Support Vector Machines

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Assignment 2 - DD2421 Machine Learning
KTH Royal Institute of Technology, Sweden

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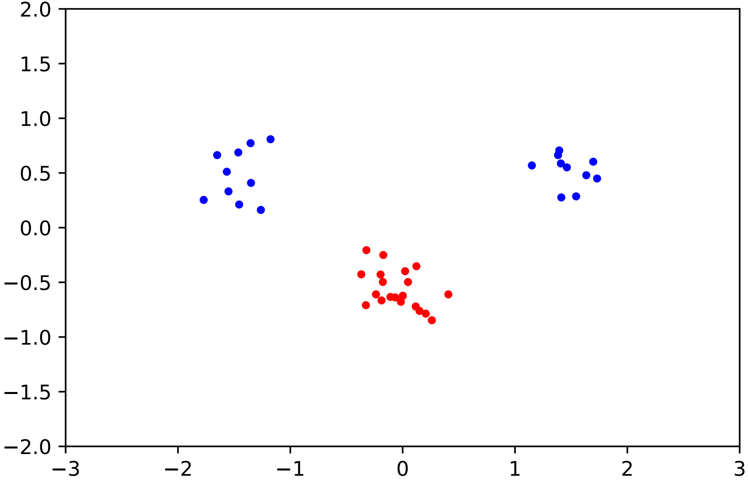
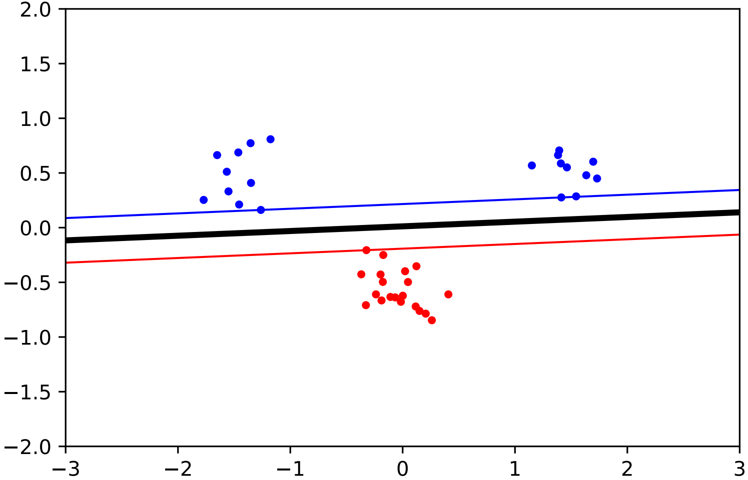
Linear kernel

Maximaize the margin (or distance to any datapoint).



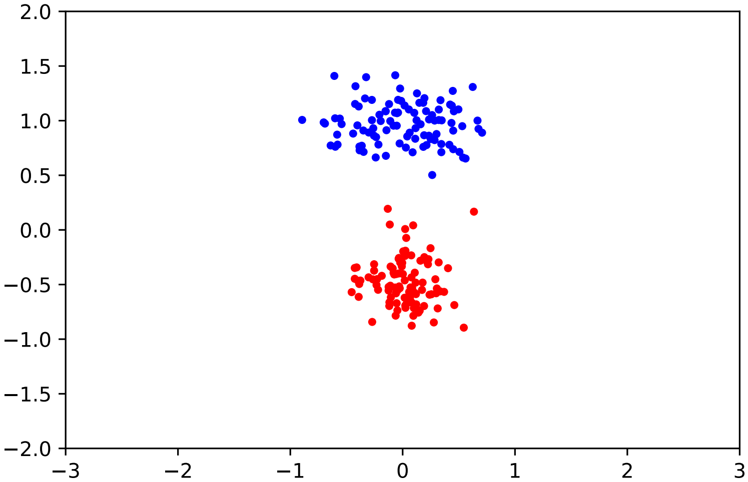
Linear kernel

Maximaize the margin (or distance to any datapoint).



