

TD régression data vehicles

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```
library(plsdepot)
data(vehicles)
```

Effectuons une régression linéaire:

```
modele=lm(price~.,data=vehicles)
summary(modele)
```

```
##
## Call:
## lm(formula = price ~ ., data = vehicles)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -2919.8 -1410.1  -355.5   1418.8   5241.7
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -16321.524  42128.829  -0.387   0.7043
## diesel       1345.112   3988.023   0.337   0.7409
## turbo        1543.223   3167.584   0.487   0.6337
## two.doors     525.496   2182.582   0.241   0.8132
## hatchback    -7120.032  2830.591  -2.515   0.0247 *
## wheel.base    29.738    462.233   0.064   0.9496
## length       -371.484   254.303  -1.461   0.1662
## width         979.577   695.139   1.409   0.1806
## height       -494.126   695.891  -0.710   0.4893
## curb.weight   10.325    10.788   0.957   0.3548
## eng.size      83.775     96.394   0.869   0.3994
## horsepower    40.904     61.632   0.664   0.5177
## peak.rpm       2.265     1.954   1.159   0.2657
## symbol       1172.065    862.383   1.359   0.1956
## city.mpg     -89.821    545.087  -0.165   0.8715
## highway.mpg   128.438    464.388   0.277   0.7861
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2959 on 14 degrees of freedom
## Multiple R-squared:  0.9436, Adjusted R-squared:  0.8832
## F-statistic: 15.62 on 15 and 14 DF, p-value: 3.19e-06
```

Le R^2 semble bon, proche de 1, alors que quasiment aucune variable n'est significative.

Examinons les VIFs :

```
library(car)
```

```
## Loading required package: carData
```

```
vif(modele)
```

```
##      diesel      turbo  two.doors  hatchback  wheel.base    length
##  8.721236   6.151519   3.791296   5.766553   34.465577   42.429644
##      width      height  curb.weight  eng.size  horsepower    peak.rpm
##  9.529732   6.434802  126.458500   44.285608   19.798272   3.009453
##      symbol  city.mpg  highway.mpg
##  3.160566   41.026076   31.572018
```

Il y a en effet plusieurs variables qui sont corrélées entre elles.

```
library(MASS)
```

```
modele2=stepAIC(modele,direction = "both")
```

```
## Start:  AIC=488.68
```

```
## price ~ diesel + turbo + two.doors + hatchback + wheel.base +
##      length + width + height + curb.weight + eng.size + horsepower +
##      peak.rpm + symbol + city.mpg + highway.mpg
```

```
##
##      Df Sum of Sq      RSS      AIC
## - wheel.base  1      36232 122584300 486.69
## - city.mpg    1      237687 122785755 486.74
## - two.doors   1      507430 123055498 486.81
## - highway.mpg 1      669584 123217652 486.85
## - diesel      1      995819 123543886 486.93
## - turbo       1     2077686 124625754 487.19
## - horsepower  1     3855681 126403749 487.61
## - height      1     4413385 126961453 487.75
## - eng.size    1     6611702 129159770 488.26
## - curb.weight 1     8017751 130565819 488.59
## <none>                122548068 488.68
## - peak.rpm     1    11764260 134312328 489.43
## - symbol       1    16168953 138717021 490.40
## - width        1    17382475 139930543 490.66
## - length       1    18678994 141227062 490.94
## - hatchback    1    55384497 177932565 497.87
##
```

```
## Step:  AIC=486.69
```

```
## price ~ diesel + turbo + two.doors + hatchback + length + width +
##      height + curb.weight + eng.size + horsepower + peak.rpm +
##      symbol + city.mpg + highway.mpg
```

```
##
##      Df Sum of Sq      RSS      AIC
## - city.mpg    1      201563 122785862 484.74
## - highway.mpg 1      634196 123218496 484.85
## - two.doors   1      660836 123245136 484.85
## - diesel      1     1193119 123777419 484.98
## - turbo       1     3167854 125752154 485.46
## - height      1     4517321 127101621 485.78
## - horsepower  1     4884503 127468803 485.87
## - eng.size    1     6667591 129251890 486.28
## <none>                122584300 486.69
```

