

# CARET\_Lab

Joud AlFarra

2023-05-16

## Package loading

```
library(caret)

## Warning: package 'caret' was built under R version 4.2.3
## Loading required package: ggplot2
## Warning: package 'ggplot2' was built under R version 4.2.3
## Loading required package: lattice

library(tidyverse)

## — Attaching packages ————— tidyverse
## 1.3.2
## —

## ✓ tibble 3.2.1      ✓ dplyr 1.1.0
## ✓ tidyr 1.3.0      ✓ stringr 1.5.0
## ✓ readr 2.1.4      ✓ forcats 1.0.0
## ✓ purrr 1.0.1

## Warning: package 'tibble' was built under R version 4.2.3

## — Conflicts —————
tidyverse_conflicts() —
## ✗ dplyr::filter() masks stats::filter()
## ✗ dplyr::lag() masks stats::lag()
## ✗ purrr::lift() masks caret::lift()
```

## Load Data

```
# attach the iris dataset to the environment
data(iris)
# rename the dataset
dataset <- iris
```

Task1: Create a Validation/Training Dataset You need to split the loaded dataset into two, 80% of which we will use to train our models and 20% that we will hold back as a validation dataset. Hint: use createDataPartition function

```
# Create the training and test datasets
set.seed(100)
```

```
# Step 1: Get row numbers for the training data
trainRowNumbers <- createDataPartition(dataset$Species, p=0.8, list=FALSE)

# Step 2: Create the training dataset
trainData <- dataset[trainRowNumbers,]

# Step 3: Create the test dataset
testData <- dataset[-trainRowNumbers,]
```

Task2: Summarize Dataset Use skimr library to summarize the dataset

```
library(skimr)

## Warning: package 'skimr' was built under R version 4.2.3

skimmed <- skim_to_wide(trainData)

## Warning: 'skim_to_wide' is deprecated.
## Use 'skim()' instead.
## See help("Deprecated")

skimmed
```

Data summary

Name	Piped data
Number of rows	120
Number of columns	5

Column type frequency:


factor	1
numeric	4




Group variables	None
-----------------	------

Variable type: factor

skim_variable	n_missing	complete_rate	ordered	n_unique	top_counts
Species	0	1	FALSE	3	set: 40, ver: 40, vir: 40

Variable type: numeric

skim_variable	n_missing	complete_rate	mean	sd	p0	p2	p5	p7	p10	hist
Sepal.Length	0	1	5.86	0.82	4.3	5.1	5.8	6.4	7.7	

skim_variable	n_missing	complete_rate	mean	sd	p0	p2.5	p5.0	p7.5	p10.0	hist
Sepal.Width	0	1	3.07	0.43	2.2	2.8	3.0	3.4	4.4	
Petal.Length	0	1	3.77	1.78	1.0	1.6	4.4	5.1	6.9	
Petal.Width	0	1	1.20	0.77	0.1	0.3	1.3	1.8	2.5	

Task3: split input and output It is the time to separate the input attributes and the output attributes. call the inputs attributes x and the output attribute (or class) y.

```
#Input attributes: X
#Output attributes: Y
x = trainData[, 1:4]
y = trainData[, 5]
```

Task4: Train Control for Validation Test

We will use 10-fold cross-validation to estimate accuracy.

```
# Run algorithms using 10-fold cross validation
control <- trainControl(method="cv", number=10)
metric <- "Accuracy"
```

Task5: Model Training Train 5 different algorithms using 'train' function:

- Linear Discriminant Analysis (LDA). (Name of the method in R: lda)

```
# Set the seed for reproducibility
set.seed(100)

# Train the model using LDA.
LDA_Model = train(Species ~ ., data=trainData, method='lda',
                  trControl = control, metric = metric)
```

- Classification and Regression Trees (CART). (Name of the method in R: rpart)

```
# Set the seed for reproducibility
set.seed(100)

# Train the model using CART.
CART_Model = train(Species ~ ., data=trainData, method='rpart',
                  trControl = control, metric = metric)
```

- k-Nearest Neighbors (kNN). (Name of the method in R: knn)

```
# Set the seed for reproducibility
set.seed(100)

# Train the model using KNN.
```

```
KNN_Model = train(Species ~ ., data=trainData, method='knn',
                  trControl = control, metric = metric)
```

