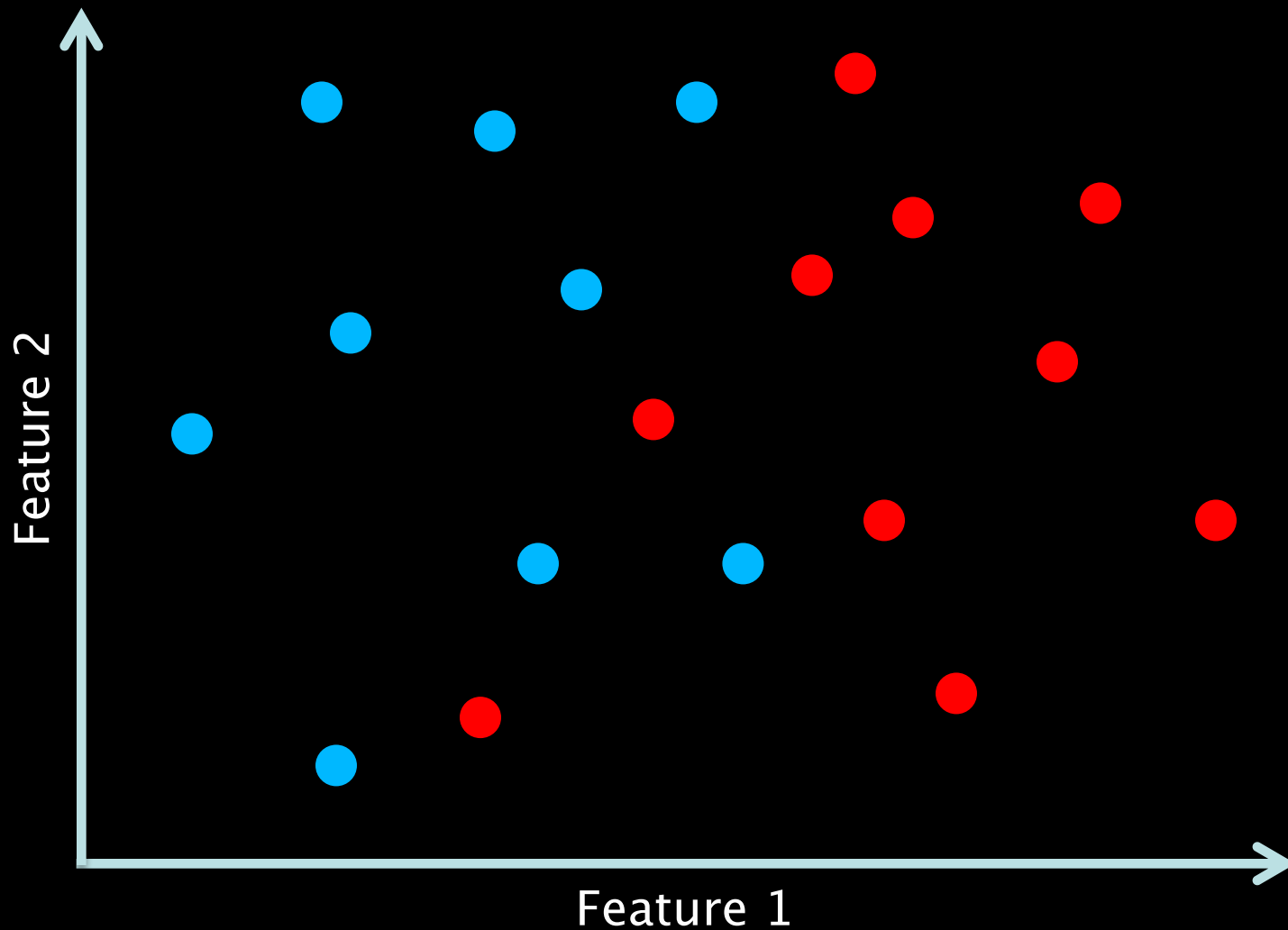


Data Science 7

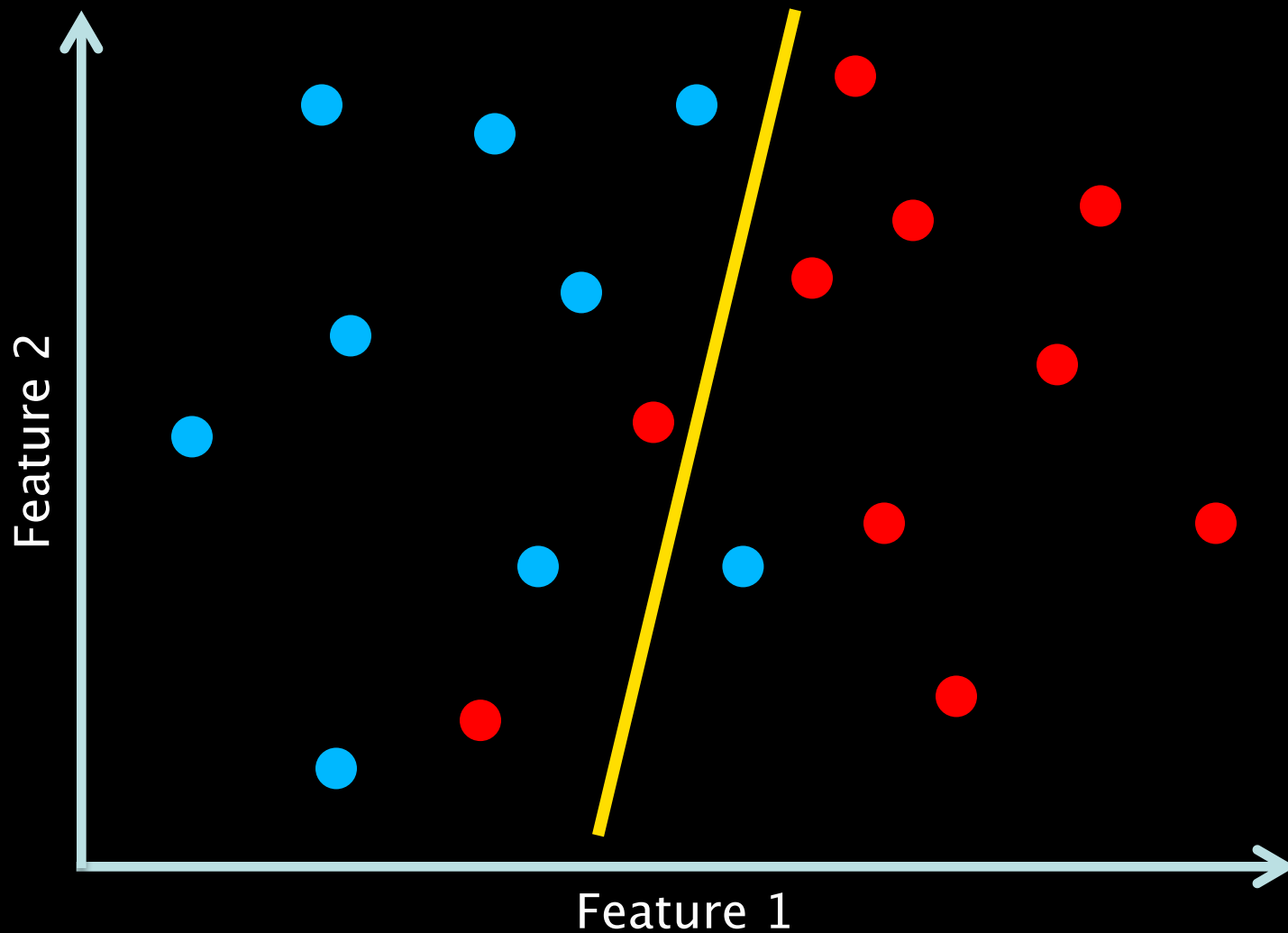
Overview

- Classification
- Model complexity = complexity of the decision boundary
- Support Vector Machines / Kernel Machines
- Kernels
- Orange

