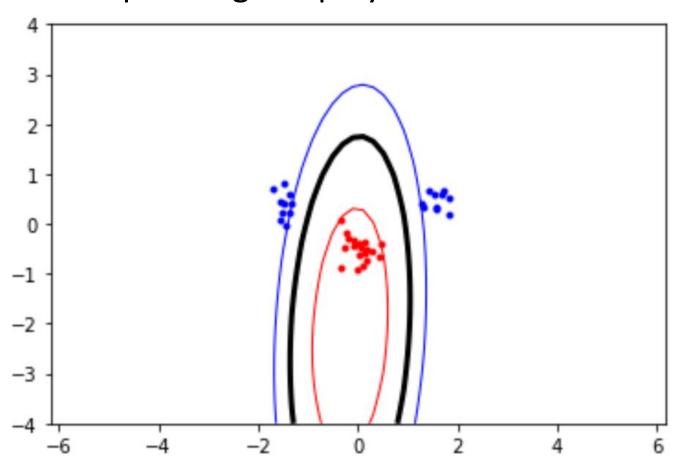
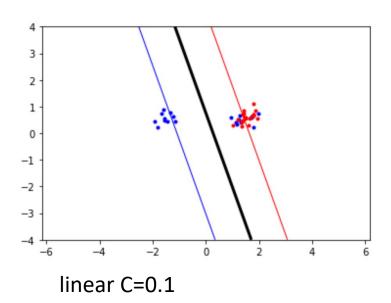
# Machine Learning Lab 2

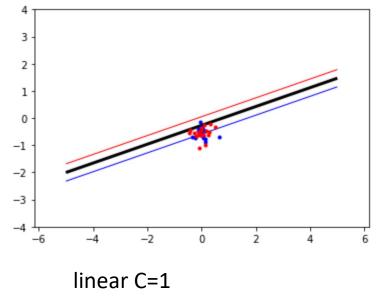
Qiao Ren, Catherine Weldon

• Graph using the poly kernel:



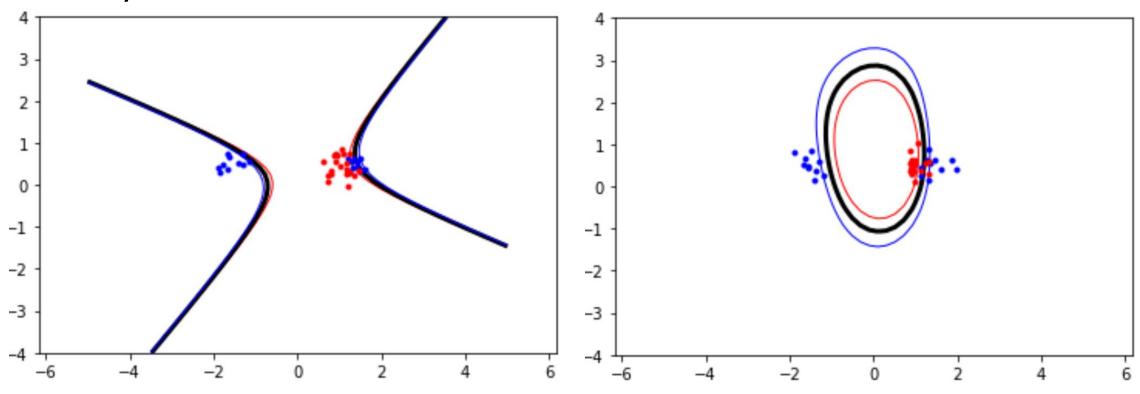
 Move the clusters around and change their sizes to make it easier or harder for the classifier to find a decent boundary. Pay attention to when the optimizer (minimize function) is not able to find a solution at all.