Linear kernel

Take longer time for large datasets.



Linear kernel

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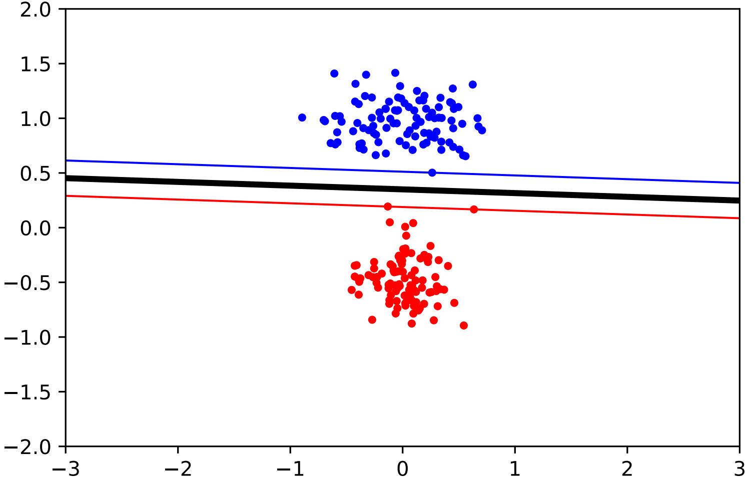
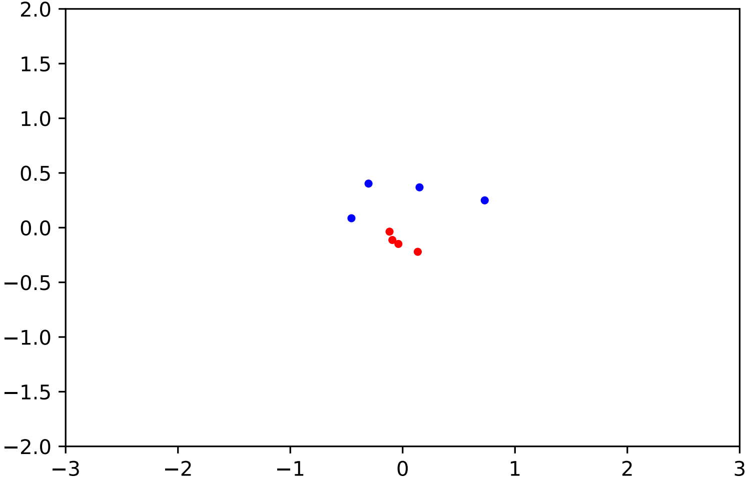


Linear kernel

Very good for small sizes samples.



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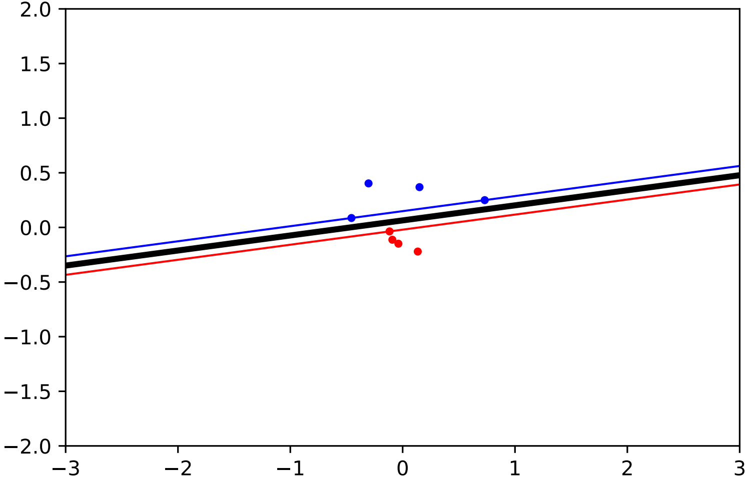
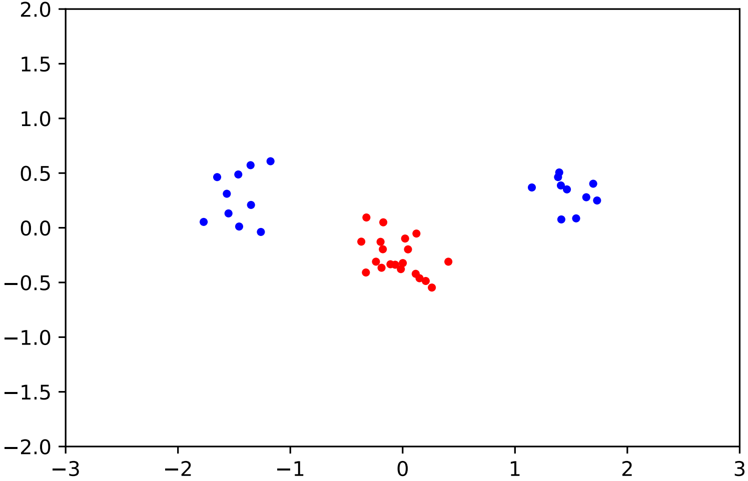