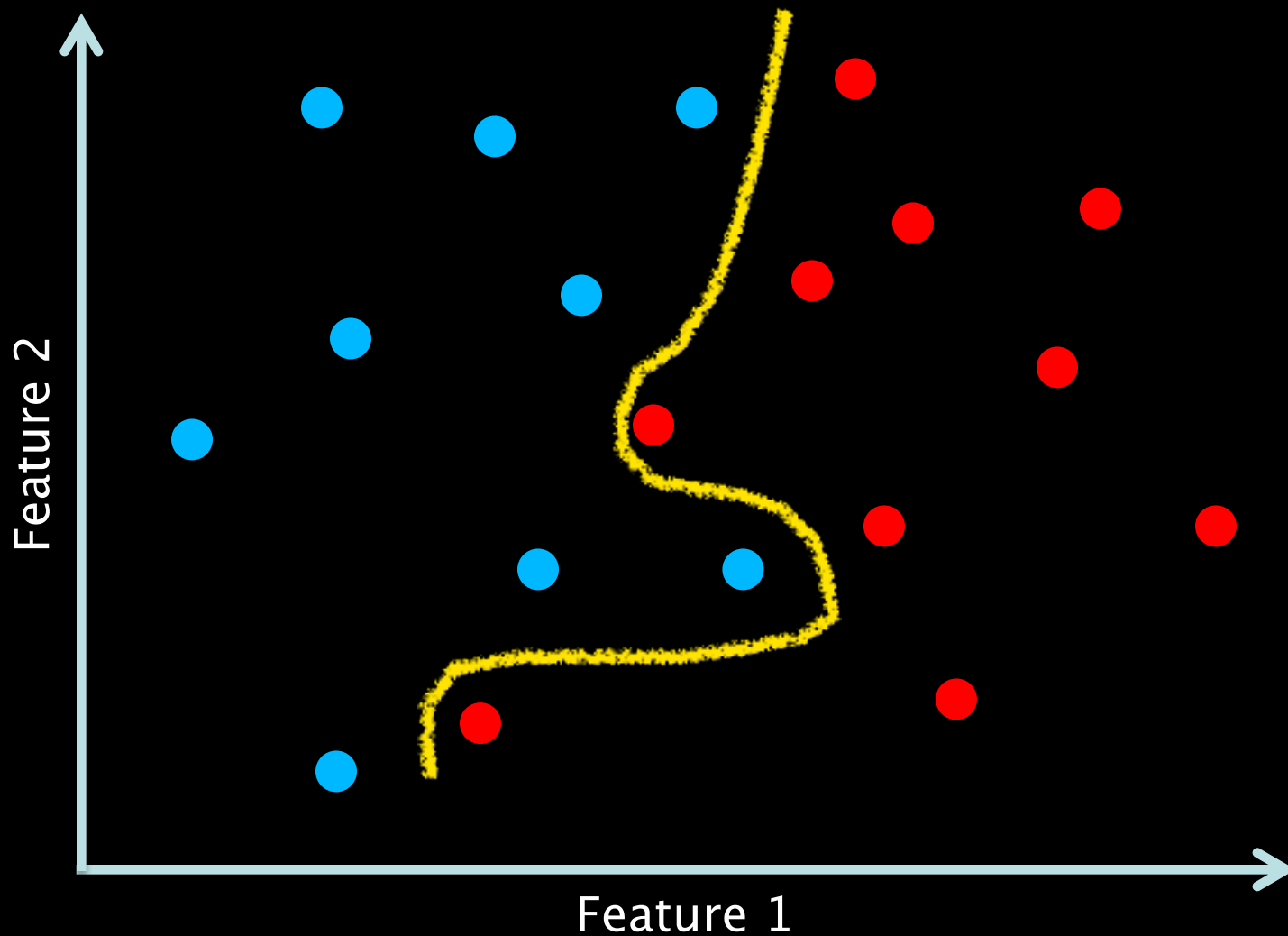
Two Classes (blue & red)



Separation by a simple model (— = decision boundary)



Separation by a complex model (— = decision boundary)



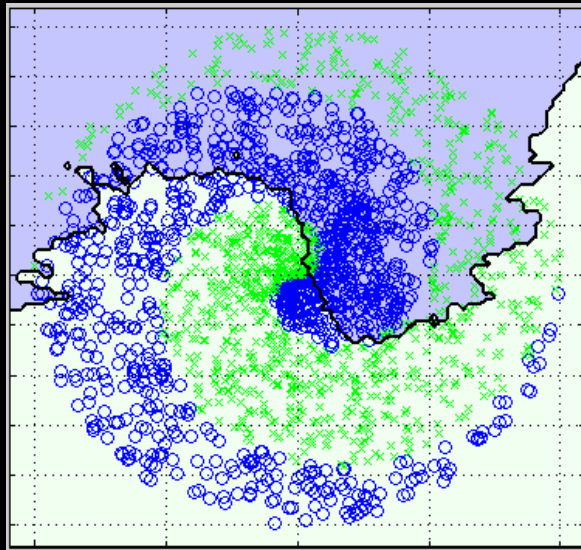
In classification...

- The complexity of a model is the flexibility of the decision boundary

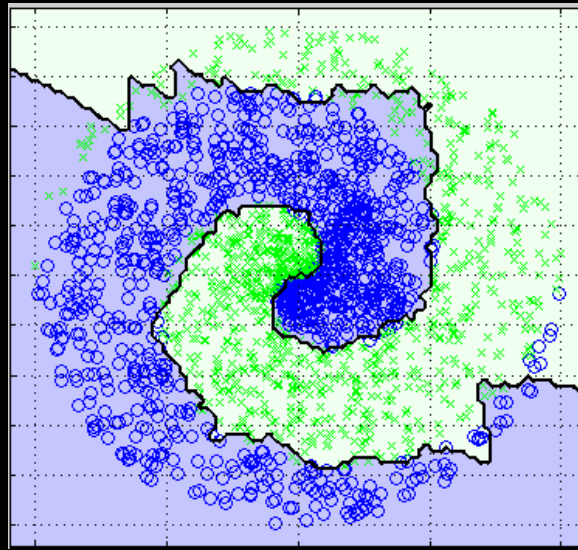


How to determine model complexity?

