Instance-Based Learning

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In [36]:
```
# Preliminaries
library(mlr)       # ML library
library(OpenML)    # ML datasets, models, sharing

# Plotting
library(ggplot2)
library(cowplot)
```

1 Instance-Based Learning

- If you have no time to learn, but have lots of examples, what do you do?
  - E.g. Frank Abagnale Jr. posing as a doctor
- Long history on learning by analogy

Nearest neighbour algorithm - Simplest and fastest learning algorithm of all time (0 training time) - Delaying learning is sometimes really beneficial - E.g. Facebook imports 300,000,000 images a day

Nearest Neighbor

- Given query instance x_q, first locate nearest training example X_n, then estimate $\hat{f}(x_q) = f(x_n)$

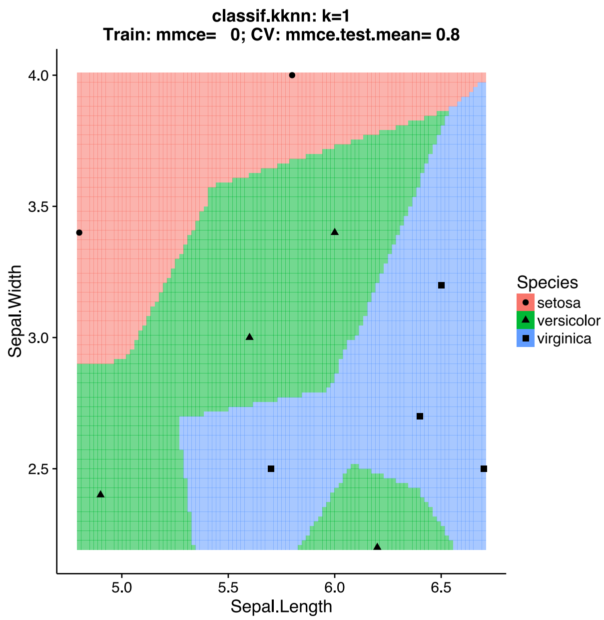
k-Nearest Neighbor

- Classification: Given x_q, take vote among its k nearest neighbors
- Regression: Take mean of f values of k nearest neighbors

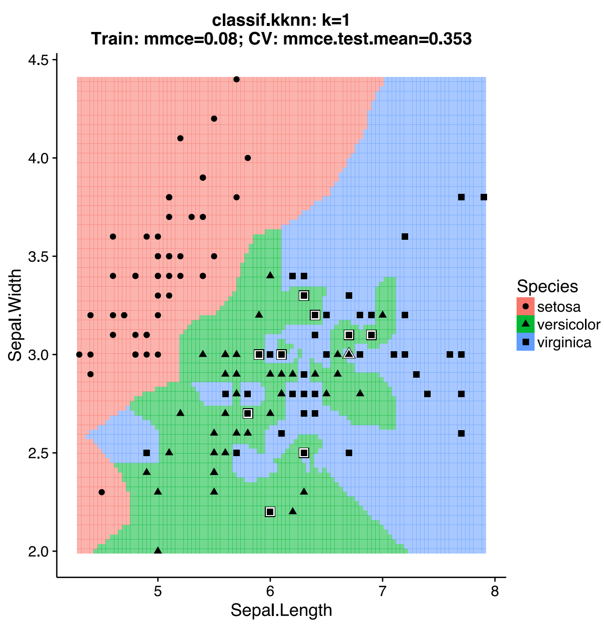
1.1 Voronoi Diagram

- Voronoi cell of $x \in S$: all points closer to x than any other in S
- Region of class C: Union of Voronoi cells of instances of C in S

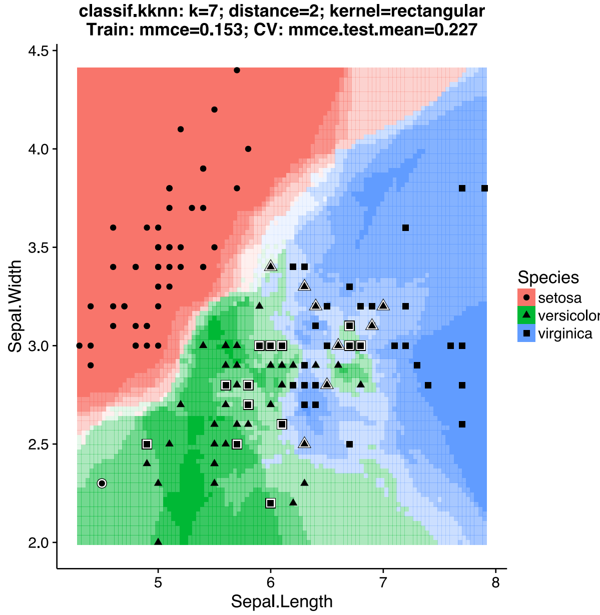
In [55]:
```
data(iris, package = "datasets")
iris_small = iris[sample(nrow(iris), 10), ]
task_small = makeClassifTask(data = iris_small, target = "Species")
lrn = makeLearner("classif.kknn", k = 1)
plotLearnerPrediction(lrn, task_small, features = c("Sepal.Length", "Sepal.Width")) + theme_co
```




```
In [45]: task = makeClassifTask(data = iris, target = "Species")
         lrn = makeLearner("classif.kknn", k = 1)
         plotLearnerPrediction(lrn, task, features = c("Sepal.Length", "Sepal.Width")) + theme_cowplot(
```




```
In [39]: # k-Nearest Neighbor. Try changing the number of neighbors and study the effect
         lrn = makeLearner("classif.kknn", par.vals = list(k = 7, distance = 2, kernel = "rectangular")
         plotLearnerPrediction(lrn, task, features = c("Sepal.Length", "Sepal.Width")) + theme_cowplot(
```