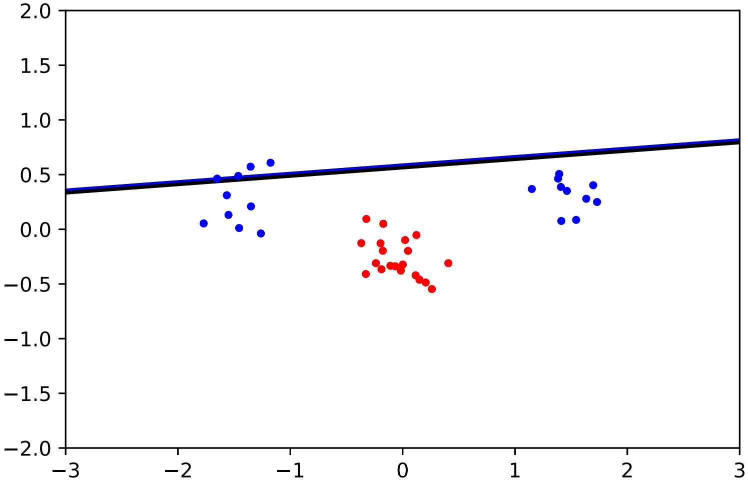
Linear kernel

No solution.



Linear kernel

No solution.



Non-linear kernels

- Polynomial kernels,

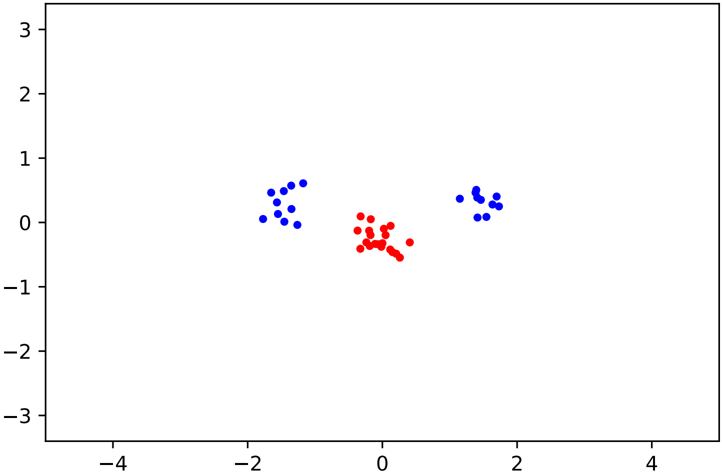
$$\mathcal{K}(\vec{x}, \vec{y}) = \left(\vec{x}^T, \vec{y} + 1\right)^p .$$

- Radial Basis Function (RBF) kernels,

$$\mathcal{K}(\vec{x}, \vec{y}) = e^{-\frac{||\vec{x}-\vec{y}||^2}{2\sigma^2}} .$$

