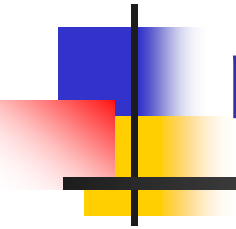

Some packages relative to machine learning in R

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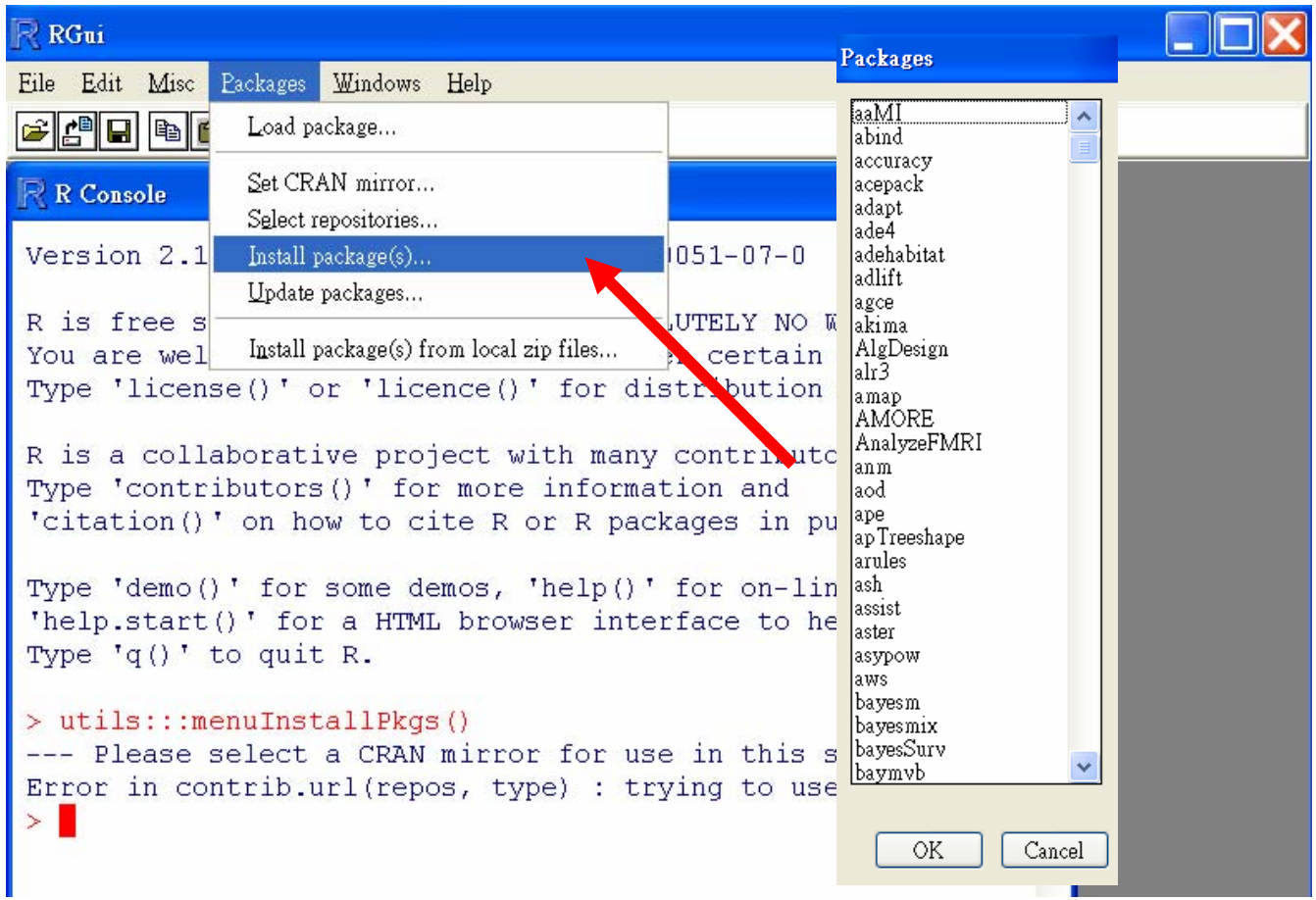
Machine learning methods

- Supervised Learning, where we get a set of training inputs and outputs
  - classification, regression
    - Tree, SVM, KNN, LDA, …
- Unsupervised Learning, where we are interested in capturing inherent organization in the data
  - clustering, density estimation
    - K-mean, EM, SOM, …