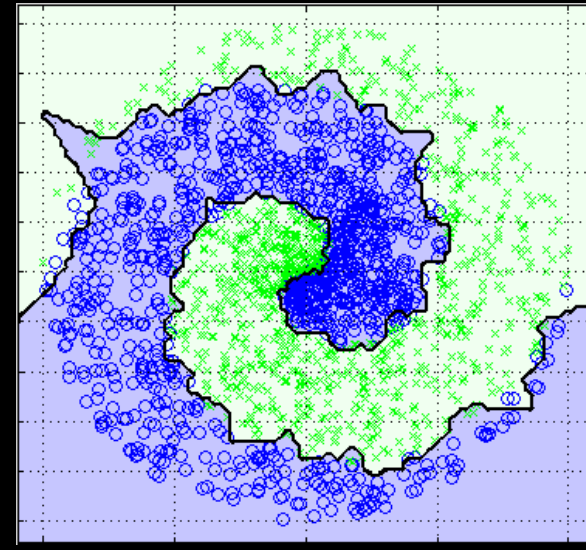
- Depends on complexity of the separation between the classes
- Start with the simplest model (large k in k NN), and increase complexity (smaller k)



$k = 100$

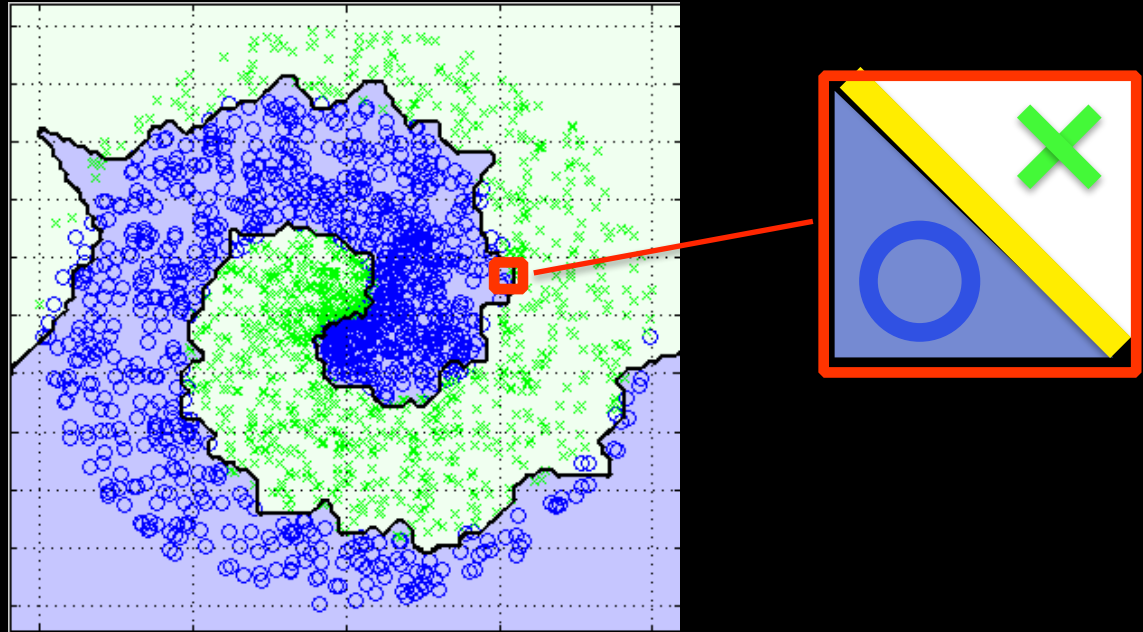


$k = 10$



$k = 1$

Increasing model complexity

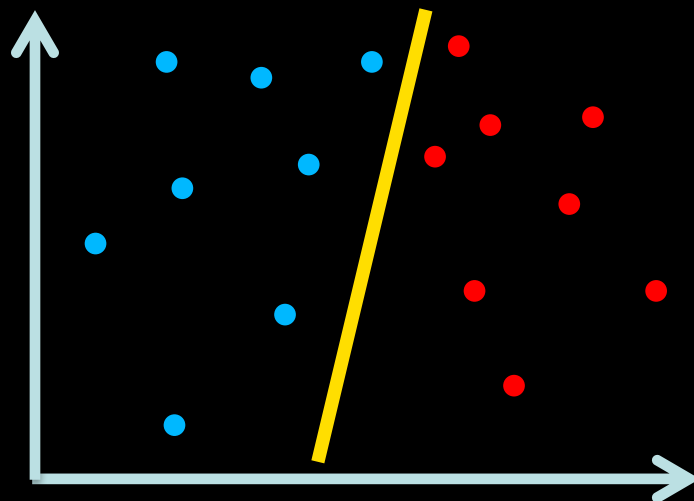


In kNN, the model (decision boundary) is defined by all instances in the training set. That is quite expensive. Can't we represent the boundary by a few instances only?

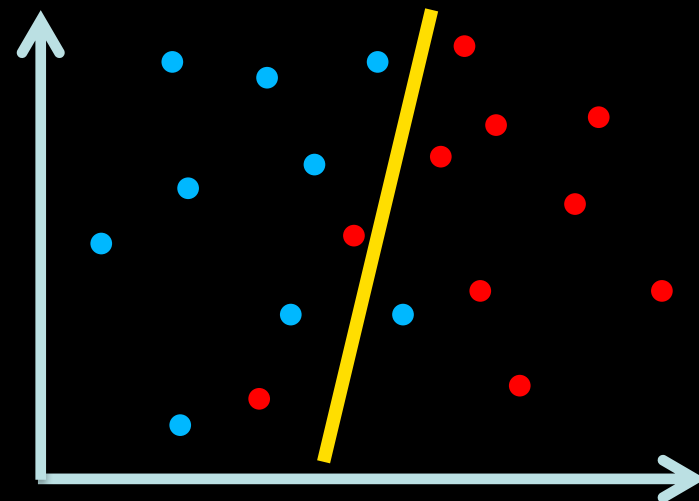
Support Vector Machines a.k.a. Kernel Machines

Simplest SVM

- Linear SVM
- Places a straight line between the classes (simplest model)