- Support Vector Machines (SVM) with a linear kernel. (Name of the method in R: svmRadial)

```
# Set the seed for reproducibility
set.seed(100)
```

```
# Train the model using SVM.
```

```
SVM_Model = train(Species ~ ., data=trainData, method='svmRadial',
                  trControl = control, metric = metric)
```

- Random Forest (RF). (Name of the method in R: rf)

```
# Set the seed for reproducibility
set.seed(100)
```

```
# Train the model using RF.
```

```
RF_Model = train(Species ~ ., data=trainData, method='rf',
                  trControl = control, metric = metric)
```

Task6: Select the Best Model We now have 5 models and accuracy estimations for each. We need to compare the models to each other and select the most accurate. Use resamples function to complete this task

```
# Compare model performances using resample()
```

```
models_compare <- resamples(list(lda = LDA_Model, rpart = CART_Model, knn =
KNN_Model, svmRadial = SVM_Model, rf = RF_Model))
```

```
# Summary of the models performances
```

```
summary(models_compare)
```

```
##
```

```
## Call:
```

```
## summary.resamples(object = models_compare)
```

```
##
```

```
## Models: lda, rpart, knn, svmRadial, rf
```

```
## Number of resamples: 10
```

```
##
```

```
## Accuracy
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
## lda	0.9166667	0.9375000	1.0000000	0.9750000	1	1	0
## rpart	0.8333333	0.8541667	0.9166667	0.9250000	1	1	0
## knn	0.9166667	1.0000000	1.0000000	0.9833333	1	1	0
## svmRadial	0.8333333	0.9166667	0.9583333	0.9416667	1	1	0
## rf	0.9166667	0.9166667	1.0000000	0.9666667	1	1	0

```
##
```

```
## Kappa
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
## lda	0.875	0.90625	1.0000	0.9625	1	1	0
## rpart	0.750	0.78125	0.8750	0.8875	1	1	0

```
## knn      0.875 1.00000 1.0000 0.9750      1      1      0
## svmRadial 0.750 0.87500 0.9375 0.9125      1      1      0
## rf       0.875 0.87500 1.0000 0.9500      1      1      0
```

What was the most accurate model? Based on the Mean Accuracy, KNN(98.3%) and LDA(97.5%) seem to be the most accurate models.

Task7: Make Prediction (Confusion Matrix) Now we want to get an idea of the accuracy of the best model on our validation set. Use 'predict' and confusionMatrix functions to complete this task.

### LDA Confusion Matrix & Prediction

```
# Predict on testData (LDA_Model)
predicted <- predict(LDA_Model, testData)

confusionMatrix(reference = testData$Species, data = predicted)

## Confusion Matrix and Statistics
##
##              Reference
## Prediction  setosa versicolor virginica
##   setosa      10          0          0
##   versicolor   0          9          0
##   virginica    0          1         10
##
## Overall Statistics
##
##              Accuracy : 0.9667
##              95% CI : (0.8278, 0.9992)
##   No Information Rate : 0.3333
##   P-Value [Acc > NIR] : 2.963e-13
##
##              Kappa : 0.95
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##              Class: setosa Class: versicolor Class: virginica
## Sensitivity              1.0000              0.9000              1.0000
## Specificity              1.0000              1.0000              0.9500
## Pos Pred Value           1.0000              1.0000              0.9091
## Neg Pred Value           1.0000              0.9524              1.0000
## Prevalence               0.3333              0.3333              0.3333
## Detection Rate           0.3333              0.3000              0.3333
## Detection Prevalence     0.3333              0.3000              0.3667
## Balanced Accuracy        1.0000              0.9500              0.9750
```

### CART Confusion Matrix & Prediction

```
# Predict on testData (CART_Model)
predicted <- predict(CART_Model, testData)

confusionMatrix(reference = testData$Species, data = predicted)

## Confusion Matrix and Statistics
##
##              Reference
## Prediction  setosa versicolor virginica
##   setosa      10          0          0
##   versicolor   0          9          3
##   virginica    0          1          7
##
## Overall Statistics
##
##              Accuracy : 0.8667
##              95% CI : (0.6928, 0.9624)
##   No Information Rate : 0.3333
##   P-Value [Acc > NIR] : 2.296e-09
##
##              Kappa : 0.8
##
##  Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##              Class: setosa Class: versicolor Class: virginica
## Sensitivity              1.0000              0.9000              0.7000
## Specificity              1.0000              0.8500              0.9500
## Pos Pred Value           1.0000              0.7500              0.8750
## Neg Pred Value           1.0000              0.9444              0.8636
## Prevalence               0.3333              0.3333              0.3333
## Detection Rate           0.3333              0.3000              0.2333
## Detection Prevalence     0.3333              0.4000              0.2667
## Balanced Accuracy        1.0000              0.8750              0.8250
```