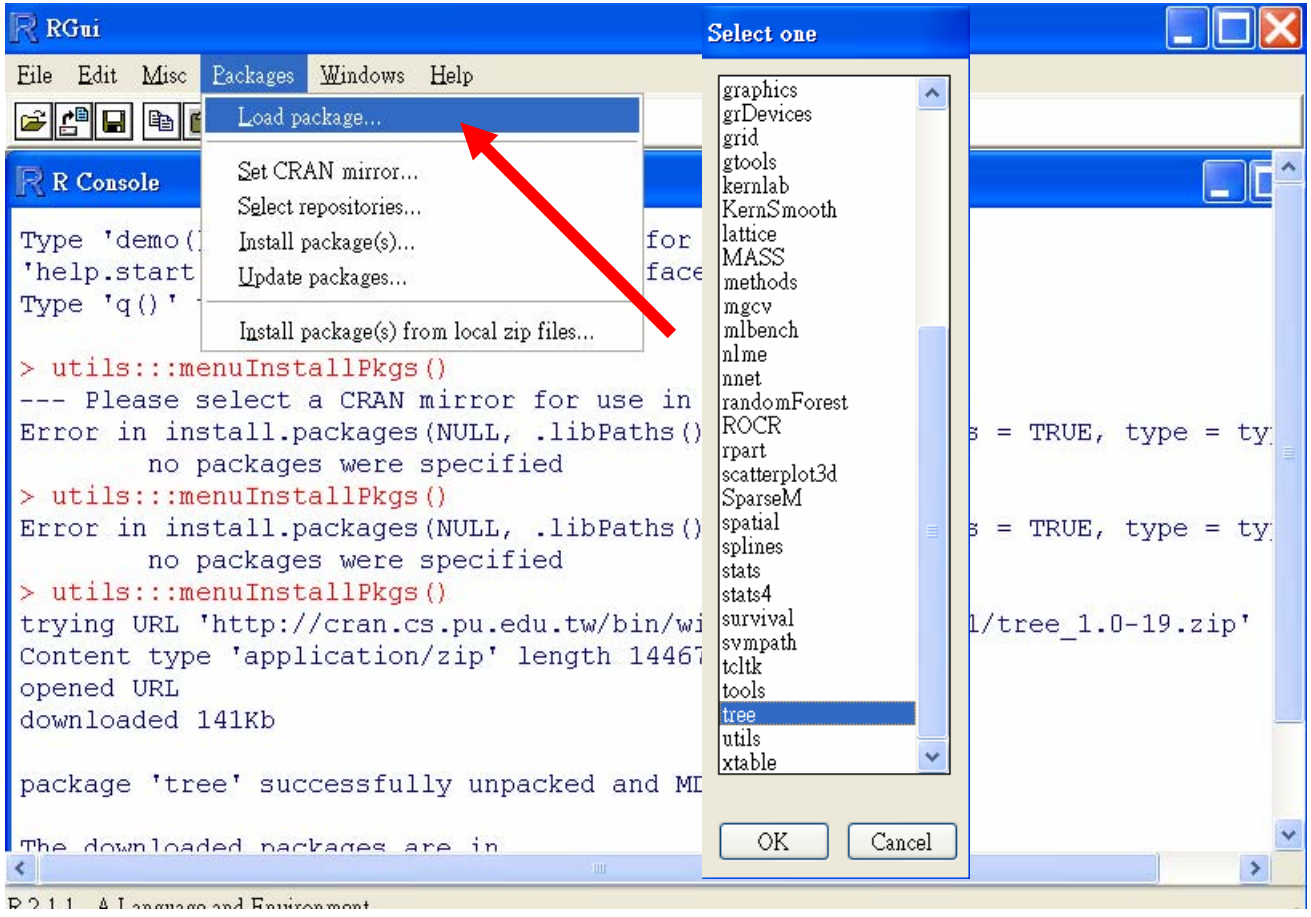
Install new packages “tree”

- For example: > install.packages(“tree”)