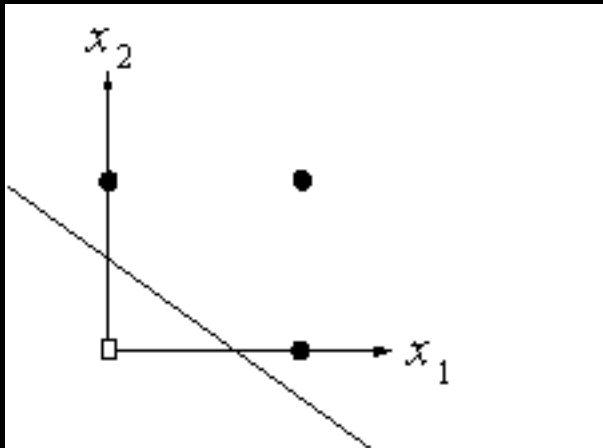
the instances are linearly separable



the instances are **not** linearly separable

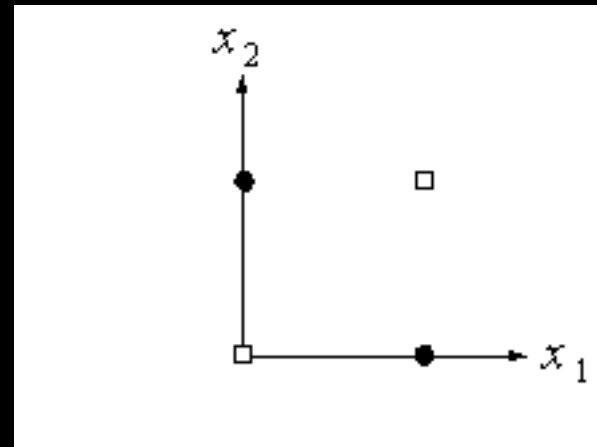
Linearly separable

The instances of the two classes can be separated by a straight decision boundary (OR problem)

