Forest Fires

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Contents

1 Dataset

Questo dataset è pubblico e a disposizione per la ricerca. I dettagli sul dataset possono essere trovati in Cortez e Morais (2007). Il dataset è composto dalle seguenti variabili:

1. Coordinata spaziale dell'asse X all'interno della mappa del parco Montesinho: da 1 a 9
2. Y coordinata spaziale dell'asse y all'interno della mappa del parco Montesinho: da 2 a 9
3. mese: mese dell'anno: da "gen" a "dic"
4. giorno della settimana: da "lunedì" a "domenica"
5. Indice FFMC dal sistema FWI: da 18,7 a 96,20
6. Indice DMC dal sistema FWI: da 1,1 a 291,3
7. Indice DC dal sistema FWI: da 7,9 a 860,6
8. Indice ISI del sistema FWI: da 0,0 a 56,10
9. temperatura temporanea in gradi Celsius: da 2,2 a 33,30
10. Umidità relativa RH in %: da 15,0 a 100
11. velocità del vento in km/h: da 0,40 a 9,40
12. pioggia in mm/m2: da 0,0 a 6,4
13. area della superficie bruciata della foresta (in ettari): da 0,00 a 1090,84.

1.1 Obiettivo

In questo dataset siamo interessati a modellare l'area bruciata della foresta come funzione delle altre variabili.

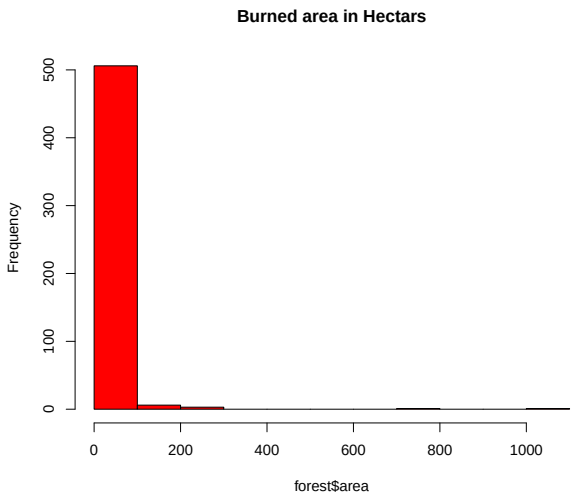
Cortez P. e Morais A. "Un approccio di data mining per prevedere gli incendi boschivi utilizzando dati meteorologici." In J. Neves, MF Santos e J. Machado Eds., "Nuove tendenze nell'intelligenza artificiale", Atti della 13a EPIA 2007 Conferenza portoghese sull'intelligenza artificiale, dicembre, Guimaraes, Por- tugal, pp. 512-523, 2007. APPIA, ISBN-13 978-989-95618-0-9. 18-0-9. Disponibile a: http://www3.dsi.uminho.pt/pcortez/fires.pdf

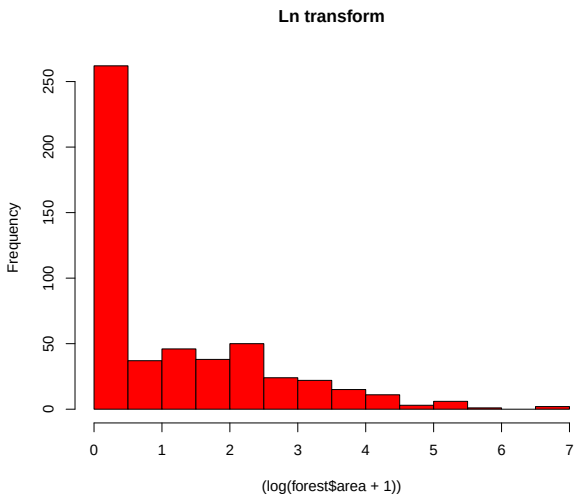
Il dataset è composto dalle seguenti rilevazioni:

```
##       Days
## Months mon tue wed thu fri sat sun
##    jan   0   0   0   0   0   1   1
##    feb   3   2   1   1   5   4   4
##    mar  12   5   4   5  11  10   7
##    apr   1   0   1   2   1   1   3
##    may   0   0   0   0   1   1   0
##    jun   3   0   3   2   3   2   4
##    jul   4   6   3   3   3   8   5
##    aug  15  28  25  26  21  29  40
##    sep  28  19  14  21  38  25  27
##    oct   4   2   2   0   1   3   3
##    nov   0   1   0   0   0   0   0
##    dic   0   0   0   0   0   0   0
```

1.2 Histogrammi area bruciata

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.00    0.00    0.52   12.85    6.57 1090.84
```

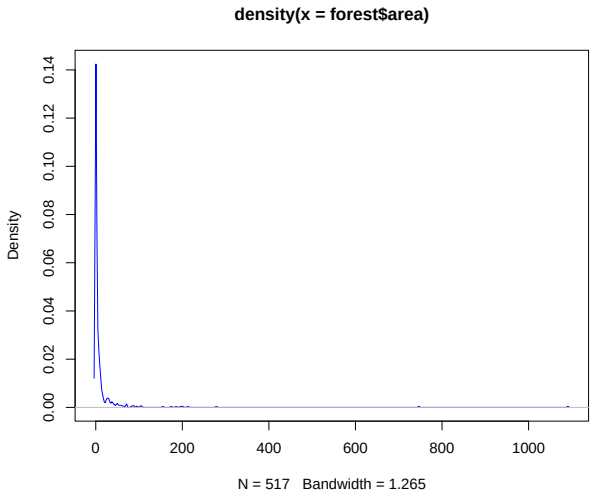


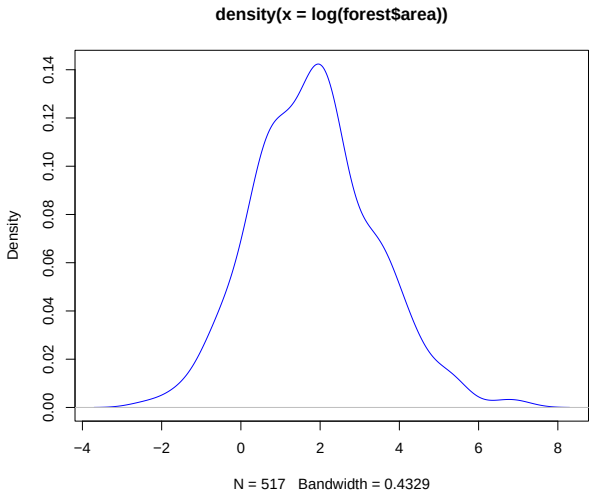


Si evidenzia che il dataset ha il 48% dei valori che valgono 0