## KNN Confusion Matrix & Prediction

```
# Predict on testData (KNN_Model)
predicted <- predict(KNN_Model, testData)

confusionMatrix(reference = testData$Species, data = predicted)

## Confusion Matrix and Statistics
##
##              Reference
## Prediction  setosa versicolor virginica
##   setosa      10          0          0
##   versicolor   0          9          2
##   virginica    0          1          8
##
```

```
## Overall Statistics
##
##           Accuracy : 0.9
##           95% CI : (0.7347, 0.9789)
##      No Information Rate : 0.3333
##      P-Value [Acc > NIR] : 1.665e-10
##
##           Kappa : 0.85
##
##  McNemar's Test P-Value : NA
##
## Statistics by Class:
##
##           Class: setosa Class: versicolor Class: virginica
## Sensitivity           1.0000           0.9000           0.8000
## Specificity           1.0000           0.9000           0.9500
## Pos Pred Value        1.0000           0.8182           0.8889
## Neg Pred Value        1.0000           0.9474           0.9048
## Prevalence            0.3333           0.3333           0.3333
## Detection Rate        0.3333           0.3000           0.2667
## Detection Prevalence  0.3333           0.3667           0.3000
## Balanced Accuracy      1.0000           0.9000           0.8750
```

#### SVM Confusion Matrix & Prediction

```
# Predict on testData (SVM_Model)
predicted <- predict(SVM_Model, testData)

confusionMatrix(reference = testData$Species, data = predicted)

## Confusion Matrix and Statistics
##
##           Reference
## Prediction  setosa versicolor virginica
##   setosa      10          0          0
## versicolor    0          9          1
##  virginica    0          1          9
##
## Overall Statistics
##
##           Accuracy : 0.9333
##           95% CI : (0.7793, 0.9918)
##      No Information Rate : 0.3333
##      P-Value [Acc > NIR] : 8.747e-12
##
##           Kappa : 0.9
##
##  McNemar's Test P-Value : NA
##
## Statistics by Class:
```

```
##
##               Class: setosa Class: versicolor Class: virginica
## Sensitivity          1.0000          0.9000          0.9000
## Specificity          1.0000          0.9500          0.9500
## Pos Pred Value       1.0000          0.9000          0.9000
## Neg Pred Value       1.0000          0.9500          0.9500
## Prevalence           0.3333          0.3333          0.3333
## Detection Rate        0.3333          0.3000          0.3000
## Detection Prevalence  0.3333          0.3333          0.3333
## Balanced Accuracy     1.0000          0.9250          0.9250
```

## RF Confusion Matrix & Prediction

```
# Predict on testData (RF_Model)
predicted <- predict(RF_Model, testData)

confusionMatrix(reference = testData$Species, data = predicted)

## Confusion Matrix and Statistics
##
##               Reference
## Prediction   setosa versicolor virginica
##   setosa      10          0          0
## versicolor    0          9          1
## virginica     0          1          9
##
## Overall Statistics
##
##               Accuracy : 0.9333
##               95% CI : (0.7793, 0.9918)
##   No Information Rate : 0.3333
##   P-Value [Acc > NIR] : 8.747e-12
##
##               Kappa : 0.9
##
## Mcnemar's Test P-Value : NA
##
## Statistics by Class:
##
##               Class: setosa Class: versicolor Class: virginica
## Sensitivity          1.0000          0.9000          0.9000
## Specificity          1.0000          0.9500          0.9500
## Pos Pred Value       1.0000          0.9000          0.9000
## Neg Pred Value       1.0000          0.9500          0.9500
## Prevalence           0.3333          0.3333          0.3333
## Detection Rate        0.3333          0.3000          0.3000
## Detection Prevalence  0.3333          0.3333          0.3333
## Balanced Accuracy     1.0000          0.9250          0.9250
```