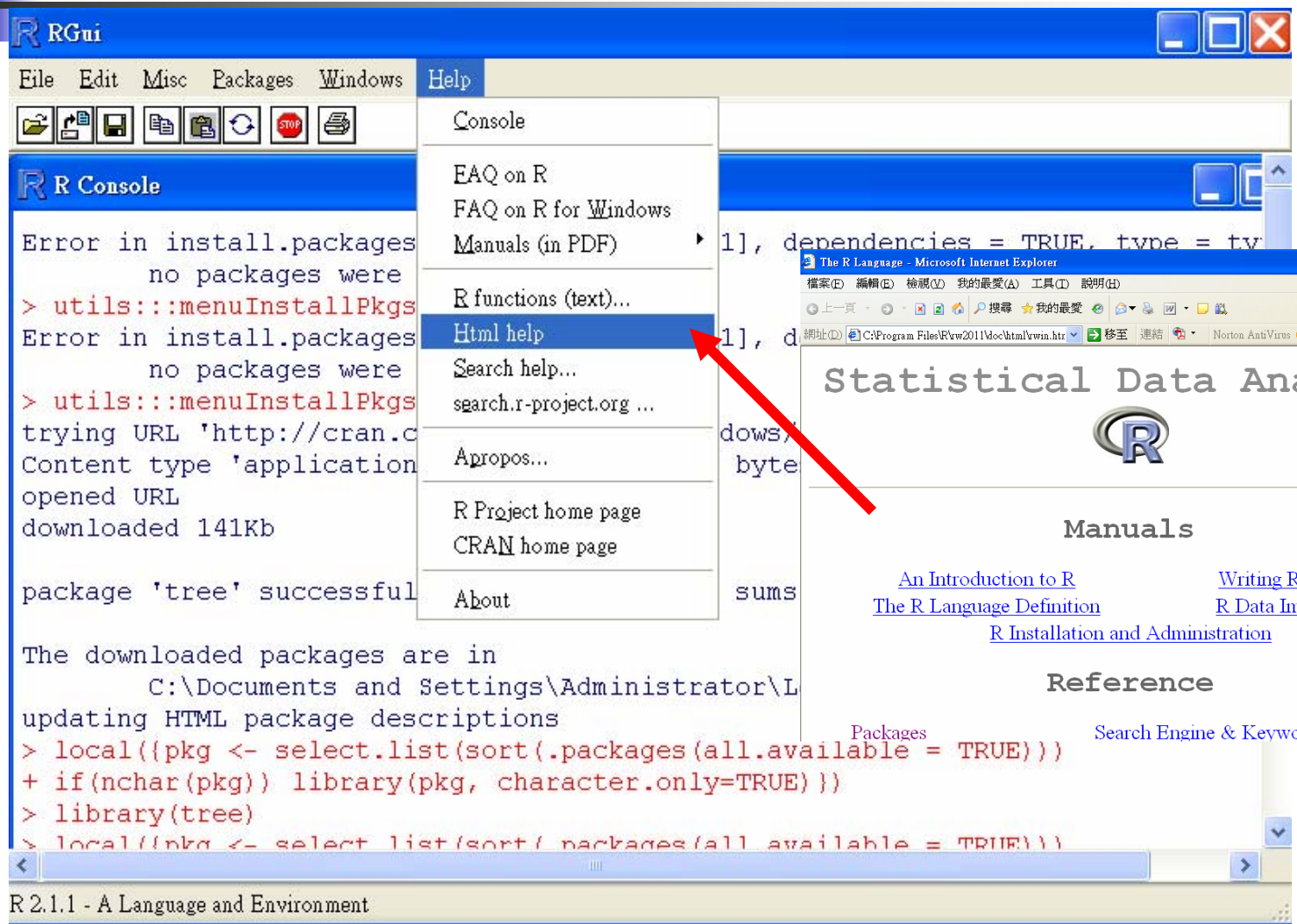


Load packages “tree”

- For example: > library(tree)