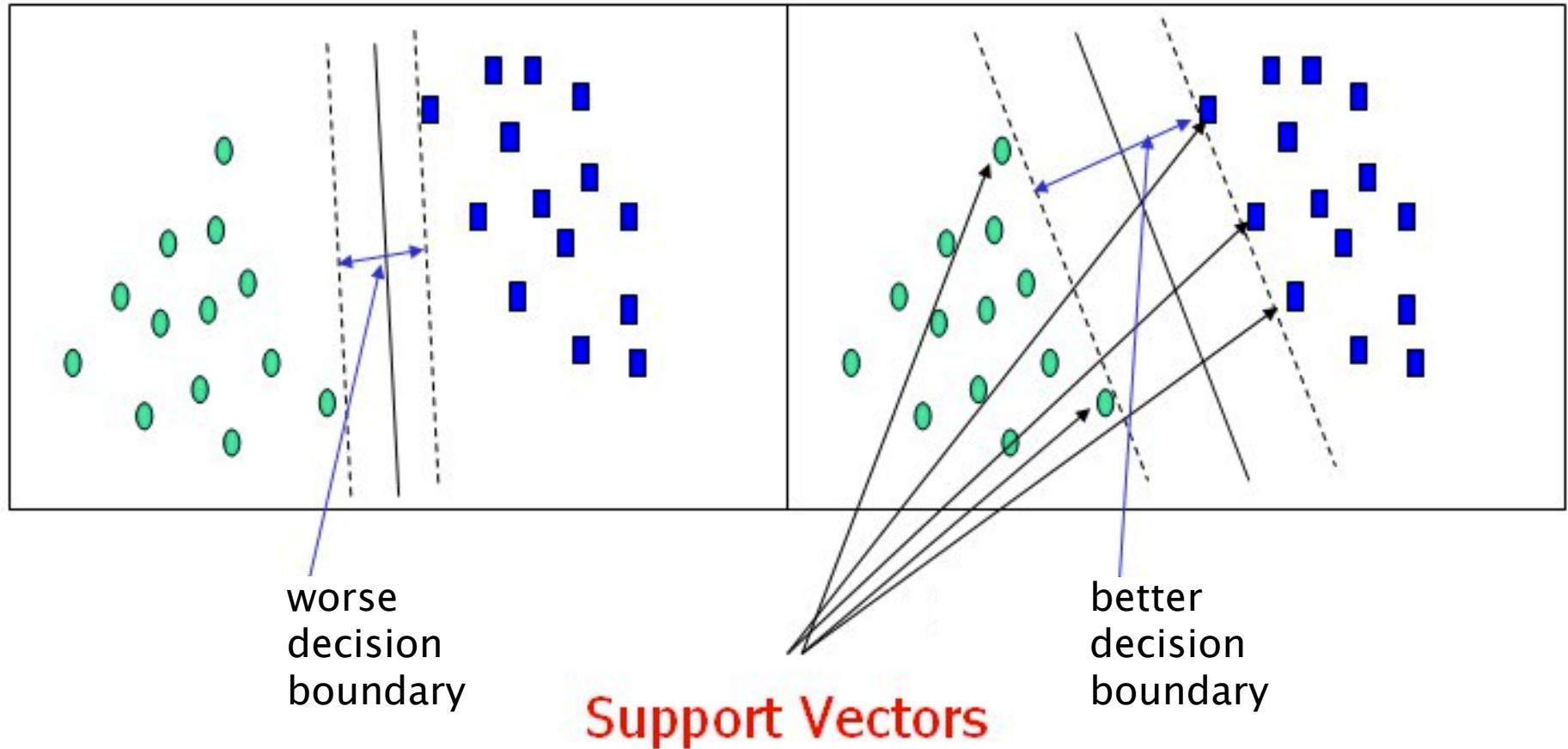


Linearly inseparable

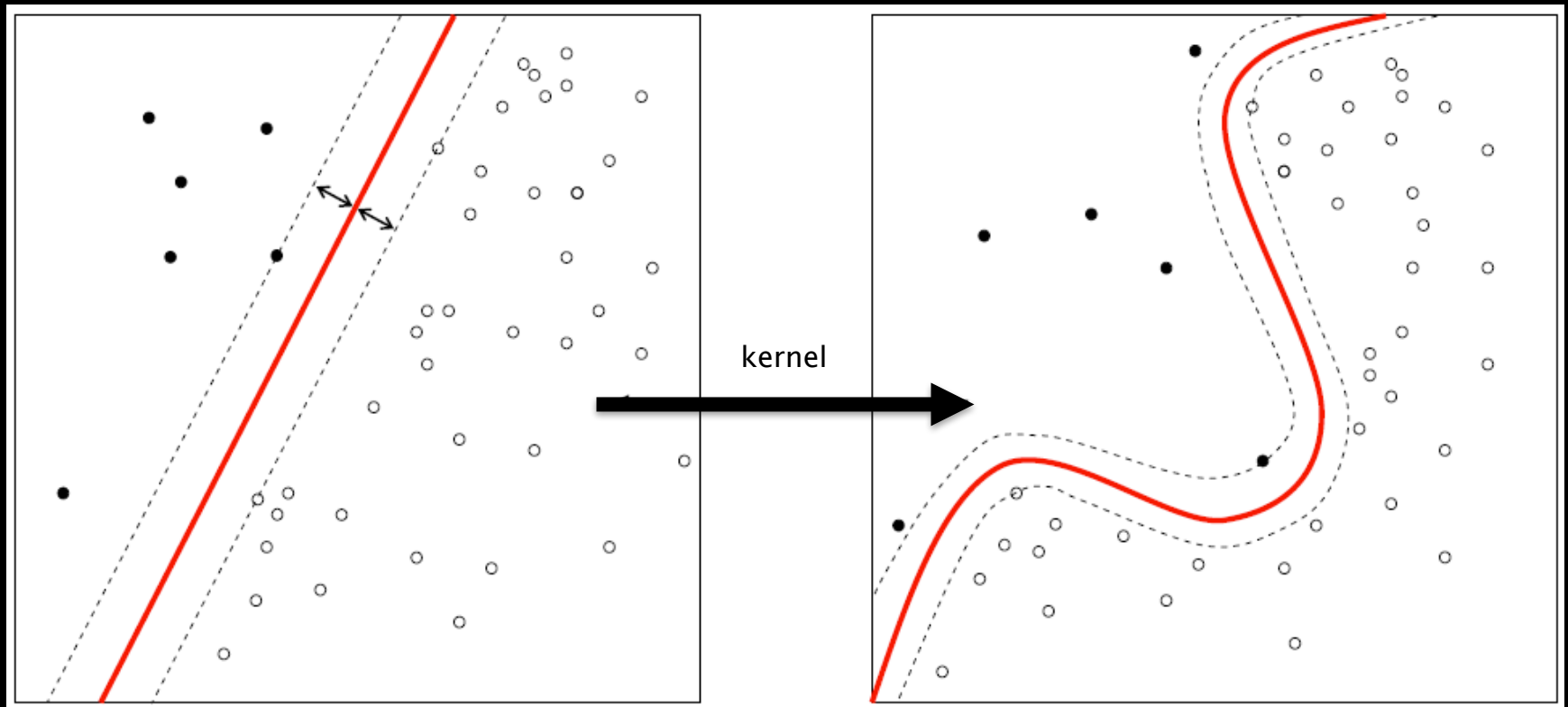
The instances of the two classes can **not** be separated by a straight decision boundary (XOR problem)



Why “Support Vector Machine”?

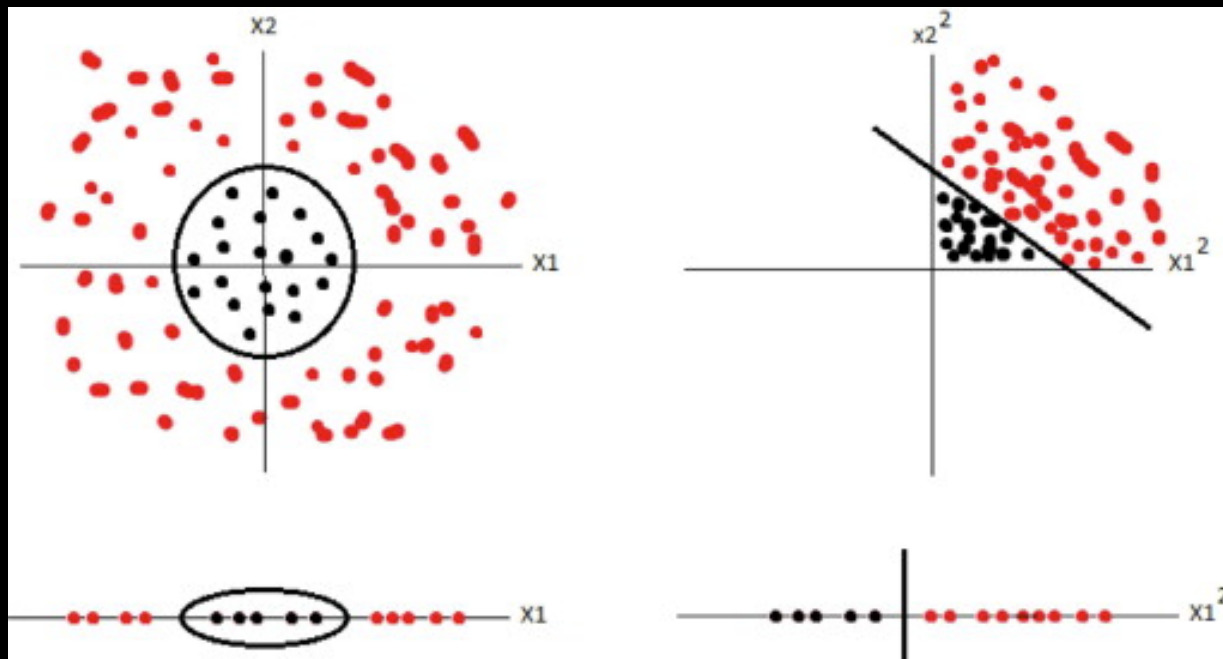


SVMs can make more complex decision boundaries by using kernels



Kernel

- A kernel performs a mathematical operation on instances in two classes that are **not** linearly separable, so that they do become linearly separable



Kernel = Similarity Measure

- A kernel takes pairs of instances and determines their similarity\
- There are many kernels
- The proper choice of a kernel depends on the domain
- The “linear kernel” (actually no kernel) is the simplest version
- The linear kernel should be used especially when you have many features (recall the previous lecture)

Kernels

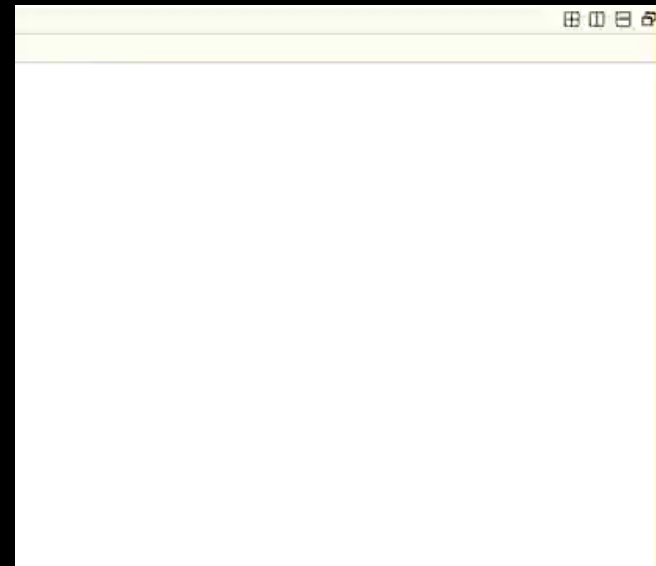
- Linear
- Polynomial
- Radial Basis Function
- Sigmoid

*SVM with a polynomial
Kernel visualization*

*Created by:
Udi Aharoni*

Kernels

- Linear
- Polynomial
- Radial Basis Function
- Sigmoid



Orange



SVM

Name

SVM Type

☒ C-SVM Cost (C)

☐ v-SVM Complexity bound (v)

Kernel

☐ Linear, $x \cdot y$

☐ Polynomial, $(g x \cdot y + c)^d$

☒ RBF, $\exp(-g|x-y|^2)$

☐ Sigmoid, $\tanh(g x \cdot y + c)$

g: c: d:

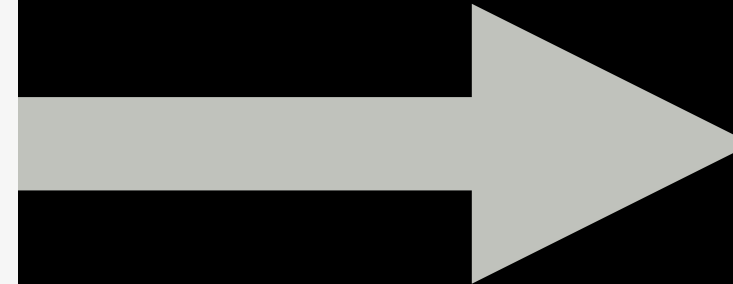
Optimization parameters

Numerical Tolerance

☒ Iteration Limit

Cost of misclassification

Number of support vectors

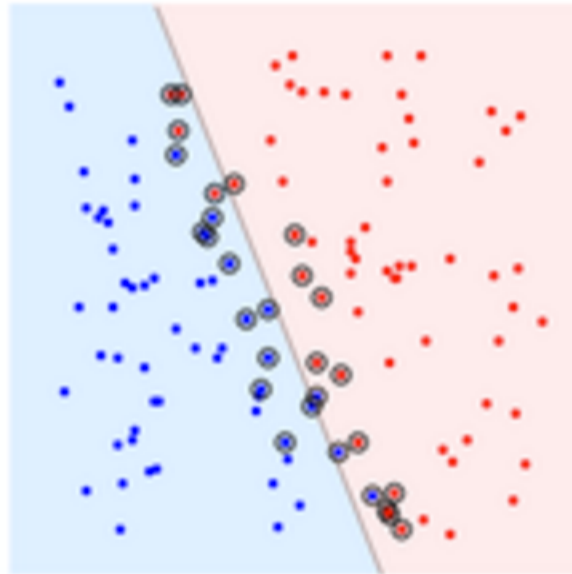


C = Cost parameter (misclassification cost)