```

## - peak.rpm      1 12023419 134607719 487.50
## - curb.weight   1 12395279 134979579 487.58
## - symbol        1 16204153 138788453 488.42
## + wheel.base    1      36232 122548068 488.68
## - length        1 19206645 141790945 489.06
## - width          1 23686779 146271079 489.99
## - hatchback     1 57070536 179654836 496.16
##
## Step: AIC=484.74
## price ~ diesel + turbo + two.doors + hatchback + length + width +
## height + curb.weight + eng.size + horsepower + peak.rpm +
## symbol + highway.mpg
##
##           Df Sum of Sq      RSS      AIC
## - two.doors  1      632951 123418813 482.90
## - highway.mpg 1      732227 123518090 482.92
## - diesel     1     1161817 123947680 483.03
## - turbo      1     2966389 125752252 483.46
## - height     1     4994171 127780033 483.94
## - eng.size   1     6466362 129252225 484.28
## - horsepower 1     8212543 130998405 484.68
## <none>                122785862 484.74
## - curb.weight 1    12248331 135034193 485.60
## - peak.rpm    1    12637444 135423306 485.68
## + city.mpg    1      201563 122584300 486.69
## + wheel.base  1         107 122785755 486.74
## - symbol      1    17855651 140641513 486.82
## - length      1    19623273 142409135 487.19
## - width       1    23490540 146276402 487.99
## - hatchback   1    57006309 179792171 494.18
##
## Step: AIC=482.9
## price ~ diesel + turbo + hatchback + length + width + height +
## curb.weight + eng.size + horsepower + peak.rpm + symbol +
## highway.mpg
##
##           Df Sum of Sq      RSS      AIC
## - highway.mpg 1      897154 124315968 481.11
## - diesel      1     1412288 124831101 481.24
## - turbo       1     3443014 126861827 481.72
## - height      1     4490560 127909374 481.97
## - eng.size    1     8010335 131429149 482.78
## <none>                123418813 482.90
## - horsepower  1     9327567 132746381 483.08
## - curb.weight 1    11672361 135091175 483.61
## - peak.rpm    1    13316947 136735761 483.97
## + two.doors   1      632951 122785862 484.74
## + city.mpg    1      173677 123245136 484.85
## + wheel.base  1      53356 123365457 484.88
## - length      1    20638640 144057454 485.54
## - width       1    22972587 146391400 486.02
## - symbol      1    25505587 148924401 486.53
## - hatchback   1    62356082 185774895 493.17
##

```

```

## Step: AIC=481.11
## price ~ diesel + turbo + hatchback + length + width + height +
##   curb.weight + eng.size + horsepower + peak.rpm + symbol
##
##           Df Sum of Sq      RSS      AIC
## - diesel    1  2023223 126339190 479.60
## - turbo     1  2988529 127304497 479.83
## - height    1  4546668 128862636 480.19
## - eng.size   1  8100400 132416368 481.01
## - horsepower 1  8450644 132766612 481.09
## <none>                124315968 481.11
## - curb.weight 1 11014306 135330273 481.66
## - peak.rpm    1 12606383 136922351 482.01
## + highway.mpg 1   897154 123418813 482.90
## + two.doors   1   797878 123518090 482.92
## + city.mpg    1   416982 123898985 483.01
## + wheel.base  1   212357 124103611 483.06
## - length     1 22840705 147156673 484.17
## - width      1 26571829 150887796 484.93
## - symbol     1 26972474 151288441 485.01
## - hatchback  1  64239297 188555265 491.61
##
## Step: AIC=479.6
## price ~ turbo + hatchback + length + width + height + curb.weight +
##   eng.size + horsepower + peak.rpm + symbol
##
##           Df Sum of Sq      RSS      AIC
## - height    1  3898236 130237427 478.51
## - turbo     1  5523729 131862919 478.88
## - horsepower 1  6463352 132802542 479.10
## - eng.size   1  7012015 133351205 479.22
## <none>                126339190 479.60
## - peak.rpm   1 10591565 136930756 480.01
## + diesel     1  2023223 124315968 481.11
## + highway.mpg 1  1508089 124831101 481.24
## + two.doors  1  1207507 125131684 481.31
## + city.mpg   1   857154 125482036 481.39
## + wheel.base 1    60620 126278570 481.58
## - curb.weight 1 21436497 147775687 482.30
## - width      1 35372225 161711416 485.00
## - symbol     1 43985240 170324430 486.56
## - length     1 49702694 176041884 487.55
## - hatchback  1 117434156 243773346 497.32
##
## Step: AIC=478.51
## price ~ turbo + hatchback + length + width + curb.weight + eng.size +
##   horsepower + peak.rpm + symbol
##
##           Df Sum of Sq      RSS      AIC
## - horsepower 1  5222511 135459938 477.69
## - turbo     1  6935969 137173396 478.07
## <none>                130237427 478.51
## - peak.rpm   1 12784771 143022198 479.32
## + height     1  3898236 126339190 479.60

```