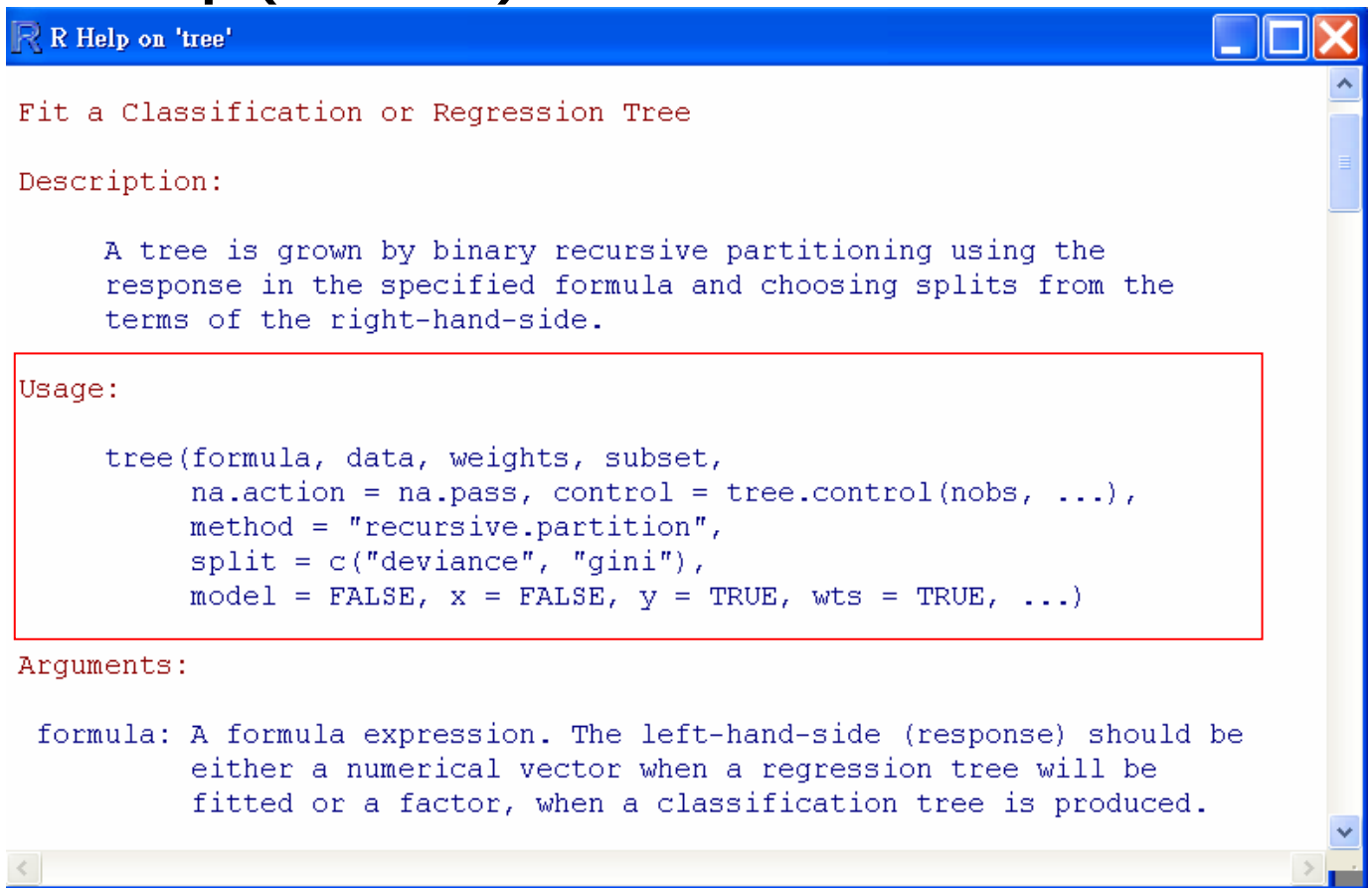


Help for new packages



Usage for tree: input argument

- > help("tree")



Usage for tree: Examples

R Help on 'tree'

Cambridge University Press, Cambridge. Chapter 7.

See Also:

'tree.control', 'prune.tree', 'predict.tree', 'snip.tree'