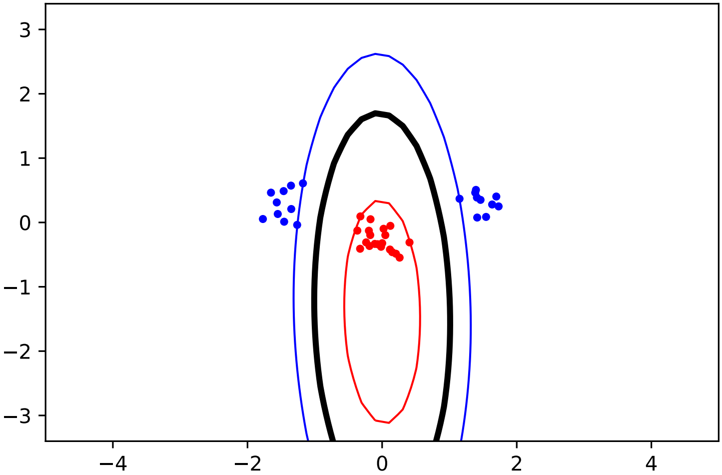
Non-linear kernels

Polynomial kernels, $p = 2$.



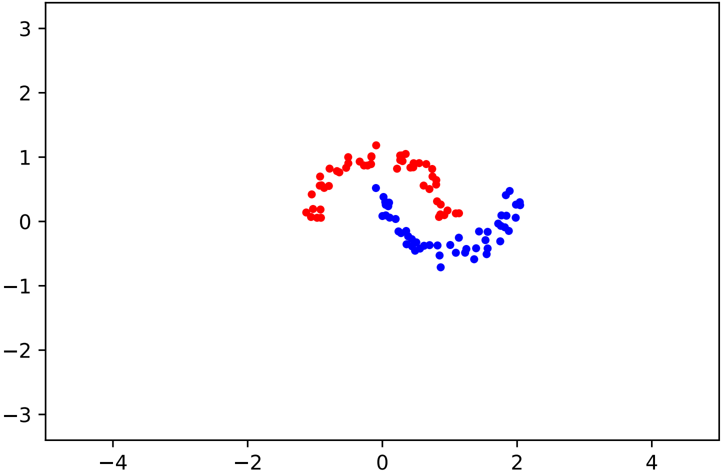
Non-linear kernels

Polynomial kernels, $p = 2$.



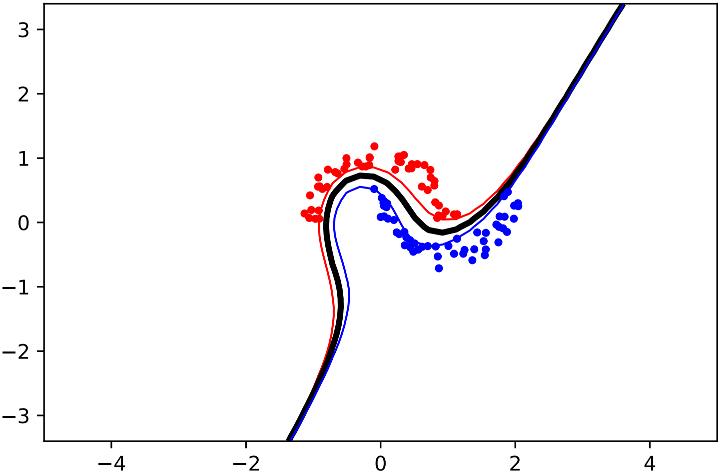
Non-linear kernels

Polynomial kernels, $p = 3$.