```
## + highway.mpg 1 1447992 128789435 480.17
## + diesel 1 1374791 128862636 480.19
## - curb.weight 1 17658007 147895434 480.32
## + city.mpg 1 482395 129755032 480.40
## - eng.size 1 18143853 148381280 480.42
## + wheel.base 1 163775 130073652 480.47
## + two.doors 1 1918 130235508 480.51
## - width 1 35299696 165537122 483.71
## - symbol 1 40656541 170893968 484.66
## - length 1 56729208 186966635 487.36
## - hatchback 1 117588100 247825527 495.81
##
## Step: AIC=477.69
## price ~ turbo + hatchback + length + width + curb.weight + eng.size +
## peak.rpm + symbol
##
## Df Sum of Sq RSS AIC
## <none> 135459938 477.69
## + horsepower 1 5222511 130237427 478.51
## - curb.weight 1 14246825 149706763 478.69
## + height 1 2657396 132802542 479.10
## + wheel.base 1 2594735 132865203 479.11
## + city.mpg 1 662921 134797017 479.54
## + two.doors 1 81936 135378002 479.67
## + diesel 1 53426 135406511 479.68
## + highway.mpg 1 18454 135441484 479.69
## - turbo 1 20555961 156015899 479.93
## - width 1 32129527 167589465 482.07
## - peak.rpm 1 38526714 173986652 483.20
## - symbol 1 48434625 183894563 484.86
## - eng.size 1 49967934 185427871 485.11
## - length 1 51736255 187196193 485.39
## - hatchback 1 112522581 247982519 493.83
```

Examinons le modèle obtenu :

```
summary(modele2)
```

```
##
## Call:
## lm(formula = price ~ turbo + hatchback + length + width + curb.weight +
## eng.size + peak.rpm + symbol, data = vehicles)
##
## Residuals:
## Min 1Q Median 3Q Max
## -3989.6 -1391.4 -480.5 1219.1 5306.4
##
## Coefficients:
## Estimate Std. Error t value Pr(>|t|)
## (Intercept) -35109.053 23964.875 -1.465 0.157727
## turbo 3140.737 1759.375 1.785 0.088691 .
## hatchback -6760.217 1618.589 -4.177 0.000426 ***
## length -433.600 153.104 -2.832 0.009984 **
## width 1049.308 470.161 2.232 0.036654 *
## curb.weight 8.848 5.953 1.486 0.152099
```

```
## eng.size      145.526      52.287      2.783 0.011140 *
## peak.rpm      2.848       1.166      2.444 0.023444 *
## symbol      1503.603     548.720      2.740 0.012264 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2540 on 21 degrees of freedom
## Multiple R-squared:  0.9377, Adjusted R-squared:  0.914
## F-statistic: 39.5 on 8 and 21 DF,  p-value: 5.974e-11
```

La variable curb.weight n'est pas significative, je l'enlève

```
modele3=lm(price ~ turbo + hatchback + length + width + eng.size + peak.rpm + symbol, data = vehicles)
summary(modele3)
```

```
##
## Call:
## lm(formula = price ~ turbo + hatchback + length + width + eng.size +
##      peak.rpm + symbol, data = vehicles)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -3282.5 -1270.8  -730.7  1712.3  5787.4
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -54010.276   20862.105   -2.589 0.016751 *
## turbo        4648.590    1476.308    3.149 0.004661 **
## hatchback   -5686.831    1487.765   -3.822 0.000929 ***
## length      -263.948     104.792   -2.519 0.019548 *
## width       1086.271     482.227    2.253 0.034593 *
## eng.size     217.736      19.838   10.976 2.16e-10 ***
## peak.rpm      2.797        1.197    2.337 0.028928 *
## symbol      1247.061     534.977    2.331 0.029314 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2609 on 22 degrees of freedom
## Multiple R-squared:  0.9311, Adjusted R-squared:  0.9092
## F-statistic: 42.5 on 7 and 22 DF,  p-value: 2.442e-11
```

Tout est significatif. On peut comparer les critères AIC (attention, avec la même fonction, par exemple AIC, car suivant les fonctions de R certains variantes du critères AIC peuvent être implémentée.)