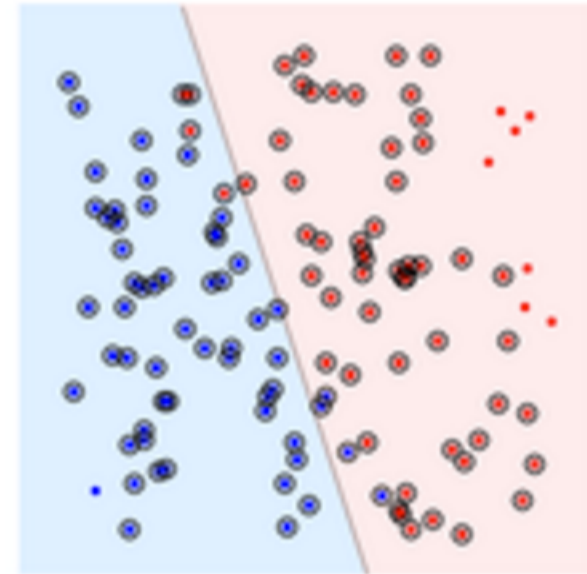
C=1000



C=10

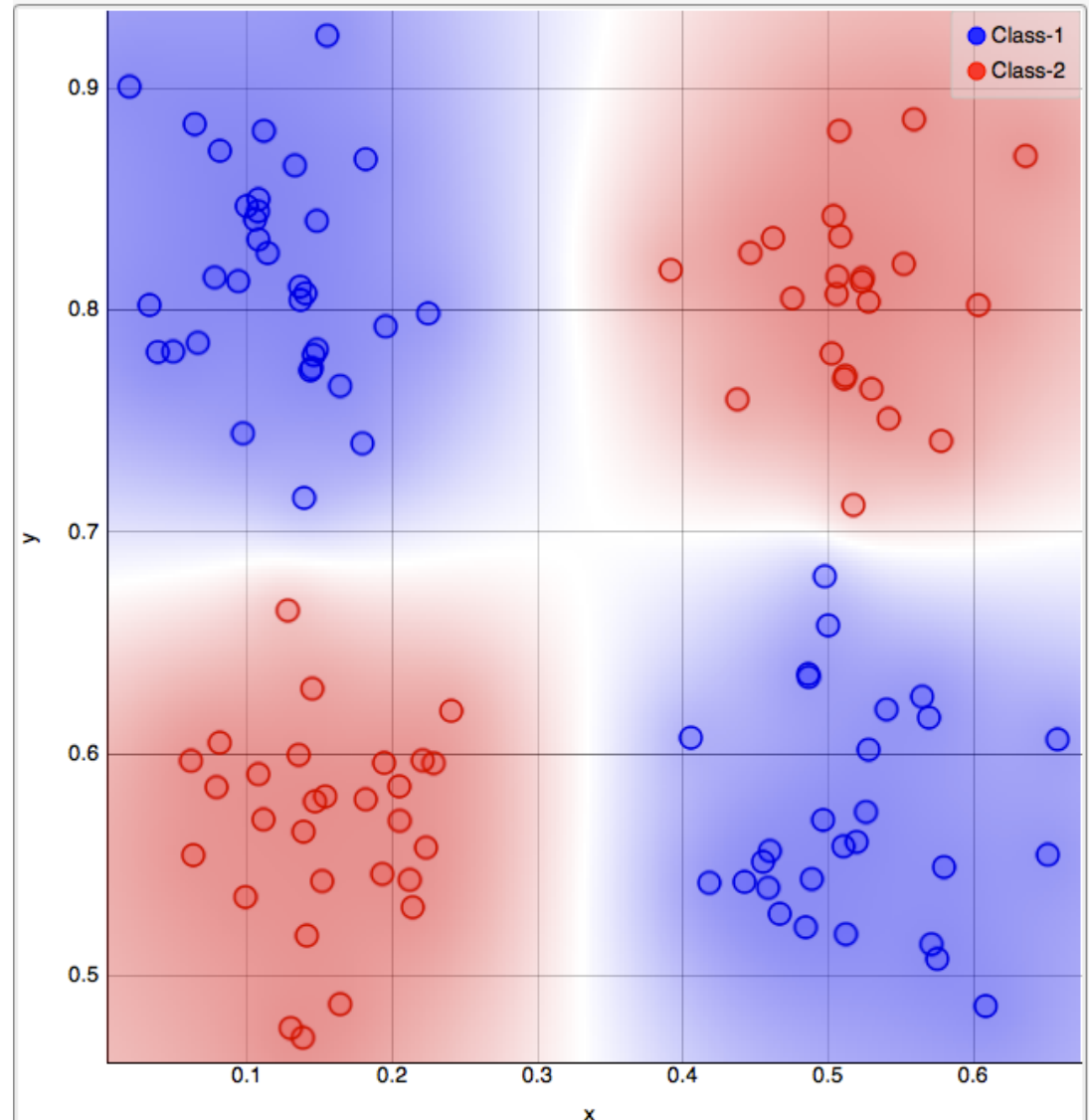


C=0.1

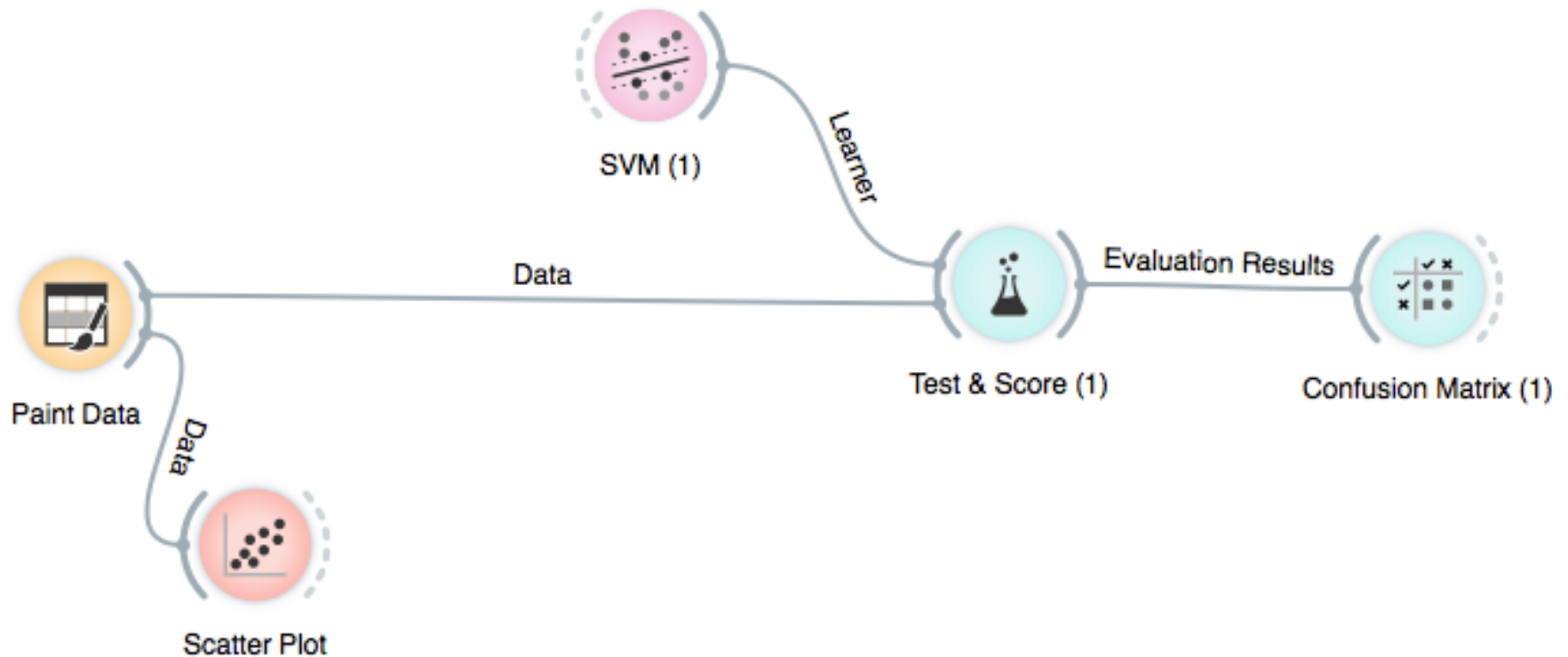


<https://www.quora.com/What-are-C-and-gamma-with-regards-to-a-support-vector-machine>

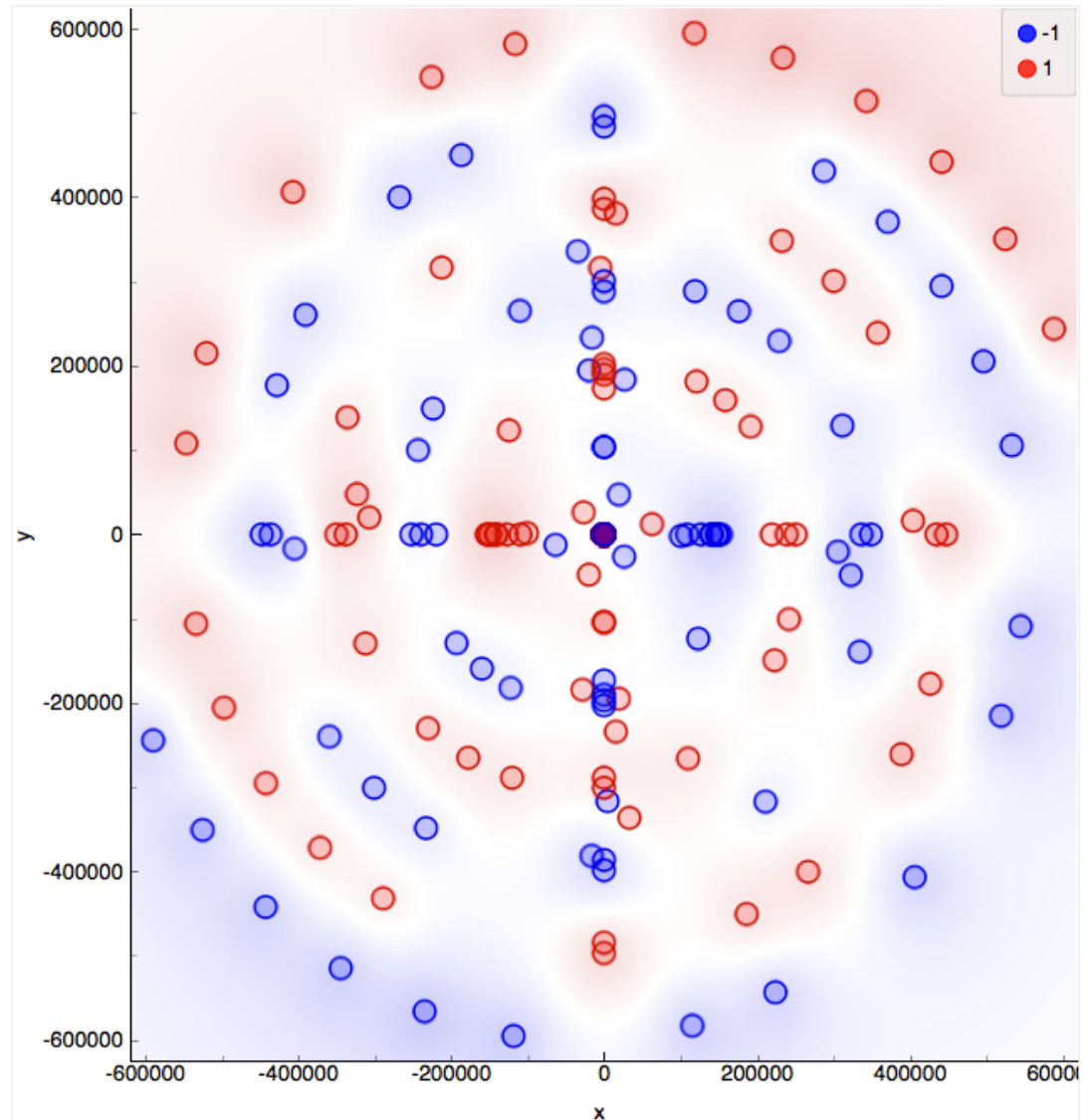
XOR dataset (create using Paint Data)



