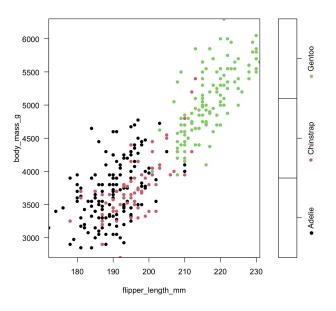
Support Vector Machines

Support Vector Machines (SVMs)

Supervised learning model for classification or regression

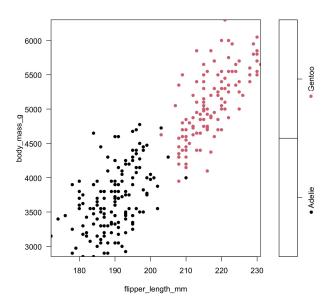
- Works well for finding the boundary between classes
- Efficient by reducing the the data set
- Supporting vectors
- Kernel functions to determine the shape of the boundary

Training Dataset - Penguins

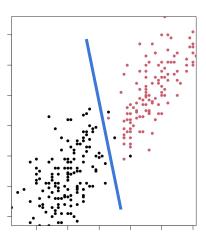


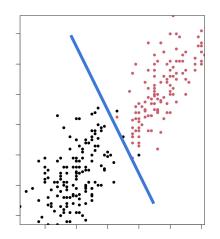
From the Palmer Penguins Library

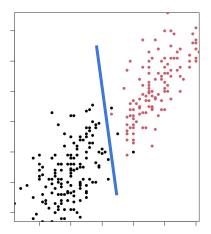
Classify Penguins Between Gentoo and Adelie



Where To Divide?







SVM Process

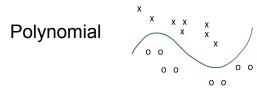
- 1. Choose a general shape for the decision body (linear, polynomial, radial)
- 2. SVM transforms the data into a higher dimensional space
- 3. SVM finds a class boundary (hyperplane)
- 4. SVM projects the class boundary back into the original dimensions space
- 5. SVM determines its most important data points
- 6. We have model (a class boundary and SV's) for classification

Step 1 - Choosing a Decision Boundary Type

SVM's can create boundaries bound by various expressions:

Linear

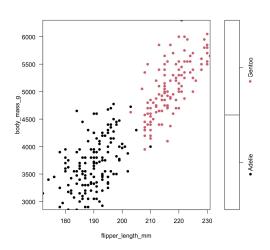




Radial Basis



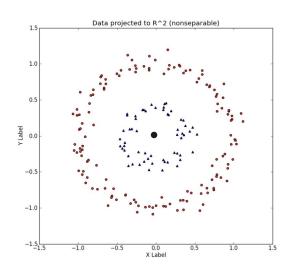
Step 2 - Transforming Linearly Separable Data



Do we need another dimension to separate the classes?

No. Data that is separable in 2D will also be separable in 3D

Step 2 - Transforming Non Linear Data

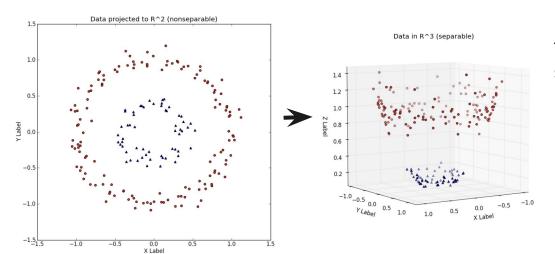


In 2D, no line can separate the two classes.

However for a z coordinate, we can define for each point:

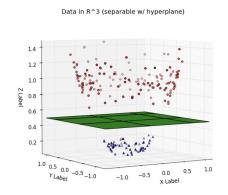
 $z = distance from the origin = sqrt(x^2 + y^2)$