```
AIC(modele2)
```

```
## [1] 564.826
```

```
AIC(modele3)
```

```
## [1] 565.8261
```

Même si le AIC est légèrement moins bon pour le modèle3, toutes les variables sont significatives donc je le préférerai.

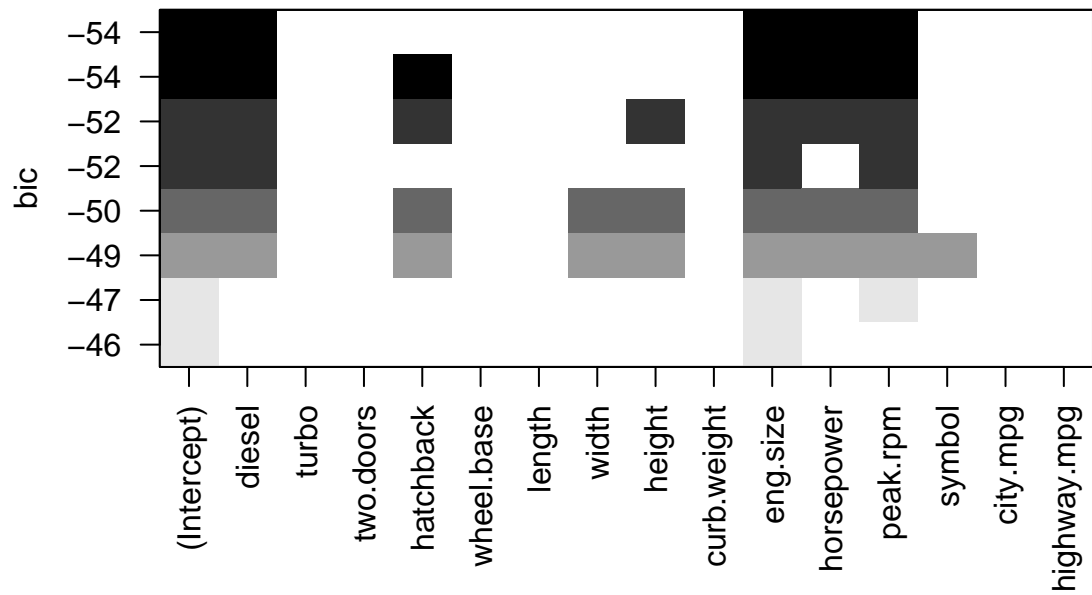
Examinons pour finir les VIF, ils sont corrects.