```
## [1] 0.4777563
```

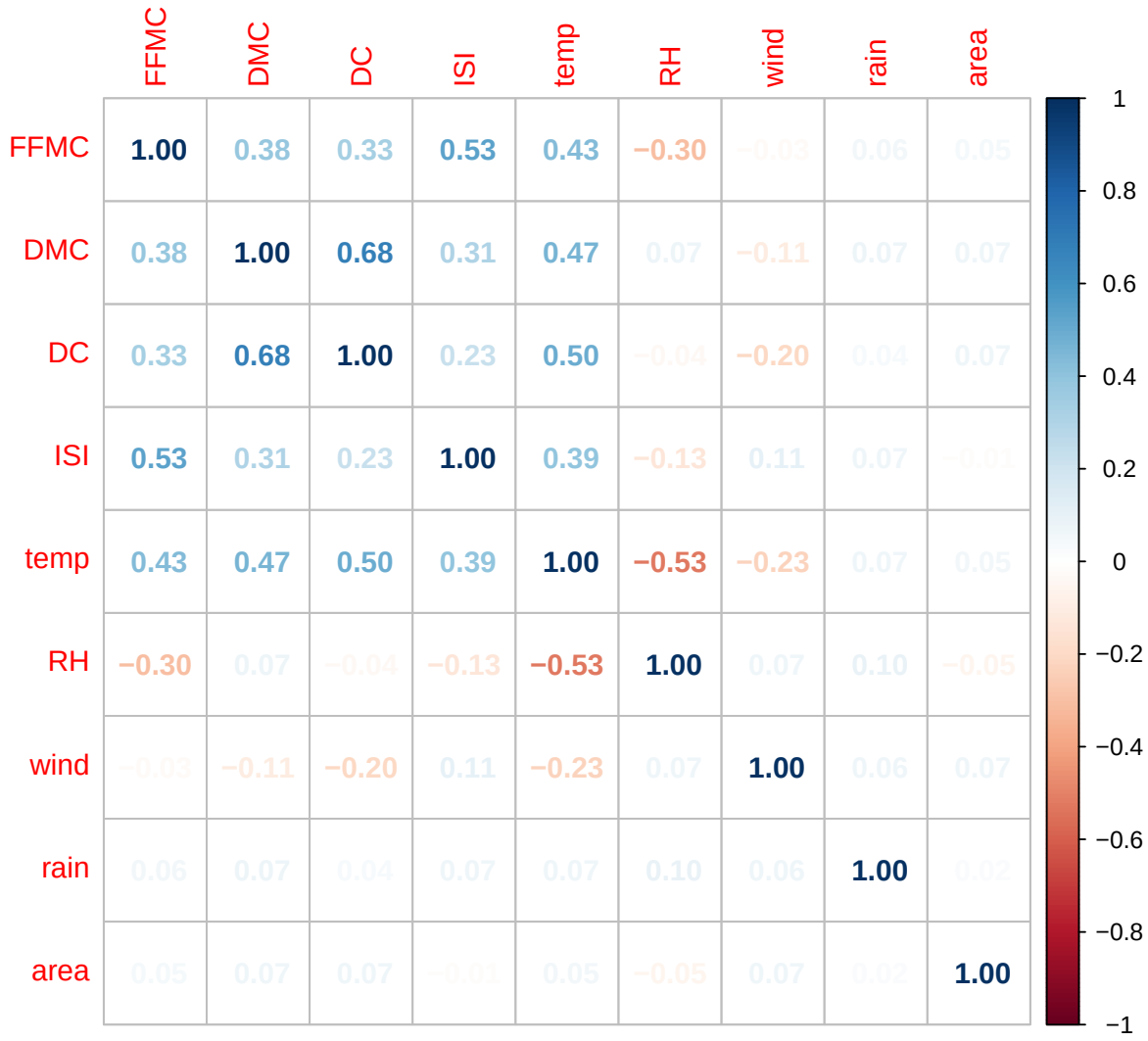
1.3 Grafici densità area bruciata

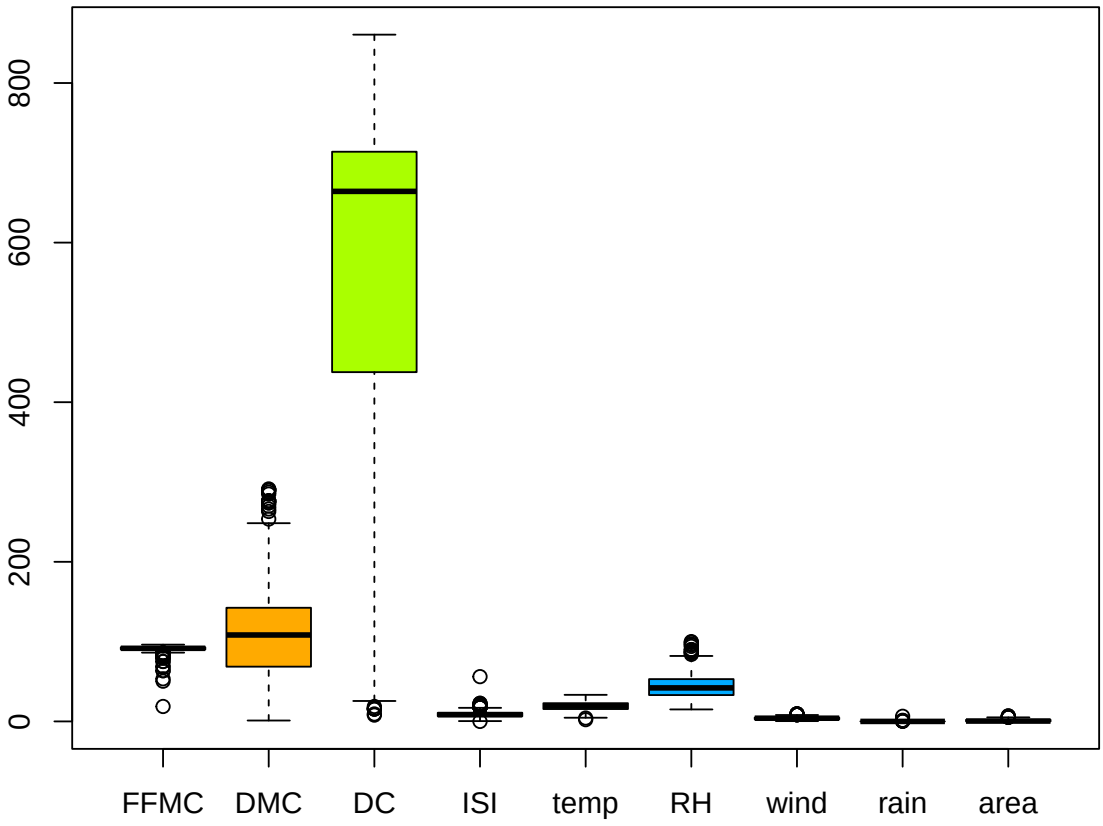


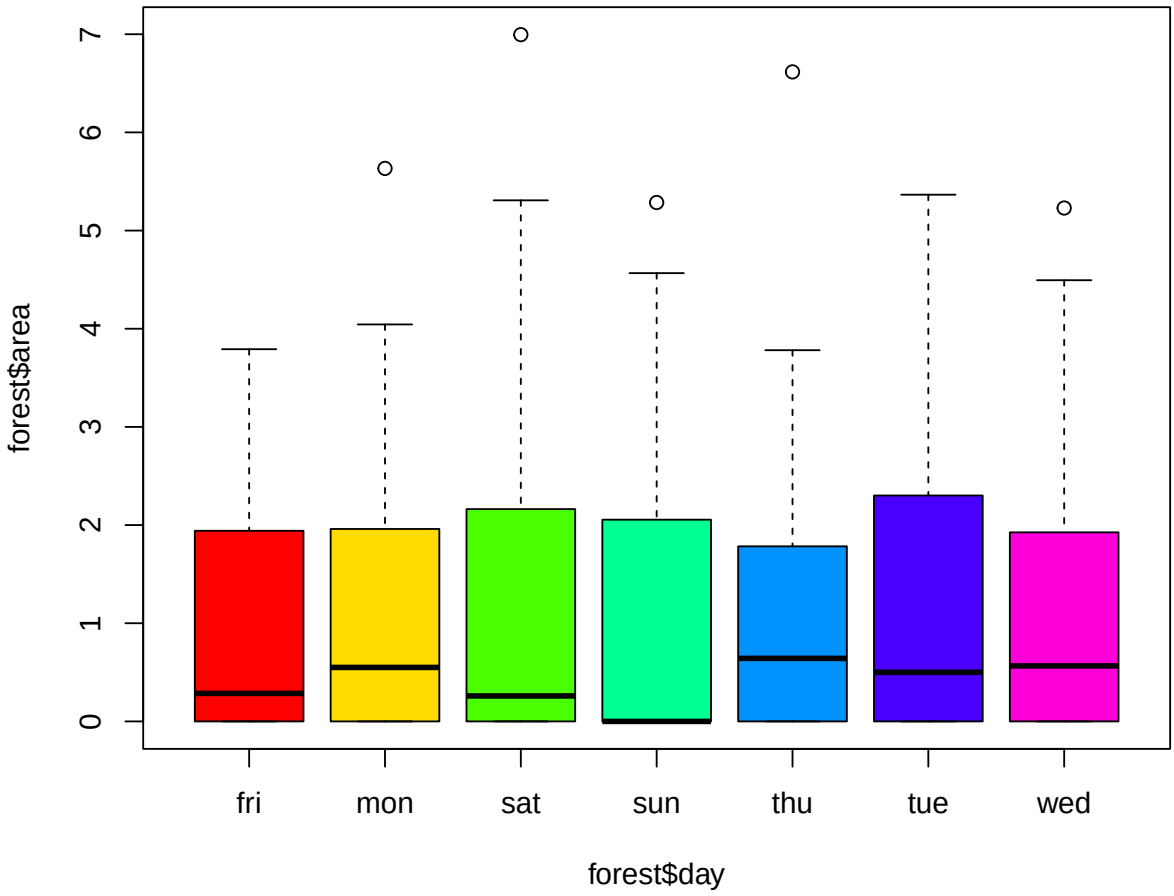


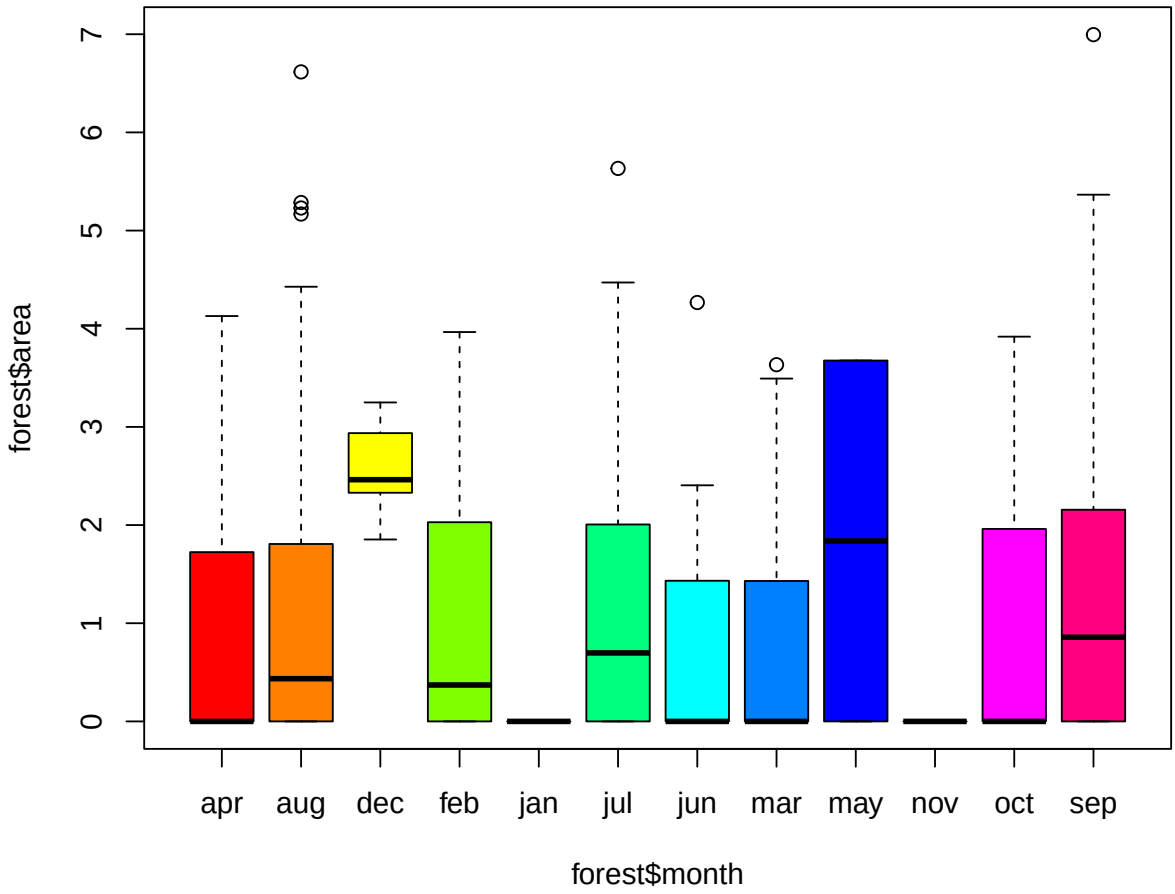

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  0.0000  0.0000  0.4187  1.1110  2.0242  6.9956
```

```
## Warning: il pacchetto 'corrplot' è stato creato con R versione 4.3.2
```