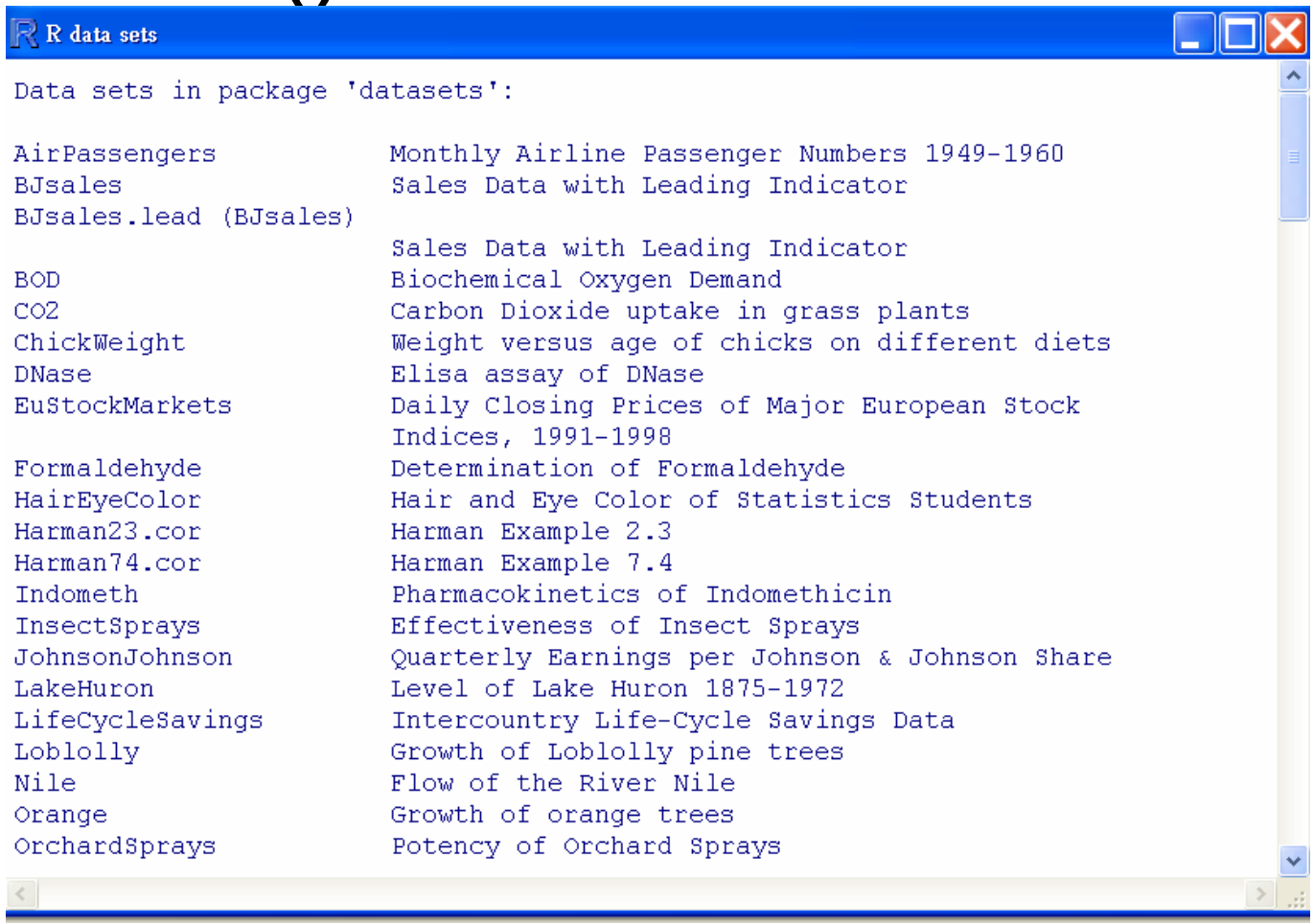
Examples:

```
library(MASS)
data(cpus)
cpus.ltr <- tree(log10(perf) ~ syct+mmin+mmax+cach+chmin+chmax, cpus)
cpus.ltr
summary(cpus.ltr)
plot(cpus.ltr);  text(cpus.ltr)

data(iris)
ir.tr <- tree(Species ~., iris)
ir.tr
summary(ir.tr)
```

Dataset in R

- > data()



For example: load “iris” dataset

- > data(iris)
- > ls()

  [1] "iris“
- > iris[1:5,]

	Sepal.Length	Sepal.Width	Petal.Length	Petal.Width	Species
1	5.1	3.5	1.4	0.2	setosa
2	4.9	3.0	1.4	0.2	setosa
3	4.7	3.2	1.3	0.2	setosa
4	4.6	3.1	1.5	0.2	setosa
5	5.0	3.6	1.4	0.2	setosa