```
vif(modele3)
```

```
##      turbo hatchback      length      width eng.size  peak.rpm   symbol
##  1.718858  2.049228  9.267903  5.899295  2.412832  1.452460  1.564567
```

On peut aussi utiliser la librairie suivante, qui permet notamment de tracer pour les meilleurs modèles parcourus l'importance de chaque variable :

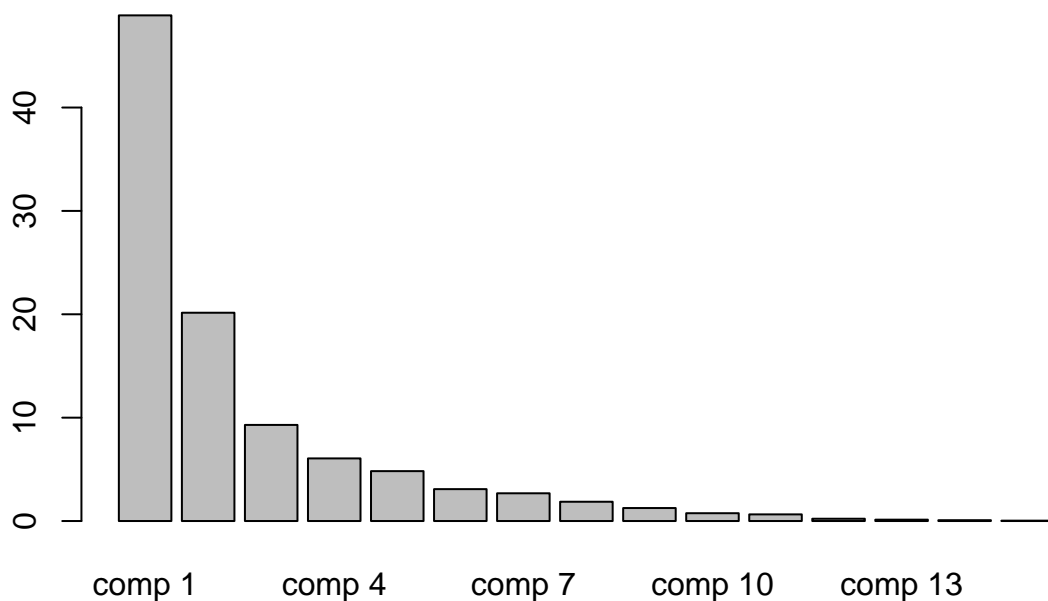
```
library(leaps)
modele4bis=regsubsets(price ~ .,method="forward", data = vehicles)
plot(modele4bis)
```



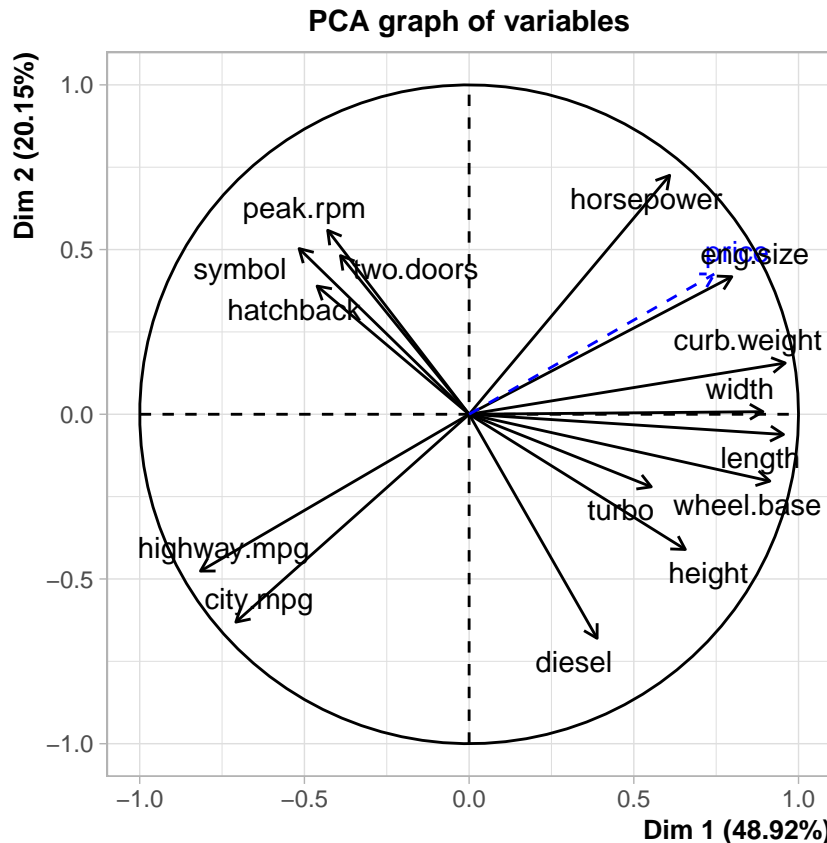
Regression sur composantes principales

On peut commencer par effectuer une ACP :

```
library(FactoMineR)
acp=PCA(vehicles,quanti.sup = 13,graph = FALSE)
barplot(acp$eig[,2])
```



```
plot(acp,choix="var")
```



Des stratégies classiques de sélection du nombre d'axe en ACP nous conduirait à choisir 3 axes. On peut aussi sélectionner ce nombre en fonction de la qualité du modèle de régression.

La régression sur composante principale peut-être réalisée directement