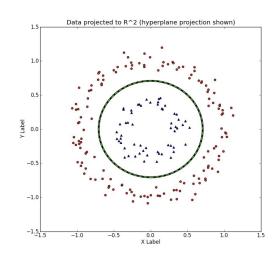
Step 2 - Transforming Non Linear Data



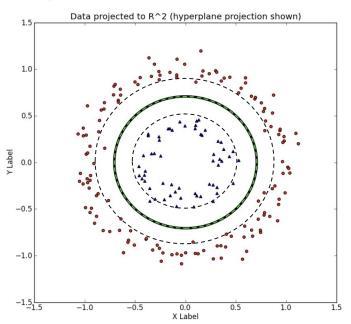
Transforming into 3D, a separation appears

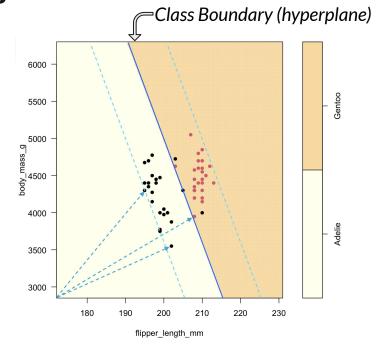
Step 3 & 4 - Class Boundaries and Back





Step 5 - Model with Margins



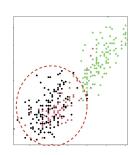


Efficiencies

- Reduced dataset
- Skip step 2 transformation (kernel trick)
- Comparing/prediction through dot-products of vectors
- Works with datasets with many features (ncol >> nrows)

But!

- Doesn't work well if the classes overlap a lot
- High number of SVs makes running slow



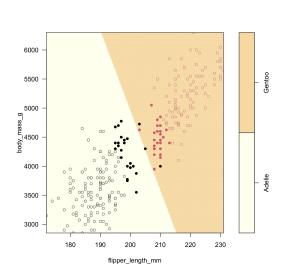
Cross Validation

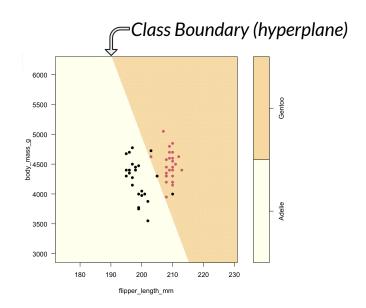
Linear Kernel: $x_i \cdot x_j - tune$ (cost)

Polynomial Kernel: $(x_i \cdot x_j + coef)^d \rightarrow tune(cost, degree, coef)$

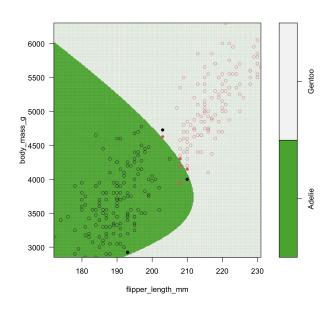
Radial Basis Kernel: $exp^{(-\frac{1}{2}|xi-xj|^2)}$ -> tune(cost, gamma)

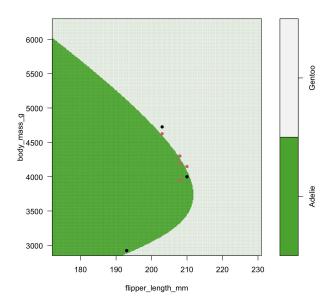
Tuned Penguin Model with Linear Kernel



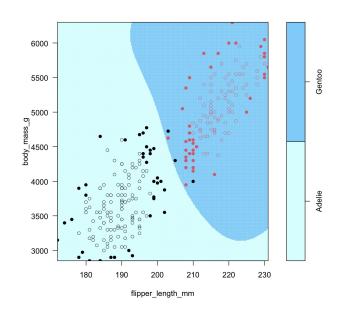


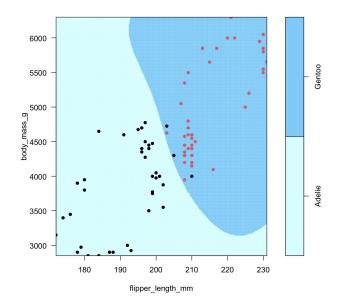
Tuned Penguin Model with Polynomial Kernel





Tuned Penguin Model with Radial Basis Kernel





Applications of SVMs

- Face recognition
- SPAM detection
- Handwriting recognition
- Datasets where the number of dimensions is higher than the number samples
- NLP