FFMC
DMC
DC
ISI
temp
RH
wind
rain
area
1.00 0.38 0.33 0.53 0.43 −0.30 −0.03 0.06 0.05
0.38 1.00 0.68 0.31 0.47 0.07 −0.11 0.07 0.07
0.33 0.68 1.00 0.23 0.50 −0.04 −0.20 0.04 0.07
0.53 0.31 0.23 1.00 0.39 −0.13 0.11 0.07 −0.01
0.43 0.47 0.50 0.39 1.00 −0.53 −0.23 0.07 0.05
−0.30 0.07 −0.04 −0.13 −0.53 1.00 0.07 0.10 −0.05
−0.03 −0.11 −0.20 0.11 −0.23 0.07 1.00 0.06 0.07
0.06 0.07 0.04 0.07 0.07 0.10 0.06 1.00 0.02
0.05 0.07 0.07 −0.01 0.05 −0.05 0.07 0.02 1.00
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
−1


0
200
400
600
800
FFMC
DMC
DC
ISI
temp
RH
wind
rain
area


forest$area
0
1
2
3
4
5
6
7
fri
mon
sat
sun
thu
tue
wed
forest$day



2 Testing

```r
# si divide il dataset in train e test (validation) così che si fitta il modello sul train e si guarda

# Optional:
forest <- fastDummies::dummy_cols(forest, remove_first_dummy = TRUE)[-c(1,2)]

# Regole classiche sono 70% training e 30% test (o 80-20 a vostra scelta)
set.seed(125) # il seme serve per riprodurre le analisi (reproducibilità del codice)
sample <- sample(c(TRUE, FALSE), nrow(forest), replace=TRUE, prob=c(0.7,0.3))
train  <- forest[sample, ]
test   <- forest[!sample, ]

# Modello con una sola variabile:
model = lm(area ~ rain, data = train)

summary(model)
```

```
##
## Call:
## lm(formula = area ~ rain, data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.1169 -1.1169 -0.6982  0.9086  5.8787
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.11694    0.07539   14.82   <2e-16 ***
## rain        -1.41984    0.92201   -1.54    0.124
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.409 on 351 degrees of freedom
## Multiple R-squared:  0.006711,   Adjusted R-squared:  0.003881
## F-statistic: 2.371 on 1 and 351 DF,  p-value: 0.1245
```