```
library(pls)
```

```
## Warning: package 'pls' was built under R version 4.4.1
```

```
##
```

```
## Attaching package: 'pls'
```

```
## The following object is masked from 'package:stats':
```

```
##
```

```
## loadings
```

```
modele5=pcr(price~.,data=vehicles,validation='LOO',scale=TRUE)
```

```
summary(modele5)
```

```
## Data: X dimension: 30 15
```

```
## Y dimension: 30 1
```

```
## Fit method: svdpc
```

```
## Number of components considered: 15
```

```
##
```

```
## VALIDATION: RMSEP
```

```
## Cross-validated using 30 leave-one-out segments.
```

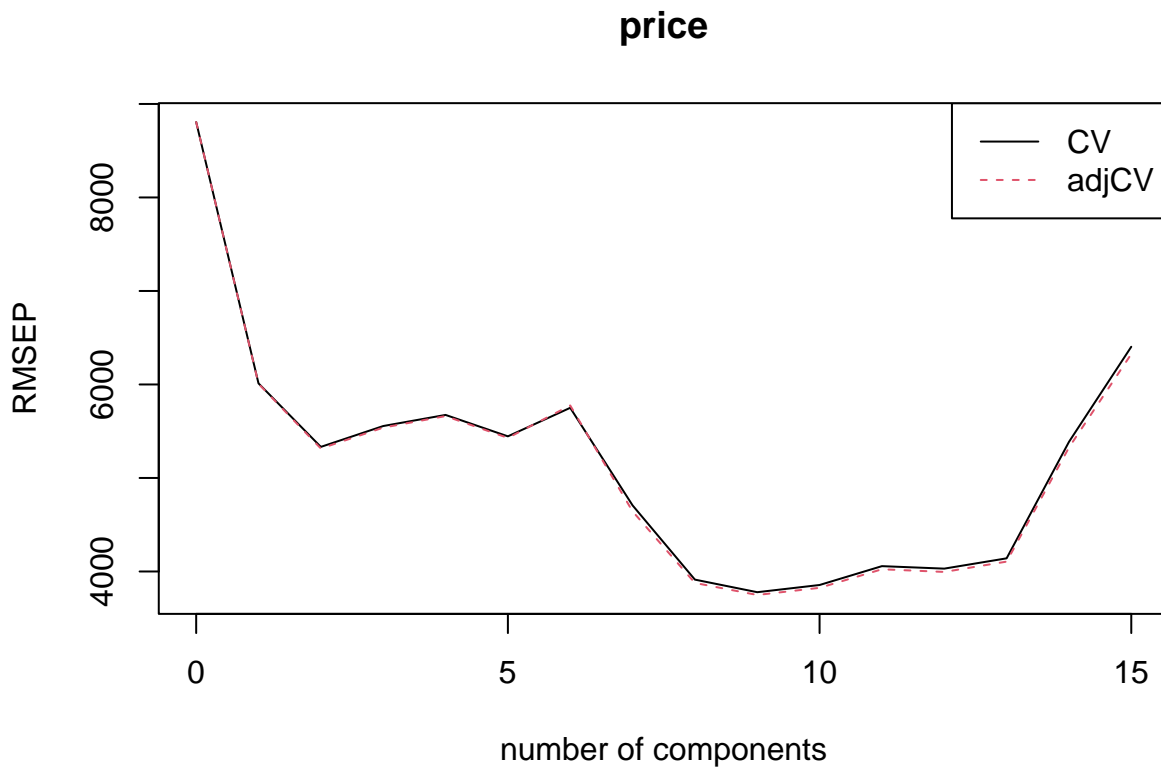
```
## (Intercept) 1 comps 2 comps 3 comps 4 comps 5 comps 6 comps
```