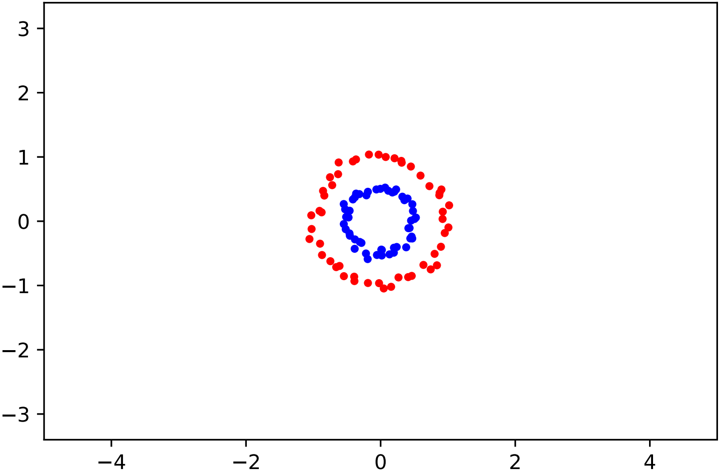
Non-linear kernels

Polynomial kernels, $p = 3$.



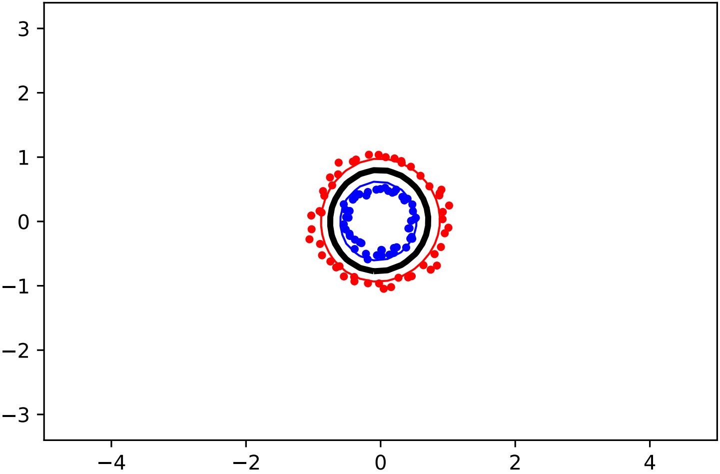
Non-linear kernels

Radial Basis Function (RBF) kernels, $\sigma = 1$,



Non-linear kernels

Radial Basis Function (RBF) kernels, $\sigma = 1$.



Bias-variance trade-off and the parameter of the kernels

Polynomial kernels:

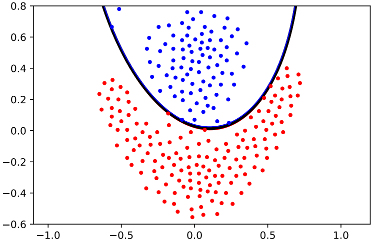
A large p corresponds to more complex decision boundary which implies high variance and low bias and vise versa.

RBF kernels:

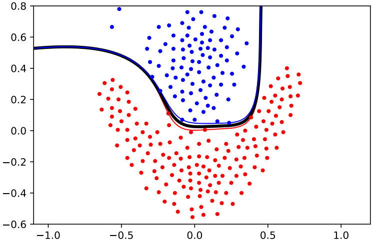
A large σ corresponds to a small value of kernel function that means the support vector does not have much influence on the classification. It allows more complex decision boundary but it faces on overfitting. Therefore, a large σ leads to high bias and low variance model.
A small σ implies that the SV has larger influence on the classifying. The decision boundary thus becomes simpler that leads to high bias, low variance model.

Bias-variance trade-off and the parameter of the kernels

Polynomial kernels



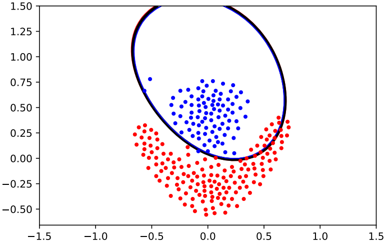
$p = 2$



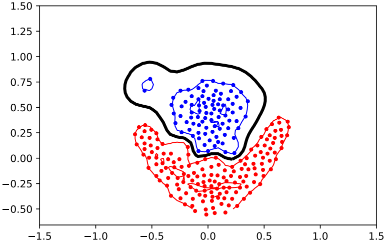
$p = 20$

Bias-variance trade-off and the parameter of the kernels

RBF kernels.