Fit a Classification Tree

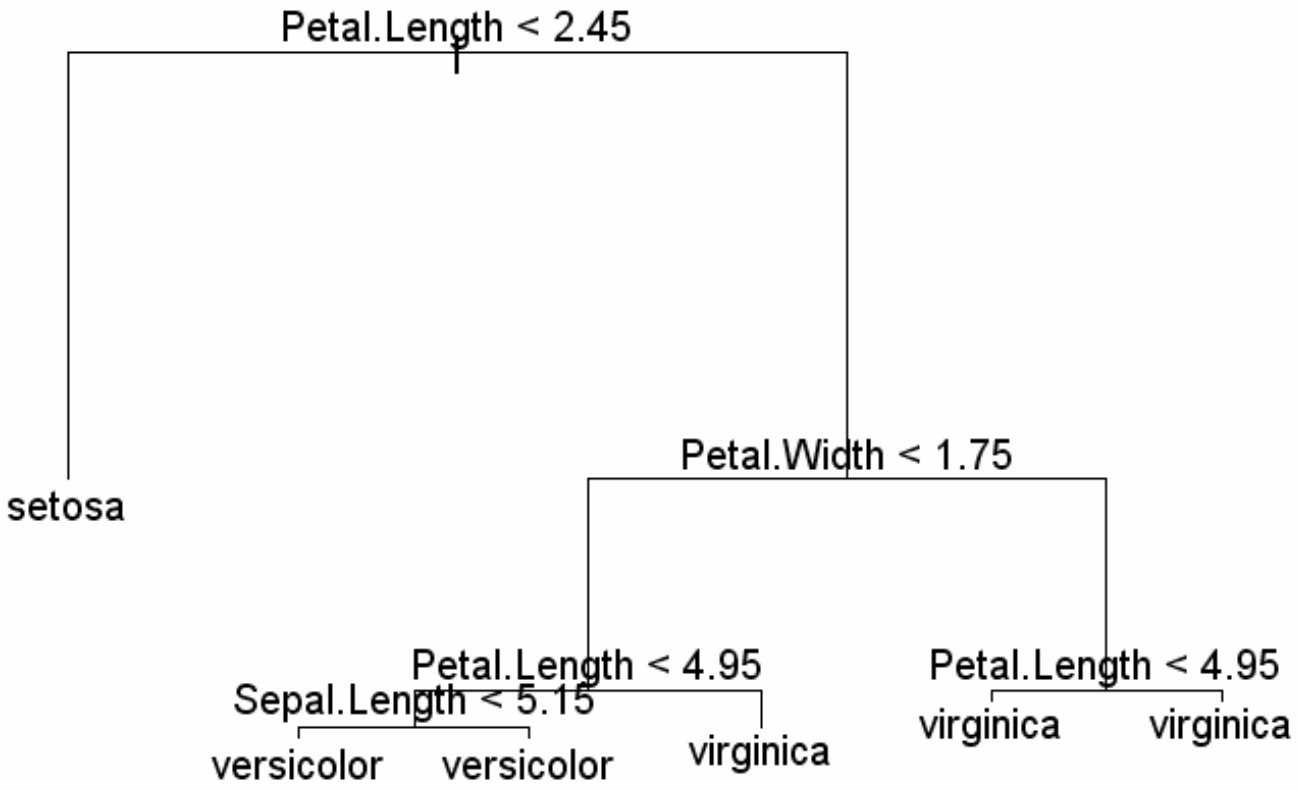
```
> ir.tr <- tree(Species ~., iris)
> ir.tr
node), split, n, deviance, yval, (yprob)
      * denotes terminal node

 1) root 150 329.600 setosa ( 0.33333 0.33333 0.33333 )
   2) Petal.Length < 2.45 50   0.000 setosa ( 1.00000 0.00000 0.00000 ) *
   3) Petal.Length > 2.45 100 138.600 versicolor ( 0.00000 0.50000 0.50000 )
     6) Petal.Width < 1.75 54  33.320 versicolor ( 0.00000 0.90741 0.09259 )
      12) Petal.Length < 4.95 48   9.721 versicolor ( 0.00000 0.97917 0.02083 )
        24) Sepal.Length < 5.15 5   5.004 versicolor ( 0.00000 0.80000 0.20000 ) *
        25) Sepal.Length > 5.15 43   0.000 versicolor ( 0.00000 1.00000 0.00000 ) *
      13) Petal.Length > 4.95 6   7.638 virginica ( 0.00000 0.33333 0.66667 ) *
     7) Petal.Width > 1.75 46   9.635 virginica ( 0.00000 0.02174 0.97826 )
      14) Petal.Length < 4.95 6   5.407 virginica ( 0.00000 0.16667 0.83333 ) *
      15) Petal.Length > 4.95 40   0.000 virginica ( 0.00000 0.00000 1.00000 ) *
> summary(ir.tr)

Classification tree:
tree(formula = Species ~ ., data = iris)
Variables actually used in tree construction:
[1] "Petal.Length" "Petal.Width"  "Sepal.Length"
```

Plot the fitted tree model

- > plot(ir.tr)
- > text(ir.tr)