```
## CV 8806 6012 5332 5556 5674 5445 5750
```



```
## adjCV      8806      6007      5315      5538      5662      5429      5775
##          7 comps  8 comps  9 comps 10 comps 11 comps 12 comps 13 comps
## CV        4707      3913      3778      3855      4057      4030      4141
## adjCV      4643      3877      3749      3825      4023      3995      4105
##          14 comps 15 comps
## CV         5386      6403
## adjCV      5325      6326
##
## TRAINING: % variance explained
##          1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X          48.92   69.06   78.36   84.42   89.25   92.33   95.01   96.88
## price      55.39   73.52   73.56   75.97   78.87   82.64   92.29   92.85
##          9 comps 10 comps 11 comps 12 comps 13 comps 14 comps 15 comps
## X          98.13   98.89   99.53   99.75   99.88   99.96  100.00
## price      93.21   93.22   93.28   93.93   93.93   94.19   94.36
```

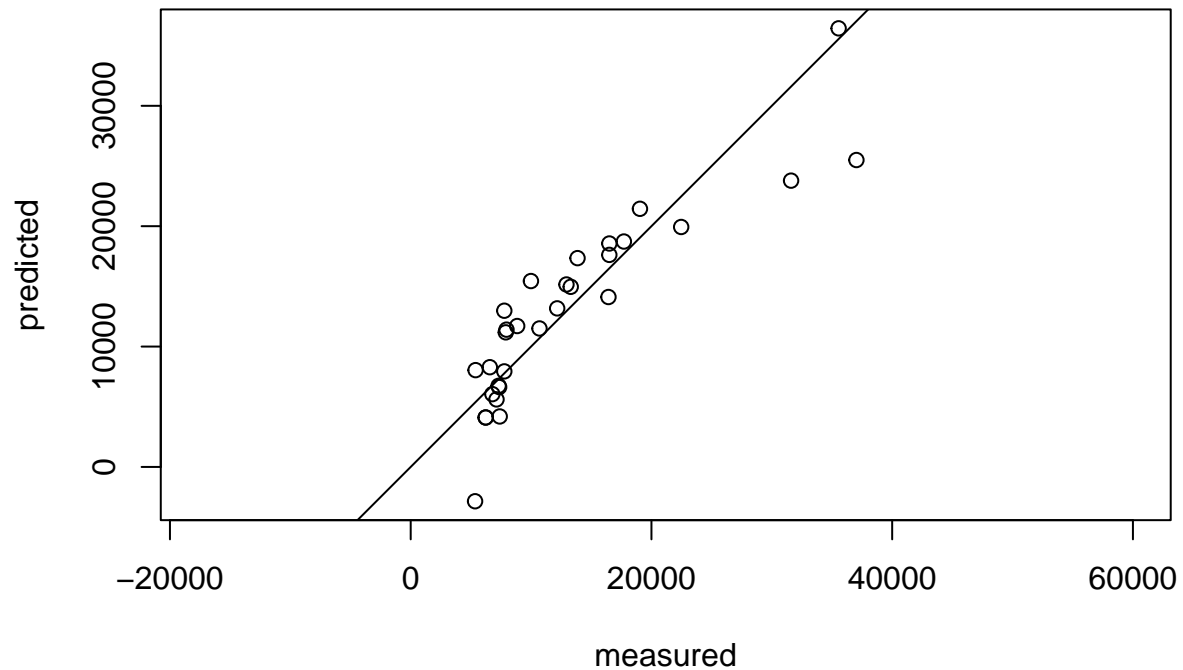
```
plot(RMSEP(modele5), legendpos = "topright")
```



Le bon nombre de composantes semble être 9. On peut regarder la qualité de la prédiction de ce modèle en traçant les valeurs prédites en fonctions des valeurs mesurées :

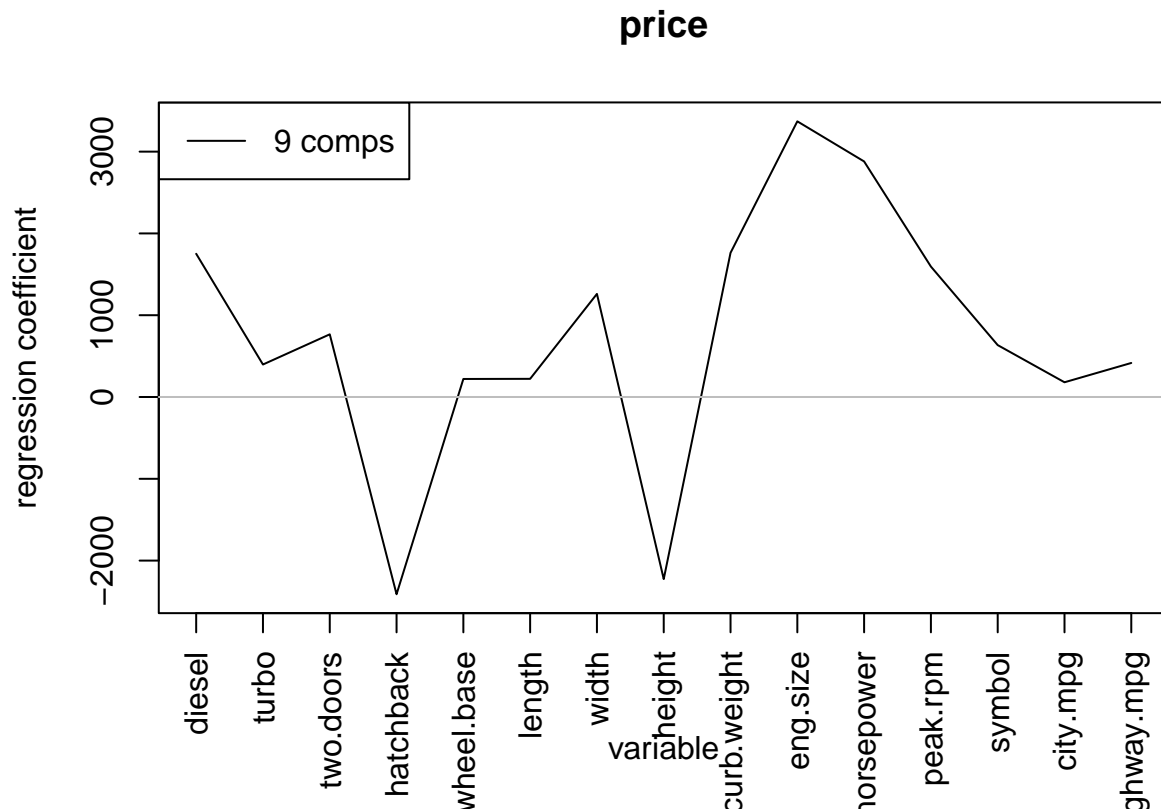
```
plot(modele5, ncomp = 9, asp = 1, line = TRUE)
```

price, 9 comps, validation



L'examen des coefficients de régression des composantes principales ne nous sera d'aucune utilité. Par contre, ces composantes étant elles-mêmes des combinaisons linéaires des variables initiales, on peut reconstruire les coefficients de régressions sur les variables initiales :