$\sigma^2 = 1$



$\sigma^2 = 0.1$

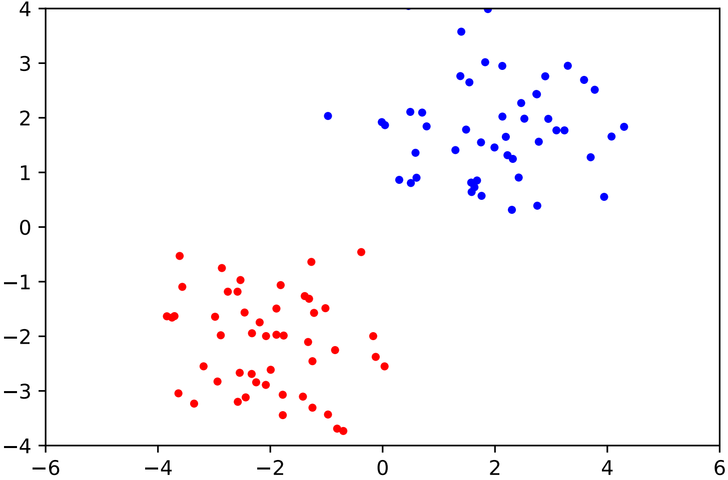
Slack parameter C

Q4: Explore the role of the slack parameter C. What happens for very large/small values?

A: The C parameter tells the SVM optimization how much you want to avoid misclassifying each training example. For large values of C, the optimization will choose a smaller-margin hyperplane if that hyperplane does a better job of getting all the training points classified correctly. Conversely, a very small value of C will cause the optimizer to look for a larger-margin separating hyperplane, even if that hyperplane misclassifies more points. For very tiny values of C, you should get misclassified examples, often even if your training data is linearly separable.
A large C leads to low bias and high variance model.

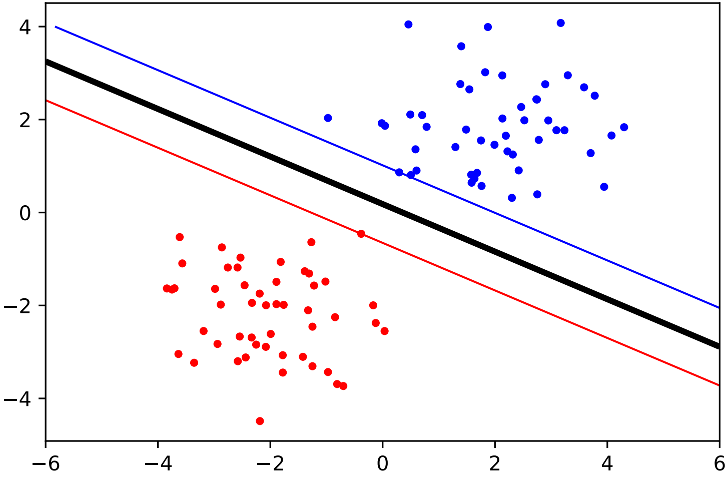
Slack parameter C

Linear classifier



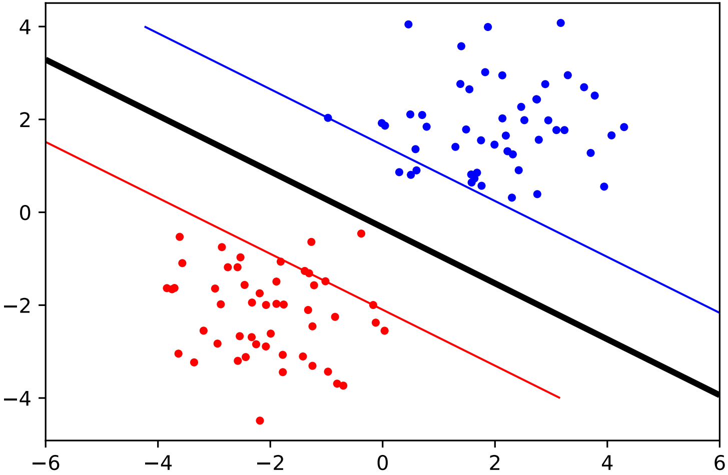
Slack parameter C

Linear classifier without C.



