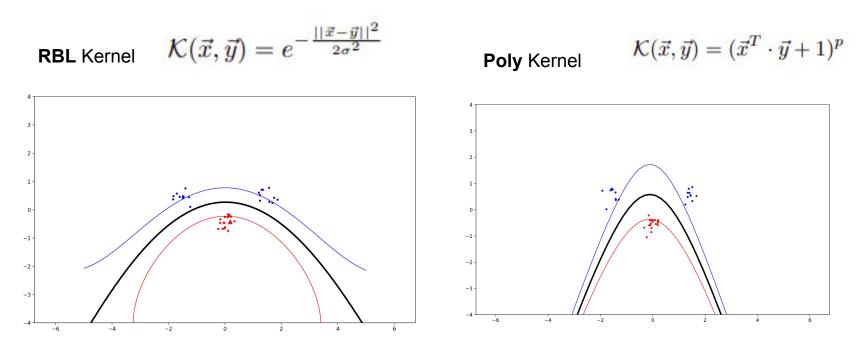


At some point, it's not possible to have linear decision boundaries anymore. At this point, we might need **non-linear Kernels**.

As soon as the dataset is not separable anymore with a linear boundary, the minimizer can't solve the problem anymore.

 \bigcirc

Implement the two **non-linear kernels**. You should be able to classify very hard data sets with these.

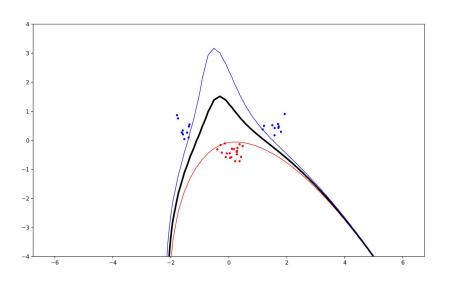


Polynomial using different degrees

Polynomial Kernel (**Degree 2**) 3 2 1 0 -1**-2 -3**

low degree -> under fitting -> low variance and high bias (complex decision boundary)

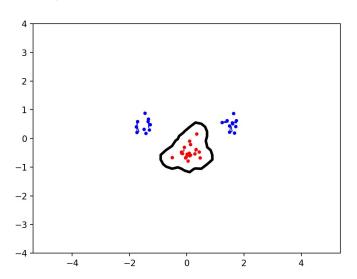
Polynomial Kernel (Degree 4)



high degree -> over fitting -> high variance and low bias (simple decision boundary)

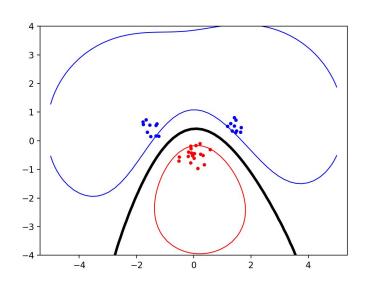
RBL using different sigma

Sigma = 0.1



Low Sigma -> complex decision boundary -> over fitting

Sigma = 2.0



High Sigma -> Smooth decision boundary -> under fitting

Imagine that you are given data that is not easily separable. When should you opt for more slack rather than going for a more complex model (kernel) and vice versa?

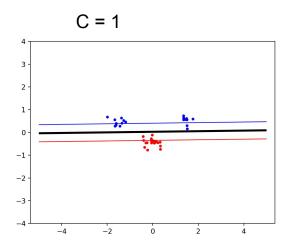
We use a non-linear Kernel in complex problems to find a separation line.

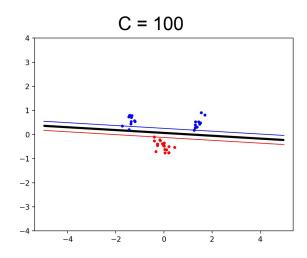
• If the dataset is noisy though and we try to seperate it, it doesn't generalize well.

• In that case, more slack is good for noisy environments

Explore the role of the slack parameter C. What happens for very large/small values?

- C controls how many points of the dataset can be misclassified by the constructed indicator function
- High C --> less misclassification allowed
- good in noisy environments





The end:)