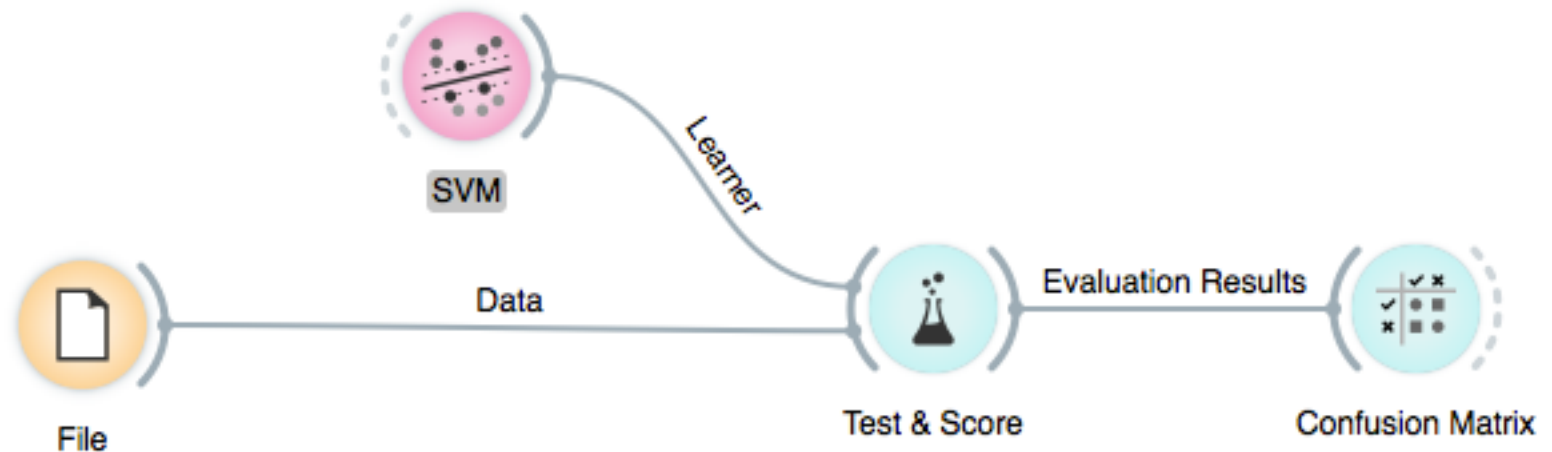
Experimenting with SVMs (XOR dataset)



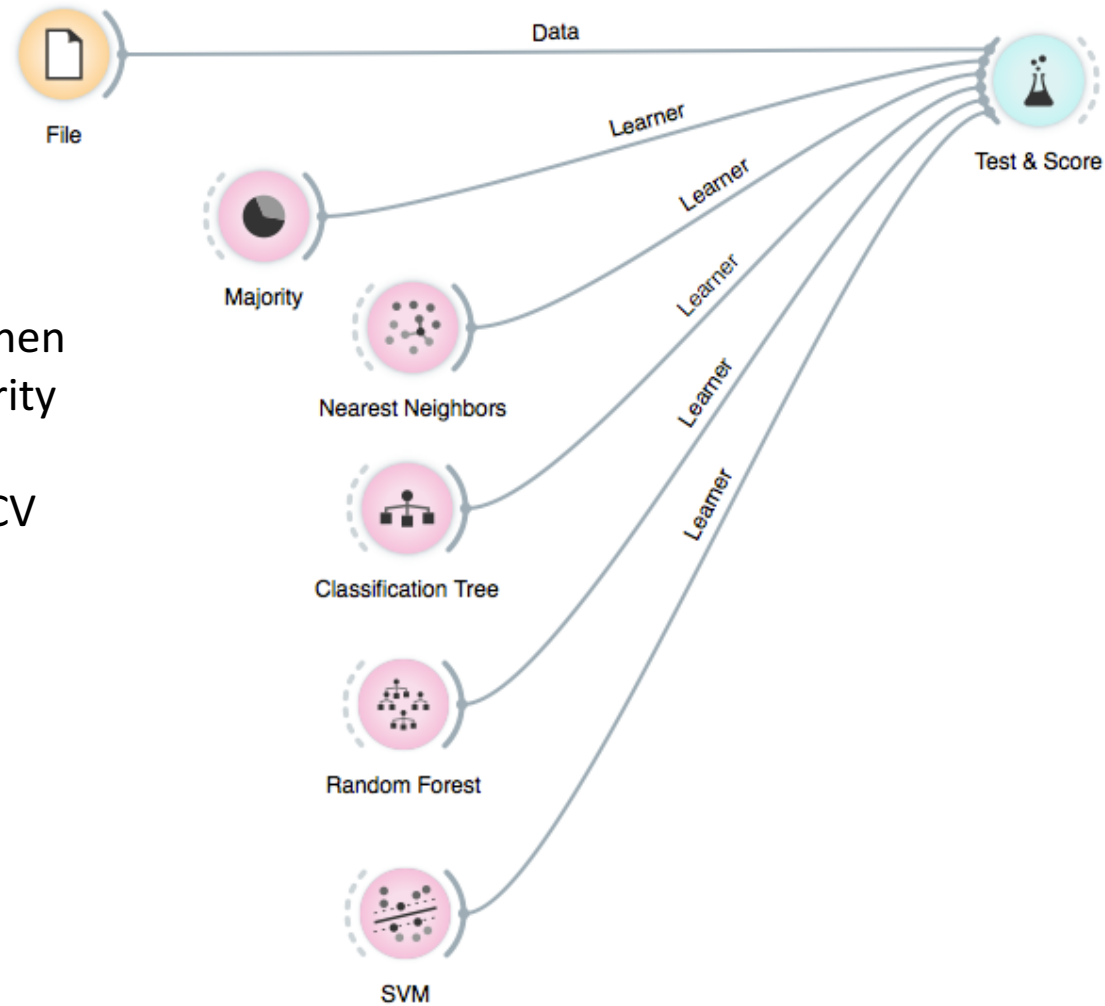
Spirals dataset



Experimenting with SVMs (spirals dataset)



Comparative Evaluation on any dataset



Please note:
Use 5 or 10 fold CV when
comparing with Majority
classifier!
NOT leaving one out CV