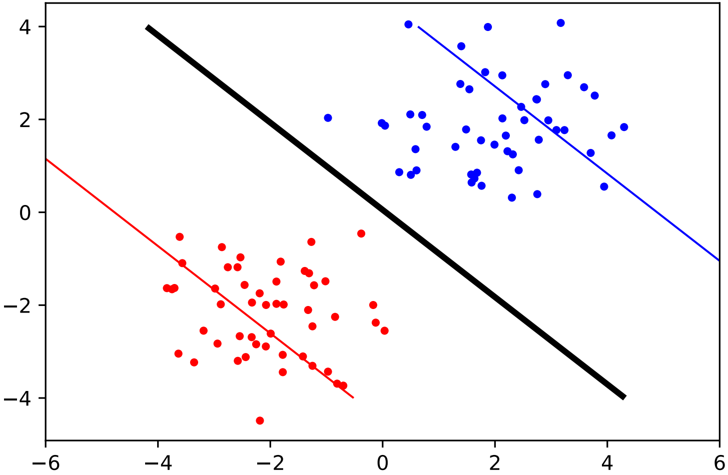
Slack parameter C

Linear classifier with $C = 0.1$.



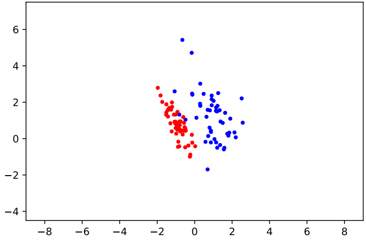
Slack parameter C

Linear classifier with $C = 0.002$.



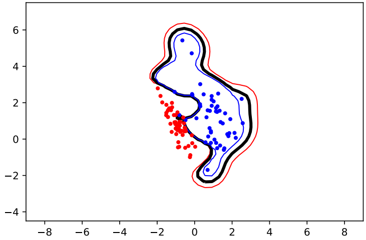
More slack or more complex model

Dataset has much noise

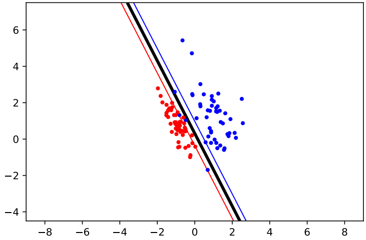


More slack or more complex model

Dataset has much noise $\rightarrow$ choose a good slack.



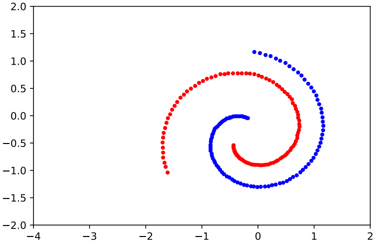
RBF kernel with $\sigma = 0.7$.



Linear kernel with $C = 10$

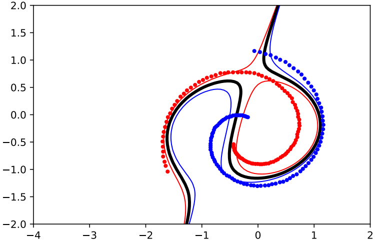
More slack or more complex model

Dataset has no noise with complex shape

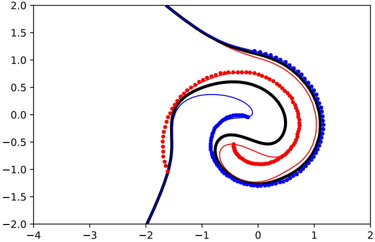


More slack or more complex model

Dataset has no noise with complex shape $\rightarrow$ choose a complex model.



Polynomial kernel with $p = 3, C = 10$.



Polynomial kernel with $p = 10$.