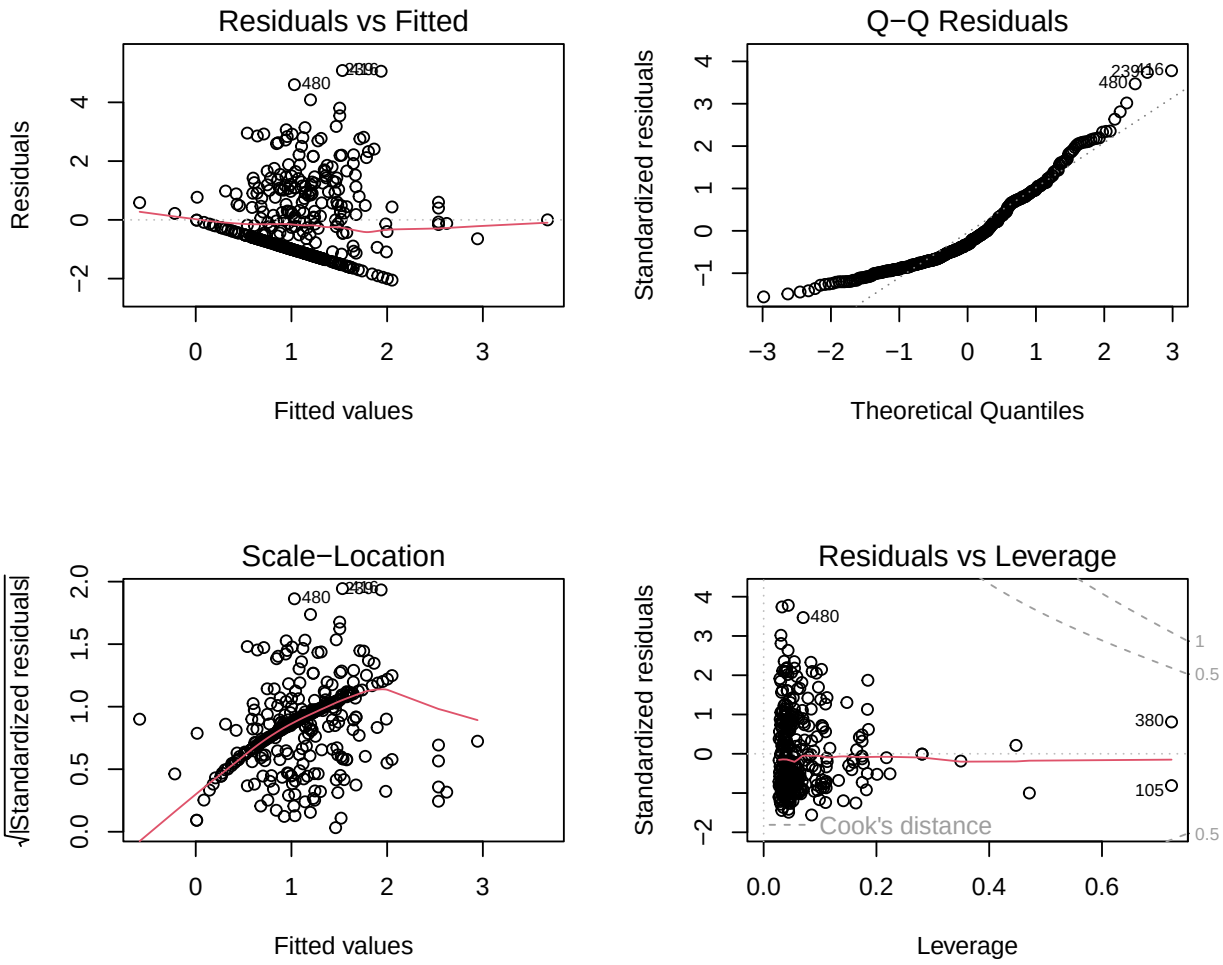
```
# Modello con tutte le variabili:
model1 = lm(area ~ ., data = train)
summary(model1)
```

```
##
## Call:
## lm(formula = area ~ ., data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.0509 -0.9930 -0.4196  0.9067  5.0839
##
## Coefficients: (1 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.104088   2.062474  -0.535   0.5928
## FFMC         0.007967   0.021031   0.379   0.7051
## DMC          0.003311   0.002244   1.476   0.1410
## DC          -0.002105   0.001694  -1.242   0.2150
## ISI          0.001891   0.020749   0.091   0.9275
## temp         0.044480   0.026364   1.687   0.0925 .
## RH           0.005247   0.007595   0.691   0.4901
## wind         0.102497   0.045852   2.235   0.0261 *
## rain        -1.781002   0.955096  -1.865   0.0631 .
## month_aug    0.248307   1.070361   0.232   0.8167
## month_dec    2.213667   0.994994   2.225   0.0268 *
## month_feb    0.408489   0.650106   0.628   0.5302
## month_jan   -0.541694   1.307862  -0.414   0.6790
## month_jul   -0.037427   0.896186  -0.042   0.9667
## month_jun   -0.696132   0.824498  -0.844   0.3991
## month_mar   -0.379072   0.576235  -0.658   0.5111
## month_may    2.705751   1.487261   1.819   0.0698 .
## month_nov          NA         NA      NA       NA
## month_oct    1.211886   1.261942   0.960   0.3376
## month_sep    1.021802   1.208243   0.846   0.3983
## day_mon      0.207708   0.274390   0.757   0.4496
```

```
## day_sat      0.616573   0.269198   2.290   0.0226 *
## day_sun      0.419913   0.263989   1.591   0.1127
## day_thu      0.473808   0.300514   1.577   0.1158
## day_tue      0.506912   0.296819   1.708   0.0886 .
## day_wed      0.121176   0.297501   0.407   0.6840
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.376 on 328 degrees of freedom
## Multiple R-squared:  0.1151, Adjusted R-squared:  0.05033
## F-statistic: 1.777 on 24 and 328 DF,  p-value: 0.01496
```

```r
# Diagnostic plot del modello:
par(mfrow=c(2,2)) # finestra grafica 2x2
plot(model1)
```

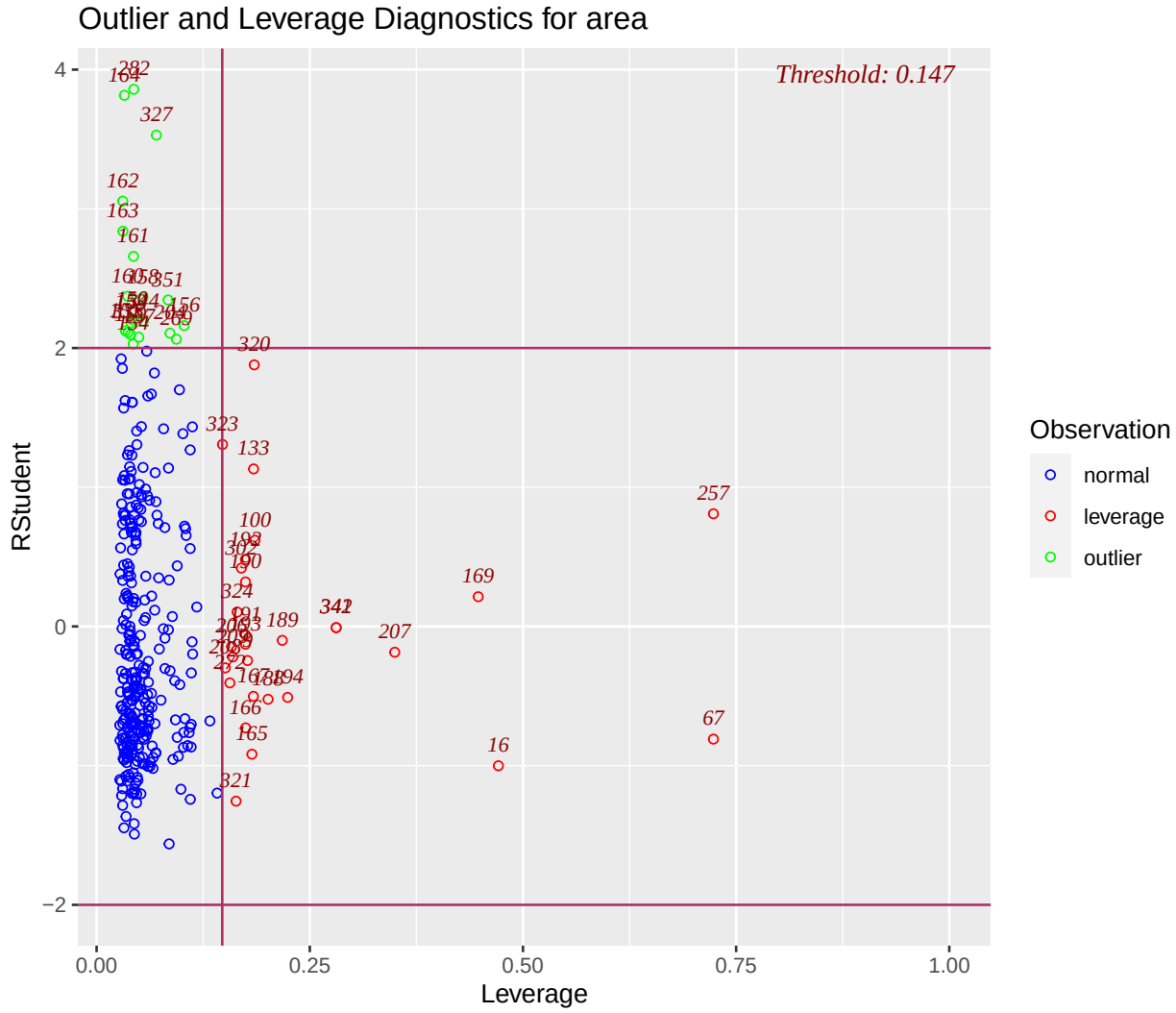
```
## Warning: non si riesce a fare il plot senza sfruttarne uno:
##    322
```



```
par(mfrow=c(1,1)) # riportiamo ai valori di default

# rimuovere outlier:
# install.packages("olsrr")
library(olsrr)
```

```
## Warning: il pacchetto 'olsrr' è stato creato con R versione 4.3.2
```

```
ols_plot_resid_lev(model1)
```




```
# Removing observations guardando numero dell'osservazione:
train = train[-c(480,380,105),]

# Rimuovere osservazioni basandoci sui valori delle variabili:
# train=train[!(train$temp>300),]

# Modello 1 senza outlier:
```

```r
model2 = lm(area ~ ., data = train)
summary(model2)
```

```
##
## Call:
## lm(formula = area ~ ., data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.0546 -0.9958 -0.4130  0.9061  5.0801
##
## Coefficients: (1 not defined because of singularities)
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.138314   2.064694  -0.551   0.5818
## FFMC         0.008022   0.021048   0.381   0.7034
## DMC          0.003353   0.002247   1.492   0.1365
## DC          -0.002139   0.001696  -1.261   0.2083
## ISI          0.001644   0.020768   0.079   0.9369
## temp         0.046366   0.026524   1.748   0.0814 .
## RH           0.005453   0.007606   0.717   0.4739
## wind         0.101662   0.045904   2.215   0.0275 *
## rain        -1.779536   0.955853  -1.862   0.0635 .
## month_aug    0.245346   1.071216   0.229   0.8190
## month_dec    2.245021   0.996804   2.252   0.0250 *
## month_feb    0.412339   0.650644   0.634   0.5267
## month_jan   -0.542138   1.308897  -0.414   0.6790
## month_jul   -0.047500   0.897013  -0.053   0.9578
## month_jun   -0.703500   0.825219  -0.853   0.3946
## month_mar   -0.379024   0.576691  -0.657   0.5115
## month_may    2.699104   1.488468   1.813   0.0707 .
## month_nov          NA         NA      NA       NA
## month_oct    1.223977   1.263060   0.969   0.3332
## month_sep    1.035993   1.209372   0.857   0.3923
## day_mon      0.209033   0.274614   0.761   0.4471
## day_sat      0.632568   0.270394   2.339   0.0199 *
## day_sun      0.421203   0.264204   1.594   0.1118
## day_thu      0.474003   0.300752   1.576   0.1160
## day_tue      0.507397   0.297055   1.708   0.0886 .
## day_wed      0.121490   0.297736   0.408   0.6835
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.377 on 327 degrees of freedom
## Multiple R-squared:  0.1164, Adjusted R-squared:  0.0515
## F-statistic: 1.794 on 24 and 327 DF,  p-value: 0.01363
```

```r
# Modello con variabili scelte da noi (scelte casualmente al momento):
model3 = lm(area ~ month_dec+wind+rain+temp+I(FFMC*month_aug), data = train)
summary(model3)
```

```
##
## Call:
```

```
## lm(formula = area ~ month_dec + wind + rain + temp + I(FFMC *
##     month_aug), data = train)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1.6371 -1.0587 -0.6195  0.8999  5.6030
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)           0.225277   0.333634   0.675   0.5000
## month_dec             1.535108   0.625141   2.456   0.0146 *
## wind                  0.083387   0.043073   1.936   0.0537 .
## rain                 -1.485245   0.920838  -1.613   0.1077
## temp                  0.033218   0.014405   2.306   0.0217 *
## I(FFMC * month_aug) -0.002712   0.001829  -1.483   0.1391
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.388 on 346 degrees of freedom
## Multiple R-squared:  0.04919,    Adjusted R-squared:  0.03545
## F-statistic:  3.58 on 5 and 346 DF,  p-value: 0.0036
```

```
# Test ANOVA
anova(model3)
```

```
## Analysis of Variance Table
##
## Response: area
##                       Df Sum Sq Mean Sq F value   Pr(>F)
## month_dec              1  13.98 13.9846  7.2568 0.007408 **
## wind                   1   3.82  3.8154  1.9798 0.160305
## rain                   1   5.60  5.6017  2.9068 0.089105 .
## temp                   1   6.86  6.8580  3.5587 0.060071 .
## I(FFMC * month_aug)    1   4.24  4.2361  2.1982 0.139084
## Residuals            346 666.78  1.9271
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

2.1 Confronto tra modelli:

```
# Create vector with values
a = c(AIC(model3), BIC(model3), AIC(model2), BIC(model2), AIC(model1), BIC(model1))

# Akaike Information Criterion (AIC) estimates the in-sample prediction error and indicates the relativ

# Create vector with nforest
b = c("AIC lm 3", "BIC lm 3", "AIC lm 2", "BIC lm 2", "AIC lm 1", "BIC lm 1")

# Link the values with nforest
names(a) = b
print(a)
```

```
## AIC lm 3 BIC lm 3 AIC lm 2 BIC lm 2 AIC lm 1 BIC lm 1
## 1237.798 1264.844 1250.011 1350.465 1252.933 1353.461
```

2.2 Previsioni con Model2:

```
#use lasso regression model to predict response value
new = test
previsioni_mod3 = predict(model3, newdata = new)

#find SST and SSE
sst <- sum((test$area - mean(test$area))^2)
sse <- sum((previsioni_mod3 - test$area)^2)

# Root Mean Squared Error: è una misura dell'errore che compiamo
sqrt(mean((test$area - previsioni_mod3)^2))
```

```
## [1] 1.596855
```

```
# intervallo di previsione
predict(model3,new,interval="predict", level=0.95)
```

```
##            fit         lwr      upr
## 1    1.0563583  -1.6995064 3.812223
## 5    0.7540603  -1.9949094 3.503030
## 6    1.1626941  -1.5815779 3.906966
## 12   1.1999348  -1.5372090 3.937079
## 18   1.1886159  -1.5492578 3.926490
## 20   0.9094470  -1.8364430 3.655337
## 22   1.0848881  -1.6536671 3.823443
## 27   1.3400658  -1.4020938 4.082225
## 31   1.3692106  -1.3766317 4.115053
## 33   1.0596671  -1.6832339 3.802568
## 35   1.1546462  -1.5853155 3.894608
## 39   1.1501076  -1.5864854 3.886701
## 41   1.2577590  -1.4841748 3.999693
## 43   0.9698926  -1.7779318 3.717717
## 47   1.0137766  -1.7239908 3.751544
## 55   0.8614214  -1.8828183 3.605661
## 57   1.2251558  -1.5128289 3.963141
## 62   0.9333146  -1.8277114 3.694341
## 63   1.0061606  -1.7375691 3.749890
## 67   1.3645353  -1.3776268 4.106697
## 68   1.3266419  -1.4140935 4.067377
## 69   1.4016901  -1.3439371 4.147317
## 71   1.3838643  -1.3703580 4.138087
## 72   1.1134310  -1.6232171 3.850079
## 74   0.9343689  -1.8090689 3.677807
## 76   0.7063382  -2.0486380 3.461314
## 77   1.0053013  -1.7326028 3.743205
## 82   0.7587131  -1.9893600 3.506786
## 85   0.9477885  -1.7941996 3.689777
```

```
## 86   1.0145152  -1.7346014 3.763632
## 88   1.1528145  -1.5900827 3.895712
## 89   1.3658887  -1.3797232 4.111501
## 90   1.2118686  -1.5260347 3.949772
## 97   0.7972439  -1.9493688 3.543857
## 98   1.2535620  -1.4860057 3.993130
## 101  1.0854113  -1.6587061 3.829529
## 102  0.9130846  -1.8364519 3.662621
## 103  0.9694144  -1.7731785 3.712007
## 107  1.0883466  -1.6490149 3.825708
## 109  1.1581047  -1.5802173 3.896427
## 113  1.2828434  -1.4579567 4.023644
## 116  1.2654958  -1.4786278 4.009619
## 120  0.8826386  -1.8610212 3.626298
## 124  1.0783812  -1.6589487 3.815711
## 126  1.3598600  -1.3818745 4.101595
## 135  0.9453720  -1.7942472 3.684991
## 136  1.0399911  -1.7077182 3.787700
## 141  1.1028506  -1.6411889 3.846890
## 144  1.2269875  -1.5125071 3.966482
## 146  1.2108219  -1.5359324 3.957576
## 148  1.3293488  -1.4139217 4.072619
## 153  1.1925396  -1.5554412 3.940520
## 159  0.9900239  -1.7516786 3.731726
## 167  0.6019738  -2.1577594 3.361707
## 171  1.1028506  -1.6411889 3.846890
## 173  1.0953768  -1.6486432 3.839397
## 174  0.9966893  -1.7435000 3.736879
## 177  0.9015866  -1.8564232 3.659596
## 180  0.9130846  -1.8364519 3.662621
## 185  1.0701561  -1.6728893 3.813201
## 189  0.7421265  -2.0099780 3.494231
## 191  0.9474770  -1.7936714 3.688625
## 193  1.1605894  -1.5832007 3.904379
## 196  1.2015385  -1.5437283 3.946805
## 200  1.2761998  -1.4642941 4.016694
## 203  0.7010480  -2.0517110 3.453807
## 213  1.3015575  -1.4378052 4.040920
## 214  1.0743208  -1.6713817 3.820023
## 217  0.8950666  -1.8503788 3.640512
## 218  1.1625197  -1.5837305 3.908770
## 224  0.9705931  -1.7684785 3.709665
## 229  1.4238496  -1.3299295 4.177629
## 231  1.4774769  -1.2722585 4.227212
## 234  1.2909772  -1.4527448 4.034699
## 238  1.0332292  -1.7070141 3.773473
## 246  1.3919017  -1.3618185 4.145622
## 247  1.2803135  -1.4667853 4.027412
## 250  0.7269808  -2.0315717 3.485533
## 254  0.9120596  -1.8316094 3.655729
## 260  0.9136843  -1.8340112 3.661380
## 262  0.9826443  -1.7869446 3.752233
## 263  0.9462280  -1.7962137 3.688670
## 264  0.9195194  -1.8228601 3.661899
```

