Machine Learning Reference for R

Contents

Data Preparation

Normalization

Features sometimes need to be scaled so they fit into a standard range. This involves transforming variables into a narrower or wider range than they are found in the observed data.

One method for scaling features is **min-max normalization**, which uses the minimum and maximum values within the feature to produce a value between 0 and 1:

$$X_{new} = \frac{X - min(X)}{max(X) - min(X)}$$

```
x <- seq(10, 30, by = 1)
x.new <- (x - min(x)) / (max(x) - min(x))
```

This method is useful when the values different features are required to be within the same range, for example with K-Nearest Neighbors classifiers and K-Means clustering.

Another method for scaling features is **z-score normalization**, which standardizes the feature to have the features of the normal distribution (with a mean of 0 and standard deviation of 1):

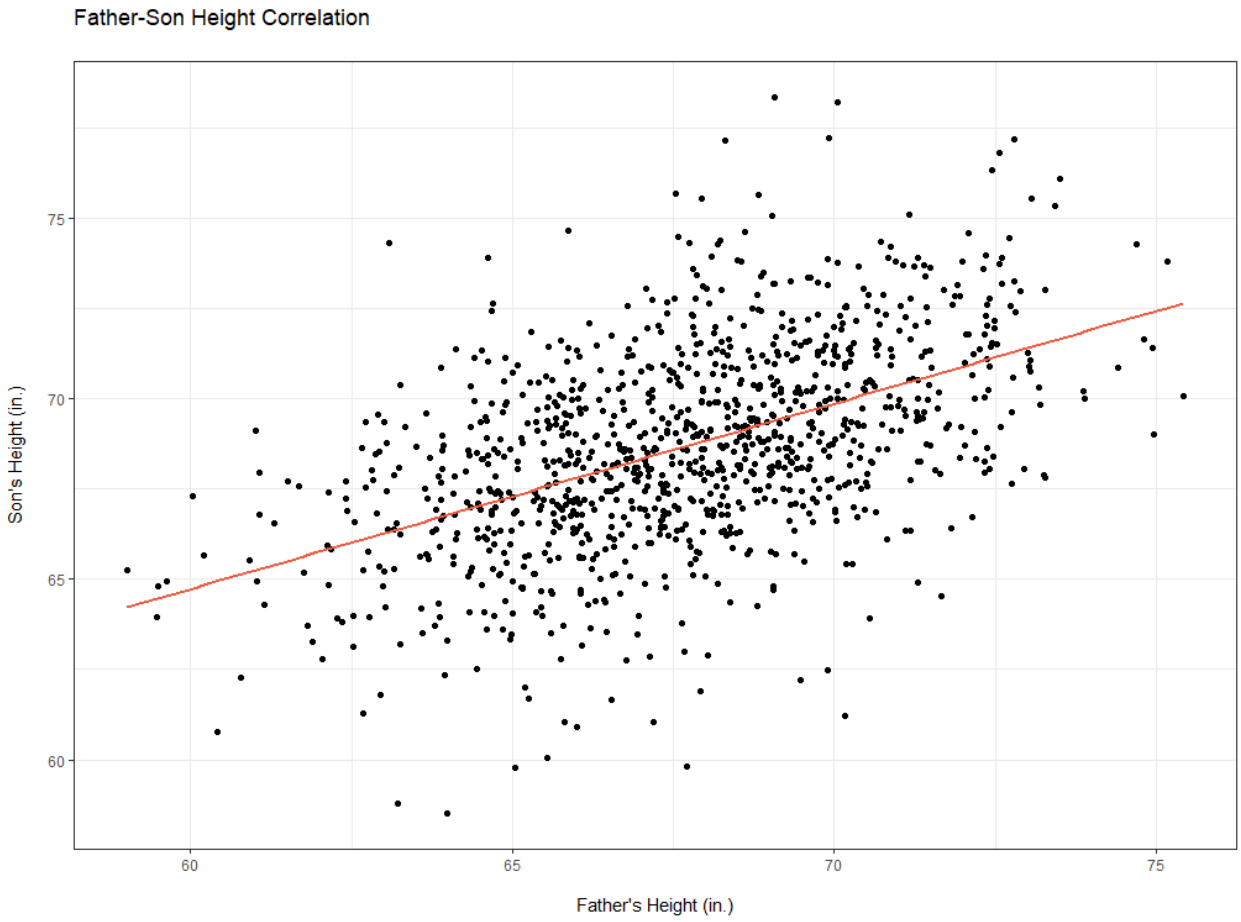
$$X_{new} = \frac{X - \mu}{\sigma} = \frac{X - mean(X)}{StdDev(X)}$$

```
x <- seq(5, 45, by = 1)
x.new <- (x - mean(x)) / sd(x)
```

Algorithms

Regression Algorithms

Simple Linear Regression



Simple linear regression is a statistical method for evaluating the relationship between two continuous variables. One variable, denoted x, is the **independent variable** (also called **predictor variable**) that is used to predict the **dependent variable** (also called **response variable**), denoted y.

In linear regression, we use methods such as **ordinary least squares** to approximate the equation of a line describing the relationship between the predictor and response variables. We find a **correlation coefficient**:

$$r = \frac{1}{n-1} \sum \left(\frac{x - \bar{x}}{s_x} \right) \left(\frac{y - \bar{y}}{s_y} \right)$$

In simple linear regression, we estimate two coefficients, β_0 (the y-intercept) and β_1 (the regression slope). Because this is an estimate, there is a residual error, ϵ. These are combined to form a **line of best fit**:

$$\hat{y} = \beta_0 + \beta_1 x + \epsilon$$

Functions related to running simple linear regression models in R are:

Function	Package	Description	Example
`cor()`	stats	Calculate correlation coefficient.	`cor(x, y)`
`lm()`	stats	Train a linear regression model.	`lm(sheight ~ fheight, data = father.son)`
`predict()`	stats	Predict values using the trained model.	`m <- lm(y ~ x)` `predict(m, test.data)`
`summary()`	base	Summarize a linear model.	`m <- lm(y ~ x)` `summary(m)`
`confint()`	stats	Compute confidence interval for model parameters.	`m <- lm(y ~ x)` `confint(m)`

Classification Algorithms

Naive Bayes

The **Naive Bayes classifier** is a probabilistic machine learning algorithm that predicts class labels for a factor by using a probability found from the training data. The classifier assumes that all features contribute equally and are independent of each other. This classifier relies on **conditional probability**, or the probability of an event A occurring, given that an event B has occurred:

$$P(A|B) = \frac{P(A \cap B)}{P(B)} = \frac{P(B|A)P(B)}{P(A)}$$

In the Naive Bayes setting, the probability of level L for class C (denoted C_L), given feature F, is:

$$P(C_L|F) = \frac{P(F|C_L)P(F)}{P(C_L)}$$

This is generalizable to:

$$P(C_L|F_1, F_2, ..., F_n) = \frac{P(F_1, F_2, ..., F_n|C_L)P(F_1, F_2, ..., F_n)}{P(C_L)} = P(C_L)\prod_{i=1}^{n} P(F_i|C_L)$$

Functions related to running Naive Bayes classification in R are:

Function	Package	Description	Example
`naiveBayes()`	e1071	Train a Naive Bayes classifier.	`naiveBayes(y ~ ., data, laplace = 1)`
`predict()`	stats	Predict values using the trained model.	`m <- naiveBayes(y ~ ., data)` `predict(m, test.data)`
`confusionMatrix()`	caret	Calculate a confusion matrix.	`confusionMatrix(predicted, ground.truth)`