1.2 Increasing k

- Reduces variance
  - small variations in the data points will have less effect because of neigbor's votes
  - decision boundaries become smoother
  - less overfitting
- Increases bias
  - some points (even if correct) are overpowered by their neighbors
  - more underfitting
- k must be optimized empirically

1.2.1 Advantages

- Training is very fast
- Learn complex target functions easily
- Don't lose information

1.2.2 Disadvantages

- Slow at query time
- Lots of storage needed
- Easily fooled by irrelevant attributes

1.3 Distance measures

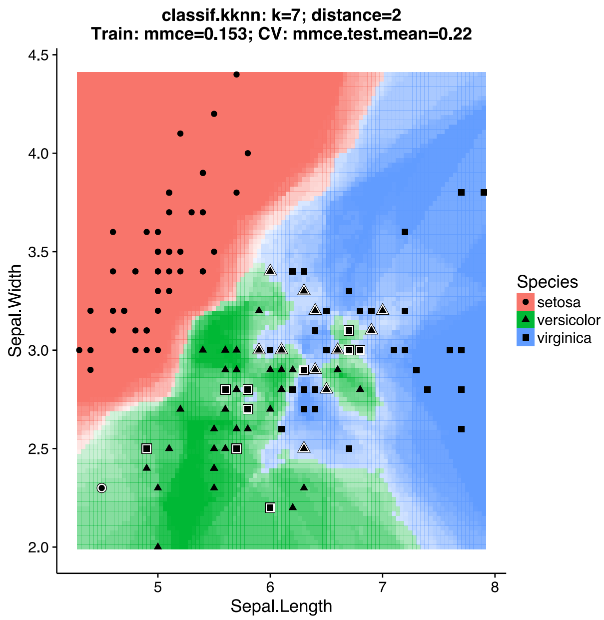
- Numeric features
  - Euclidean, Manhattan, L^n norm
  - Normalized by: range, std. deviation
- Symbolic features

- Hamming/overlap
- Value difference measure (VDM)

$$\delta(val_i, val_j) = \sum_{h=1}^{classcount} |P(c_h|val_i) - P(c_h|val_j)|^n$$

- In general: domain-specific, encode knowledge

```
In [40]: # The distance parameter allows you to change the distance measure (as the degree of the Minko
         lrn = makeLearner("classif.kknn", k = 7, distance = 2)
         plotLearnerPrediction(lrn, task, features = c("Sepal.Length", "Sepal.Width")) + theme_cowplot(
```



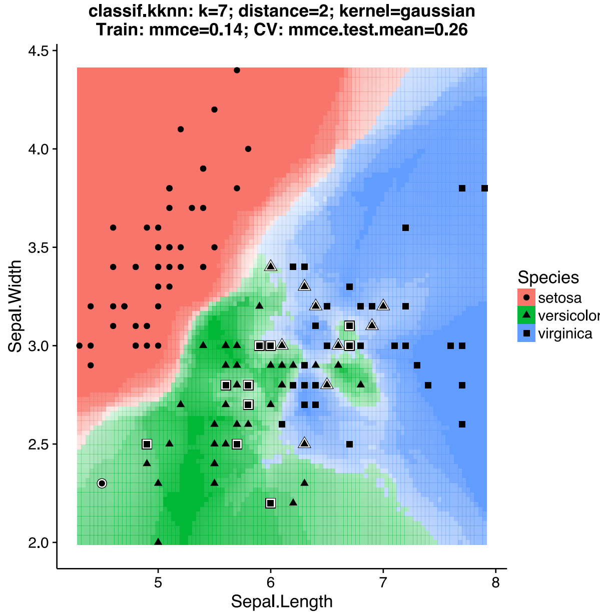
1.4 Distance-weighted kNN

- It may help to weight nearer neighbors more heavily, e.g.

$$\hat{f}(x_q) = \frac{\sum_{i=1}^{k} w_i f(x_i)}{\sum_{i=1}^{k} w_i}$$

  with weight $w_i = \frac{1}{d(x_q,x_i)^2}$ and $d(x_q, x_i)$ the distance between x_q and x_i
- We can now use all training examples instead of just k
  - No need to set k, but much more expensive to compute

```
In [41]: # Distance weighting is set by parameter 'kernel'. Rectangle = no weighting, Guassian = gaussi
         lrn = makeLearner("classif.kknn", par.vals = list(k = 7, distance = 2, kernel = "gaussian"))
         plotLearnerPrediction(lrn, task, features = c("Sepal.Length", "Sepal.Width")) + theme_cowplot(
```



1.5 Curse of dimensionality

- Nearest neighbor (and most distance-based algorithms) will fail
  - Easily misled by non-relevant features
  - Even with many relevant features, the problem becomes harder
    - You need exponentially more data points with every new dimension
- Low dimensional intuitions don't apply in high dimension
  - Normal distribution: increasing chance that random samples fall in the tail
  - Uniformly distributed points in a hypercube increasingly near the faces
  - Ratio of volume of center vs outer shell of hypersphere becomes very small
  - ...
- Use feature selection whenever you deal with high dimensionality