Predictions from a Fitted Tree Object

```
> predict(ir.tr, iris[,1:4], type="class")
  [1] setosa     setosa     setosa     setosa     setosa     setosa
  [7] setosa     setosa     setosa     setosa     setosa     setosa
 [13] setosa     setosa     setosa     setosa     setosa     setosa
 [19] setosa     setosa     setosa     setosa     setosa     setosa
 [25] setosa     setosa     setosa     setosa     setosa     setosa
 [31] setosa     setosa     setosa     setosa     setosa     setosa
 [37] setosa     setosa     setosa     setosa     setosa     setosa
 [43] setosa     setosa     setosa     setosa     setosa     setosa
 [49] setosa     setosa     versicolor versicolor versicolor versicolor
 [55] versicolor versicolor versicolor versicolor versicolor versicolor
 [61] versicolor versicolor versicolor versicolor versicolor versicolor
 [67] versicolor versicolor versicolor versicolor virginica  versicolor
 [73] versicolor versicolor versicolor versicolor versicolor virginica
 [79] versicolor versicolor versicolor versicolor versicolor virginica
 [85] versicolor versicolor versicolor versicolor versicolor versicolor
 [91] versicolor versicolor versicolor versicolor versicolor versicolor
 [97] versicolor versicolor versicolor versicolor virginica  virginica
[103] virginica  virginica  virginica  virginica  versicolor virginica
[109] virginica  virginica  virginica  virginica  virginica  virginica
[115] virginica  virginica  virginica  virginica  virginica  virginica
[121] virginica  virginica  virginica  virginica  virginica  virginica
[127] virginica  virginica  virginica  virginica  virginica  virginica
[133] virginica  virginica  virginica  virginica  virginica  virginica
[139] virginica  virginica  virginica  virginica  virginica  virginica
[145] virginica  virginica  virginica  virginica  virginica  virginica
Levels: setosa versicolor virginica
>
```

Computing the accuracy

- > predict(ir.tr, iris[,1:4], type="class")->ir.pred
- > sum(ir.pred==iris[,5])/nrow(iris)

  [1] 0.9733333 ⟵ accuracy

Package : “e1071”

- Install new packages for
  - > install.packages("e1071")
- Include “svm”, “naiveBayes” , …. functions
- Can tunes hyperparameters of statistical methods : “tune” function

Using **svm** in "e1071" (1)

- > library(e1071); help("svm")

Usage

```
## S3 method for class 'formula':
svm(formula, data = NULL, ..., subset, na.action =
na.omit, scale = TRUE)
## Default S3 method:
svm(x, y = NULL, scale = TRUE, type = NULL, kernel =
"radial", degree = 3, gamma = 1 / ncol(as.matrix(x)), coef0 =
class.weights = NULL, cachesize = 40, tolerance = 0.001, epsi
shrinking = TRUE, cross = 0, probability = FALSE, fitted = TR
..., subset, na.action = na.omit)
```

Arguments

formula	a symbolic description of the model to be fit.
data	an optional data frame containing the variables in the model. By default the variables are taken from the environment which 'svm' is called from.
x	a data matrix, a vector, or a sparse matrix (object of class

Using **svm** in "e1071" (2)

- Fitted a svm model for iris dataset

```
> model <- svm(factor(Species) ~ ., data = iris)
> summary(model)

Call:
 svm(formula = factor(Species) ~ ., data = iris)

Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  1
      gamma:  0.25

Number of Support Vectors:  51

 ( 8 22 21 )


Number of Classes:  3

Levels:
 setosa versicolor virginica
```

Default setting

Using **svm** in "e1071" (3)

- Predict from svm model

```
> x<-iris[,-5]
> y<-iris[,5]
> predict(model,x)->pred
> print(pred)
```

- Compute accuracy for prediction

```
> sum(pred==y)/length(y)
[1] 0.9733333
```

Using **svm** in "e1071" (4)

- Using ***Linear*** kernel to fit svm model

```
> model <- svm(factor(Species) ~ ., data = iris, kernel="linear")
> summary(model)

Call:
 svm(formula = factor(Species) ~ ., data = iris, kernel = "linear")

Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  linear
       cost:  1
      gamma:  0.25

Number of Support Vectors:  29

 ( 2 15 12 )


Number of Classes:  3

Levels:
 setosa versicolor virginica
```

Using **svm** in "e1071" (5)

- Predict from svm ***Linear*** model

```
> predict(model,x)->linear.pred
> sum(linear.pred==y)/length(y)
[1] 0.9666667
```

- Confusion matrix

```
> table(linear.pred, y)
linear.pred  setosa versicolor virginica
  setosa         50          0         0
  versicolor      0         46         1
  virginica       0          4        49
```

Parameter Tuning Function:"**tune**" in "e1071" (1/2)

