# Practical Machine Learning in R 

# Classification 

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## Classification



Goal: Predict a class (discrete quantity), or membership probabilities

## Logistic Regression

$\triangleright$ estimates probability of binary response
$\triangleright$ i.e. predict whether example belongs to one class or another
$\triangleright$ logistic function has output between 0 and 1 , can be interpreted as probability
$\triangleright$ essentially determines coefficients (importance) of each feature

## Logistic Regression



$$
\begin{aligned}
f(x)= & -40.2447695+-1.7247776 x_{1}+-5.0182373 x_{2}+ \\
& 8.0163583 x_{3}+15.500357 x_{4}
\end{aligned}
$$

## Binary vs. Multi-class

$\triangleright$ some learners can handle only two classes (e.g. logistic regression)
$\triangleright$ can distinguish between more classes with more models
$\triangleright$ e.g. one-vs-all approach:

- for each class, learn to predict score of how likely data point is in class
$\triangleright$ aggregate scores over all models (classes)


## Linear Discriminant Analysis

$\triangleright$ finds linear combination of features that separate classes
$\triangleright$ maps feature space into lower-dimensional space (dimensions are linear combinations of features)
$\triangleright$ determines centroid for each class in mapped space
$\triangleright$ classifies by assigning data point to centroid

## Linear Discriminant Analysis

## 3-class feature data


https://www.quora.com/How-does-Linear-Discriminant-Analysis-work-in-laymans-terms

## Support Vector Machines



## Support Vector Machines

$\triangleright$ data points with minimal margin are the support vectors (SV)
$\triangleright$ finding a hyperplane to maximize the margin is a straightforward optimization problem


## Support Vector Machines

Non-separable data

maximal margin

minimal margin violations

## Support Vector Machines - Kernel Trick

$\triangleright$ Kernels allow to extend SVMs to non-linear separation and non-vectorial data
$\triangleright$ maps the original feature space into higher-dimensional space
$\triangleright$ classes become linearly separable in this higher-dimensional space
$\triangleright$ input and output spaces can be infinite-dimensional

## Support Vector Machines - Kernel Trick



## Support Vector Machines - Kernel Trick

Examples:
$\triangleright$ linear kernel
$\triangleright$ polynomial kernel
$\triangleright$ Gaussian kernel

## Support Vector Machines - Kernel Trick



## Classification Trees

$\triangleright$ divide the feature space into rectangles and fit simple models (i.e. constant) in each
$\triangleright$ prediction is class distribution / most frequent label in subspace
$\triangleright$ rectangles can be further subdivided

## Tree Induction Algorithms

$\triangleright$ Greedy: Pick the best feature and it best split point in each iteration
$\triangleright$ Binary splits vs. multi-way splits
$\triangleright$ Criteria for the selection of a variable and its split point(s) (e.g. entropy)
$\triangleright$ Stopping criteria (e.g. minimum number of data points)
$\triangleright$ Handling missing values
$\triangleright$ Pruning

## Tree Building Example



## Tree Building Example



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## Tree Building Example



## Classification Forests

Random Forests:
$\triangleright$ Example of an ensemble method: instead of a single model, use several and combine the results
$\triangleright$ train trees on different subsamples (with replacement) of the data/features
$\triangleright$ aggregate predictions across trees by counting "votes" for each class
$\triangleright$ general method for improving unstable learners
$\triangleright$ usually done without pruning to increase variance

## Classification Forests



## Exercises

http://www.cs.uwyo.edu/~larsko/ml-fac/ 01-classification-exercises.Rmd


[^0]:    ${ }^{1}$ with slides from Bernd Bischl and Michel Lang
    ${ }^{2}$ slides available at http://www.cs.uwyo.edu/~larsko/ml-fac