```
## 270  0.8351156  -1.9099639 3.580195
## 271  0.9581593  -1.7843500 3.700669
## 272  1.0184302  -1.7236791 3.760539
## 276  2.3383935  -0.6256161 5.302403
## 281  2.2420610  -0.7239890 5.208111
## 282  2.6385865  -0.3105846 5.587758
## 286  1.5279190  -1.2234836 4.279322
## 296  1.0711226  -1.6759890 3.818234
## 297  0.8503929  -1.8939947 3.594780
## 299  1.2849484  -1.4539828 4.023880
## 302  1.3100328  -1.4303127 4.050378
## 304  1.2383064  -1.4993805 3.975993
## 305  1.0092380  -1.7332326 3.751709
## 306  1.0398729  -1.7004184 3.780164
## 308  1.3160616  -1.4264448 4.058568
## 311  1.2908405  -1.4555825 4.037264
## 312  1.1991832  -1.5491739 3.947540
## 313  1.1558760  -1.5906077 3.902360
## 314  1.4410736  -1.3047968 4.186944
## 315  1.0297708  -1.7126315 3.772173
## 318  1.2716612  -1.4669777 4.010300
## 319  1.1262400  -1.6157398 3.868220
## 320  1.4681264  -1.2800163 4.216269
## 325  0.8304620  -1.9146725 3.575597
## 327  1.2843335  -1.4590075 4.027675
## 328  1.1129527  -1.6286385 3.854544
## 330  1.3394509  -1.4027407 4.081642
## 332  1.3147081  -1.4251830 4.054599
## 334  1.0850248  -1.6523233 3.822373
## 337  1.0498383  -1.6905468 3.790223
## 338  1.1727454  -1.5709625 3.916453
## 341  1.0498383  -1.6905468 3.790223
## 347  1.1162745  -1.6254094 3.857959
## 348  0.8609733  -1.8836267 3.605573
## 353  1.2097636  -1.5283112 3.947838
## 354  1.1081408  -1.6307397 3.847021
## 356  1.3248102  -1.4152793 4.064900
## 367  1.2037349  -1.5358496 3.943319
## 369  1.1919377  -1.5459315 3.929807
## 378  0.8820937  -1.8639433 3.628131
## 381  1.4667729  -1.2855399 4.219086
## 384  0.8829769  -1.8609573 3.626911
## 386  0.8545707  -1.8912405 3.600382
## 389  1.0006641  -1.7426709 3.743999
## 399  1.0900144  -1.6549072 3.834936
## 401  1.5306259  -1.2238322 4.285084
## 403  1.1321832  -1.6114372 3.875804
## 408  1.0305223  -1.7074410 3.768486
## 409  1.1448174  -1.5932219 3.882857
## 412  1.2815030  -1.5004097 4.063416
## 415  1.1055412  -1.6371041 3.848187
## 420  1.1342179  -1.6085774 3.877013
## 421  1.2221455  -1.5228643 3.967155
## 423  1.4987612  -1.2583197 4.255842
```

```
## 426  0.8379616  -1.9081148 3.584038
## 429  1.3221414  -1.4280818 4.072365
## 430  1.1275742  -1.6150442 3.870193
## 431  1.1699018  -1.5672836 3.907087
## 446  0.9202667  -1.8246983 3.665232
## 448  1.1880140  -1.5766394 3.952667
## 452  0.7804137  -1.9747708 3.535598
## 457  0.7534262  -1.9947223 3.501575
## 458  0.9711779  -1.7706832 3.713039
## 460  1.1588370  -1.6059618 3.923636
## 462  1.0075840  -1.7362662 3.751434
## 463  1.3406807  -1.4137612 4.095123
## 469  0.9672713  -1.7719211 3.706464
## 473  1.0338442  -1.7040298 3.771718
## 474  1.2976208  -1.4464937 4.041735
## 478  1.4258180  -1.3220773 4.173713
## 483  1.2288595  -1.5183180 3.976037
## 485  1.4009788  -1.3597001 4.161658
## 486  1.2843075  -1.4688499 4.037465
## 487  1.2932632  -1.4573385 4.043865
## 491  1.2542767  -1.4948155 4.003369
## 493  1.2249177  -1.5354168 3.985252
## 500 -8.2254626 -20.0916986 3.640773
## 503  0.4667698  -2.3585463 3.292086
## 510 -0.7662125  -4.4635771 2.931152
## 513  1.1525889  -1.5940055 3.899183
## 517  0.9924923  -1.7486211 3.733606
```

2.3 LASSO regression:

```
# install.packages("glmnet") # se non è già stato installato
library(glmnet)
```

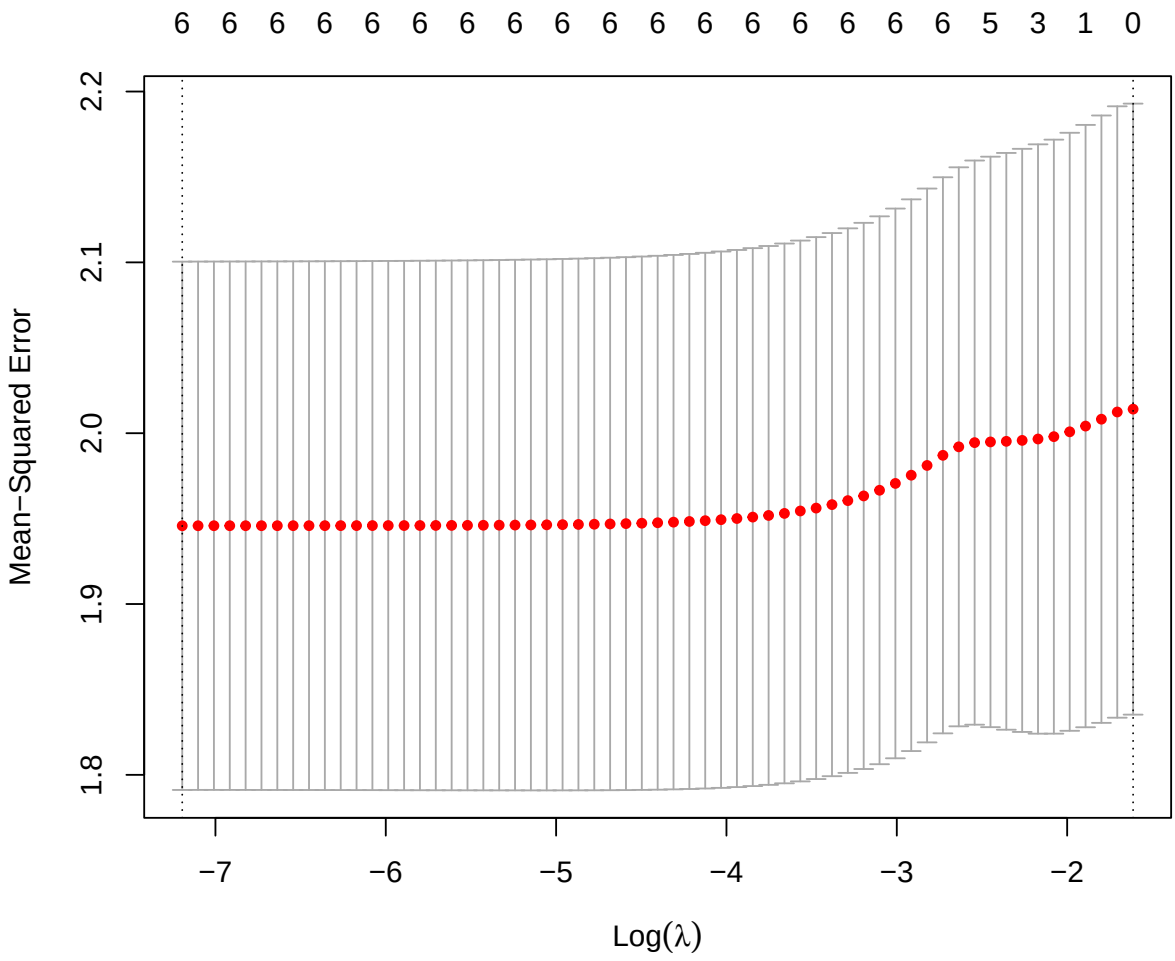
```
## Warning: il pacchetto 'glmnet' è stato creato con R versione 4.3.2
```