- "**tune**" function in e1071

```
Usage:

     tune(method, train.x, train.y = NULL, data = list(), validation.x =
          NULL, validation.y = NULL, ranges = NULL, predict.func = predict,
          tunecontrol = tune.control(), ...)
     best.tune(...)

Arguments:

  method: function to be tuned.

 train.x: either a formula or a matrix of predictors.

 train.y: the response variable if 'train.x' is a predictor matrix.
          Ignored if 'train.x' is a formula.

    data: data, if a formula interface is used. Ignored, if predictor
          matrix and response are supplied directly.

validation.x: an optional validation set. Depending on whether a
          formula interface is used or not, the response can be
          included in 'validation.x' or separately specified using
          'validation.y'.

validation.y: if no formula interface is used, the response of the
          (optional) validation set.

  ranges: a named list of parameter vectors spanning the sampling
          space. The vectors will usually be created by 'seq'.
```

Parameter Tuning Function:"**tune**" in "e1071" (2/2)

- tune "svm" for classification with RBF-kernel (default in svm)
  - gamma=0.5,1,2 and cost=4,8,16

```
> obj <- tune(svm, Species~., data = iris,
+ ranges = list(gamma = 2^(-1:1), cost = 2^(2:4)))
> obj

Parameter tuning of `svm':

- sampling method: 10-fold cross validation

- best parameters:
 gamma cost
   0.5    4

- best performance: 0.04
```

k-Nearest Neighbour Classification : **knn** in "class" (1/2)

```
Usage:

     knn(train, test, cl, k = 1, l = 0, prob = FALSE, use.all = TRUE)

Arguments:

   train: matrix or data frame of training set cases.

    test: matrix or data frame of test set cases. A vector will be
          interpreted as a row vector for a single case.

      cl: factor of true classifications of training set

       k: number of neighbours considered.

       l: minimum vote for definite decision, otherwise 'doubt'. (More
          precisely, less than 'k-l' dissenting votes are allowed, even
          if 'k' is increased by ties.)

    prob: If this is true, the proportion of the votes for the winning
          class are returned as attribute 'prob'.

 use.all: controls handling of ties. If true, all distances equal to
          the 'k'th largest are included. If false, a random selection
          of distances equal to the 'k'th is chosen to use exactly 'k'
          neighbours.
```

k-Nearest Neighbour Classification : **knn** in "class" (2/2)

- For example: iris dataset

```
> trn.x<-iris[,-5] ; tst.x<-iris[,-5]
> trn.y<-iris[,5] ; tst.y<-iris[,5]
```

- Fit the knn with k=3

```
> knn(trn.x, tst.x, trn.y, k = 3, prob=TRUE)->knn.pred
> print(knn.pred)
```

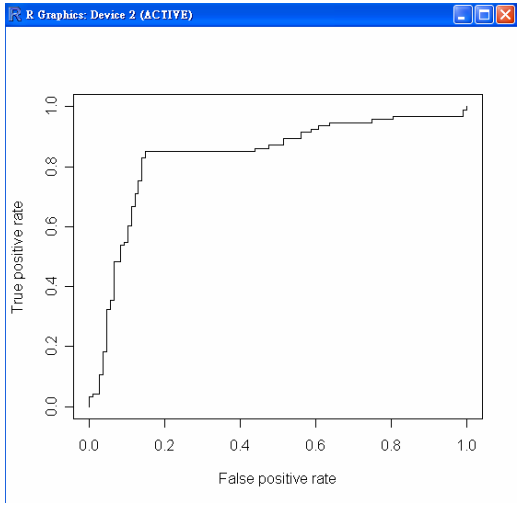
- Confusion matrix

```
> table(knn.pred, tst.y)
knn.pred     setosa versicolor virginica
  setosa         50          0         0
  versicolor      0         47         3
  virginica       0          3        47
```

Evaluation : Receiver Operating Characteristic (ROC) curve analysis

- Plot ROC Curve : “ROCR” package

```
> library(ROCR); data(ROCR.simple)
> pred<-prediction( ROCR.simple$predictions,
  ROCR.simple$labels)
> perf <- performance(pred,"tpr","fpr")
> plot(perf)
```



Packages for Machine learning

- For classification
  - tree in “tree”
  - svm in “e1071”
  - knn in “class”
  - lda in “MASS”
  - adaboost in “boost”
- For clustering
  - kmean in “stats”
- Other useful packages
  - caTools、kernlab、mlbench、cluster、…