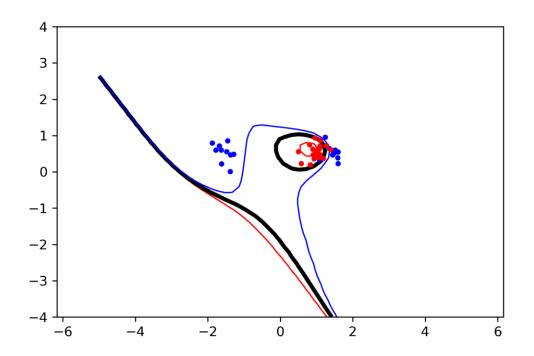
- Linear Kernel does not allow for good separation when clusters overlap
- if cost C is too large
  (1000), then slack is low,
  → not able to find a
  solution

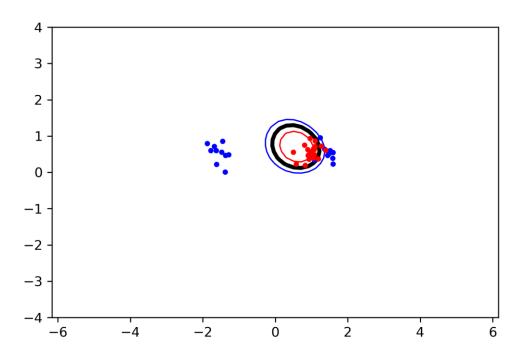
• Implement the two non-linear kernels. You should be able to classify very hard data sets with these.



Poly: order 3

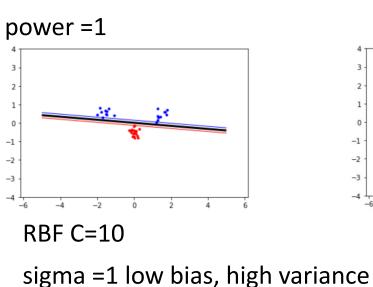
RBF: Sigma = 1

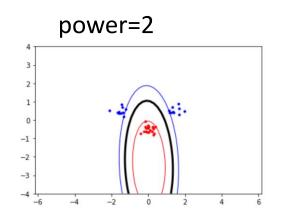


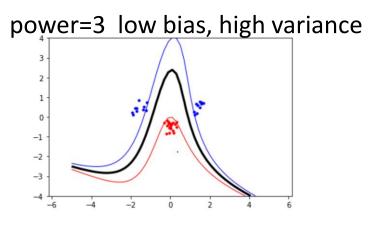


 The non-linear kernels have parameters; explore how they influence the decision boundary. Reason about this in terms of the bias/variance tradeoff.

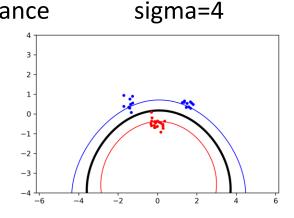
polynomial C=10

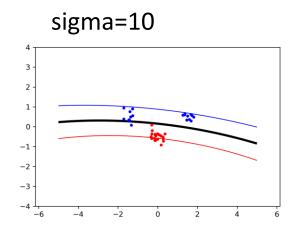






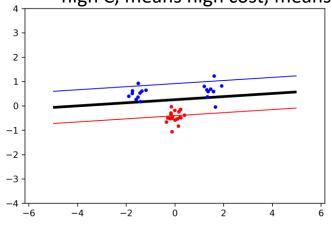
1 0 -1 -2 -3 -4 -6 -4 -2 0 2 4 6



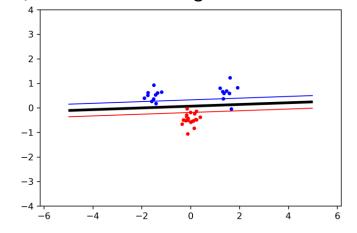


- Explore the role of the slack parameter C. What happens for very large/small values?
- C: cost of misclassification
- slack: how many data points are allowed to be misclassified

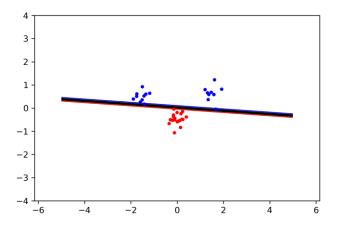
• high C, means high cost, means low slack, could be overfitting



c = 0.1



c = 10



c = 100

 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?

when the dataset is too noisy (or too many outliers), better to use a simple kernel. if we choose a complex kernel, then we need to low down the cost in order to allow more slack. therefore, overfitting could be avoided.