```
## Warning: il pacchetto 'Matrix' è stato creato con R versione 4.3.2
```

```
#define response variable
y <- train$area

#define matrix of predictor variables (uso solo poche variabili ma potete farlo con tutte da togliere p
x <- data.matrix(train[, c("month_dec","wind","rain","temp","FFMC","month_aug")])

#perform k-fold cross-validation to find optimal lambda value, la cross-validation è un ottimo modo per
cv_model <- cv.glmnet(x, y, alpha = 1)

#find optimal lambda value that minimizes test MSE
best_lambda <- cv_model$lambda.min
best_lambda
```

```
## [1] 0.0007504308
```

```r
#produce plot of test MSE by lambda value
plot(cv_model)
```




```r
# Fittiamo il modello con il best lambda (penalizzazione)

best_model <- glmnet(x, y, alpha = 1, lambda = best_lambda)
coef(best_model)
```

```
## 7 x 1 sparse Matrix of class "dgCMatrix"
##                       s0
## (Intercept) -0.66874065
## month_dec    1.53364829
## wind         0.08010813
## rain        -1.50538828
## temp         0.02821263
## FFMC         0.01107049
## month_aug   -0.26019301
```

2.4 Previsioni con Lasso:

```
#use lasso regression model to predict response value
new = data.matrix(test[,c("month_dec","wind","rain","temp","FFMC","month_aug")])
previsioni = predict(best_model, s = best_lambda, newx = new)

# Root Mean Squared Error (RMSE): è una misura dell'errore che compiamo
sqrt(mean((test$area - previsioni)^2))
```

```
## [1] 1.602608
```

Ora potete confrontare modelli diversi con lasso e lm classici, vedete cosa vi dice BIC/AIC e RMSE per decidere quale è il modello ottimale.

2.5 Modello con soglia scelta: logit - glm

```
forest$area2 <- as.factor(ifelse(forest$area>0.5,1,0))

# Regole classiche sono 70% training e 30% test (o 80-20 a vostra scelta)
set.seed(125) # il seme serve per riprodurre le analisi (reproducibilità del codice)
sample <- sample(c(TRUE, FALSE), nrow(forest), replace=TRUE, prob=c(0.7,0.3))
train  <- forest[sample, ]
test   <- forest[!sample, ]

# Modello con una sola variabile:
model = glm(area2 ~ rain, data = train, family = binomial(link="logit"))
```

```
## Warning: glm.fit: si sono verificate probabilità stimate numericamente pari a 0
## o 1
```

```
# o va bene anche: family="binomial"
summary(model)
```

```
##
## Call:
## glm(formula = area2 ~ rain, family = binomial(link = "logit"),
##     data = train)
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -0.04599    0.10724  -0.429    0.668
## rain         -73.92369 3562.53148  -0.021    0.983
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 488.88  on 352  degrees of freedom
## Residual deviance: 482.25  on 351  degrees of freedom
## AIC: 486.25
##
## Number of Fisher Scoring iterations: 16
```

```r
# Modello con tutte le variabili:
model1 = glm(area2 ~ ., data = train, family = binomial(link="logit"))
```

```
## Warning: glm.fit: l'algoritmo non converge
```

```
## Warning: glm.fit: si sono verificate probabilità stimate numericamente pari a 0
## o 1
```

```r
summary(model1)
```

```
##
## Call:
## glm(formula = area2 ~ ., family = binomial(link = "logit"), data = train)
##
## Coefficients: (1 not defined because of singularities)
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -7.179e+02  7.479e+05  -0.001    0.999
## FFMC         2.824e+00  6.219e+03   0.000    1.000
## DMC         -4.230e-01  1.343e+03   0.000    1.000
## DC           3.245e-01  3.106e+02   0.001    0.999
## ISI          7.254e-02  1.145e+04   0.000    1.000
## temp         6.947e+00  4.898e+03   0.001    0.999
## RH           1.534e+00  1.572e+03   0.001    0.999
## wind         6.871e+00  3.230e+03   0.002    0.998
## rain         3.588e+00  1.989e+05   0.000    1.000
## area         1.784e+02  2.636e+04   0.007    0.995
## month_aug   -5.657e+01  4.200e+05   0.000    1.000
## month_dec   -1.850e+02  4.481e+05   0.000    1.000
## month_feb    1.989e+02  4.335e+05   0.000    1.000
## month_jan    2.193e+02  4.645e+05   0.000    1.000
## month_jul   -4.400e+00  4.197e+05   0.000    1.000
## month_jun    3.193e+01  4.392e+05   0.000    1.000
## month_mar    1.769e+02  4.480e+05   0.000    1.000
## month_may   -3.916e+02  5.518e+05  -0.001    0.999
## month_nov           NA         NA      NA       NA
## month_oct   -2.743e+02  6.258e+05   0.000    1.000
## month_sep   -6.737e+01  4.248e+05   0.000    1.000
## day_mon      3.591e+01  4.249e+04   0.001    0.999
## day_sat      6.189e+01  3.421e+04   0.002    0.999
## day_sun      1.663e+01  5.950e+04   0.000    1.000
## day_thu      2.756e+01  4.208e+04   0.001    0.999
## day_tue      4.598e+01  9.720e+04   0.000    1.000
## day_wed      4.357e+01  3.758e+04   0.001    0.999
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 4.8888e+02  on 352  degrees of freedom
## Residual deviance: 1.3527e-07  on 327  degrees of freedom
## AIC: 52
##
## Number of Fisher Scoring iterations: 25
```

```r
# Removing observations guardando numero dell'osservazione:
train = train[-c(145,142,258),]

# Rimuovere osservazioni basandoci sui valori delle variabili:
# train=train[!(train$temp>300),]

# Modello 1 senza outlier:
model2 = glm(area2 ~ ., data = train, family = binomial(link="logit"))
```

```
## Warning: glm.fit: l'algoritmo non converge

## Warning: glm.fit: si sono verificate probabilità stimate numericamente pari a 0
## o 1
```

```r
summary(model2)
```

```
##
## Call:
## glm(formula = area2 ~ ., family = binomial(link = "logit"), data = train)
##
## Coefficients: (1 not defined because of singularities)
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept) -7.183e+02  7.527e+05  -0.001    0.999
## FFMC         2.823e+00  6.331e+03   0.000    1.000
## DMC         -4.206e-01  1.364e+03   0.000    1.000
## DC           3.241e-01  3.144e+02   0.001    0.999
## ISI          8.703e-02  1.158e+04   0.000    1.000
## temp         6.944e+00  4.952e+03   0.001    0.999
## RH           1.537e+00  1.596e+03   0.001    0.999
## wind         6.879e+00  3.255e+03   0.002    0.998
## rain         3.379e+00  2.012e+05   0.000    1.000
## area         1.785e+02  2.655e+04   0.007    0.995
## month_aug   -5.658e+01  4.130e+05   0.000    1.000
## month_dec   -1.848e+02  4.421e+05   0.000    1.000
## month_feb    1.991e+02  4.277e+05   0.000    1.000
## month_jan    2.194e+02  4.580e+05   0.000    1.000
## month_jul   -4.279e+00  4.126e+05   0.000    1.000
## month_jun    3.203e+01  4.324e+05   0.000    1.000
## month_mar    1.770e+02  4.413e+05   0.000    1.000
## month_may   -3.918e+02  5.464e+05  -0.001    0.999
## month_nov           NA         NA      NA       NA
## month_oct   -2.705e+02  2.198e+06   0.000    1.000
## month_sep   -6.723e+01  4.179e+05   0.000    1.000
## day_mon      3.586e+01  4.308e+04   0.001    0.999
## day_sat      6.198e+01  3.467e+04   0.002    0.999
## day_sun      1.670e+01  6.042e+04   0.000    1.000
## day_thu      2.764e+01  4.264e+04   0.001    0.999
## day_tue      4.612e+01  9.331e+04   0.000    1.000
## day_wed      4.366e+01  3.815e+04   0.001    0.999
##
## (Dispersion parameter for binomial family taken to be 1)
##
```

```
##     Null deviance: 4.8447e+02  on 349  degrees of freedom
## Residual deviance: 1.3333e-07  on 324  degrees of freedom
## AIC: 52
##
## Number of Fisher Scoring iterations: 25
```

```
# Modello con variabili scelte da noi (scelte casualmente al momento):
model3 = glm(area2 ~ month_dec+wind+rain+temp+I(FFMC*month_aug), data = train, family = binomial(link="
```

```
## Warning: glm.fit: si sono verificate probabilità stimate numericamente pari a 0
## o 1
```

```
summary(model3)
```

```
##
## Call:
## glm(formula = area2 ~ month_dec + wind + rain + temp + I(FFMC *
##     month_aug), family = binomial(link = "logit"), data = train)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -1.268e+00  5.027e-01  -2.522   0.0117 *
## month_dec            1.774e+01  1.615e+03   0.011   0.9912
## wind                 1.037e-01  6.381e-02   1.625   0.1041
## rain                -7.350e+01  3.592e+03  -0.020   0.9837
## temp                 4.593e-02  2.143e-02   2.144   0.0321 *
## I(FFMC * month_aug) -3.432e-03  2.693e-03  -1.274   0.2026
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 484.47  on 349  degrees of freedom
## Residual deviance: 462.47  on 344  degrees of freedom
## AIC: 474.47
##
## Number of Fisher Scoring iterations: 16
```

```
# per un aumento unitario di variabile_X_modello c'è un aumento del tot% del log dell'odds.
# per un aumento unitario di variabile_X_modello c'è un aumento di exp(valore) = valore_new volte dell'
# (Il vecchio odds và moltiplicato per exp(beta) )

#use lasso regression model to predict response value
new = test
previsioni_mod3 = predict(model3, newdata = new, type="response")
# la previsione è la probabilità di essere 1!

prev <- ifelse(previsioni_mod3 > 0.5,"1","0")

prev<- as.factor(as.vector(prev))

# Questa tabella mostra previsioni vs valore reale, è chiamata: confusionMatrix
table(prev, test$area2)
```

```
##
## prev  0  1
##    0 53 45
##    1 26 40
```

```
cm <- table(prev, test$area2)

# Indicatori per vedere la bontà del modello:
accuracy <- sum(cm[1], cm[4]) / sum(cm[1:4])
precision <- cm[4] / sum(cm[4], cm[2])
sensitivity <- cm[4] / sum(cm[4], cm[3])
fscore <- (2 * (sensitivity * precision))/(sensitivity + precision)
specificity <- cm[1] / sum(cm[1], cm[2])

# install.packages("pROC")
library(pROC)
```

```
## Warning: il pacchetto 'pROC' è stato creato con R versione 4.3.2
```

```
## Type 'citation("pROC")' for a citation.
```

```
##
## Caricamento pacchetto: 'pROC'
```

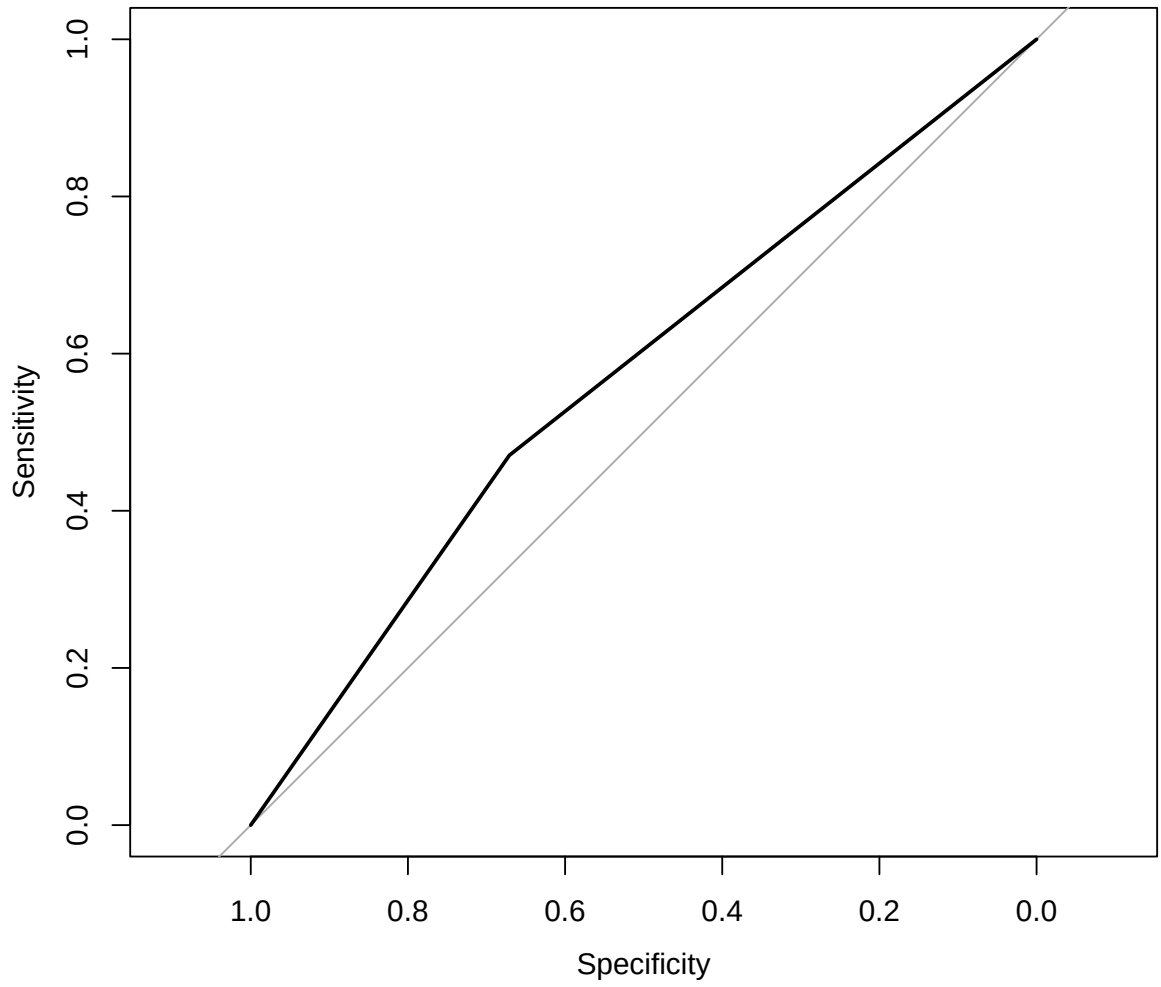
```
## I seguenti oggetti sono mascherati da 'package:stats':
##
##     cov, smooth, var
```

```
roc_object <- roc( as.numeric(test$area2), as.numeric(prev))
```

```
## Setting levels: control = 1, case = 2
```

```
## Setting direction: controls < cases
```

```
plot(roc_object)
```




```
# calculate area under curve
auc(roc_object)
```

```
## Area under the curve: 0.5707
```