```
plot(modele5, plottype = "coef", ncomp=9, legendpos = "topleft", xaxt='n')
axis(1, at=1:15, labels=colnames(vehicles)[-13], las = 2)
```



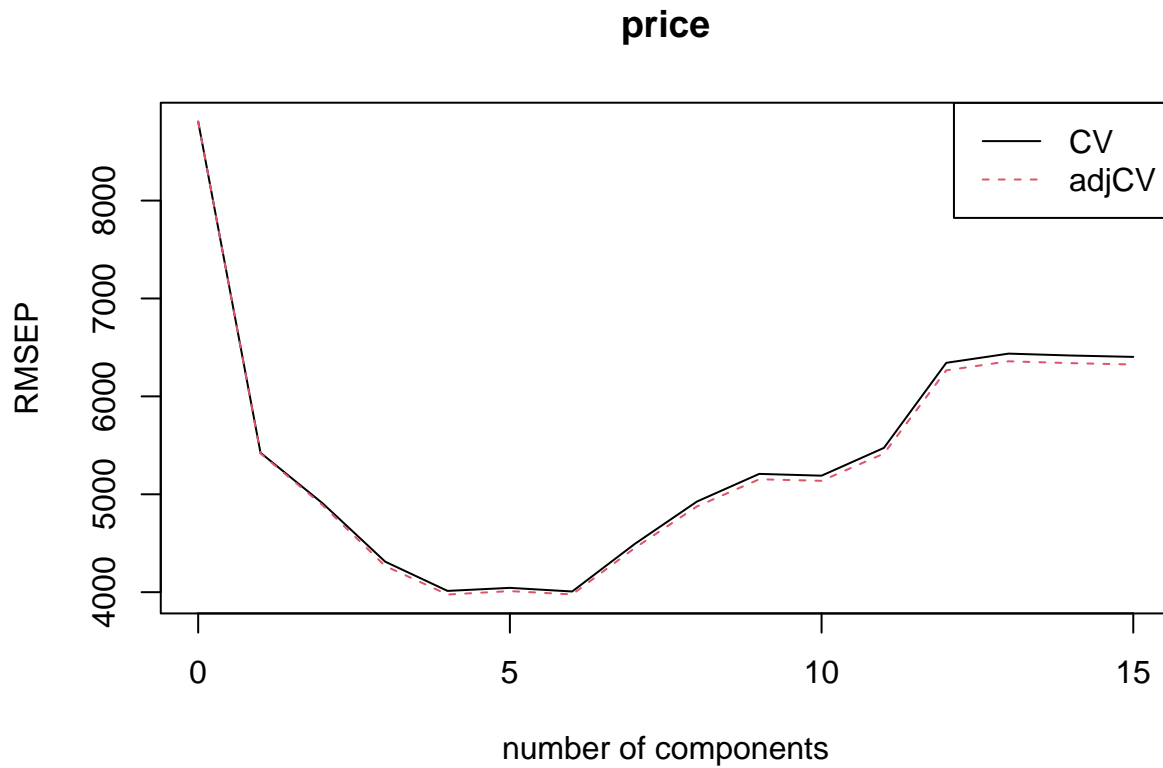
Regression sur composantes PLS

```
library(pls)
modele6=plsr(price~.,data=vehicles,validation='LOO',scale=TRUE)
summary(modele6)
```

```
## Data:      X dimension: 30 15
## Y dimension: 30 1
## Fit method: kernelppls
## Number of components considered: 15
##
## VALIDATION: RMSEP
## Cross-validated using 30 leave-one-out segments.
##      (Intercept)  1 comps  2 comps  3 comps  4 comps  5 comps  6 comps
## CV           8806    5424    4906    4312    4013    4044    4007
## adjCV        8806    5417    4886    4267    3976    4011    3977
##      7 comps  8 comps  9 comps 10 comps 11 comps 12 comps 13 comps
## CV       4491    4926    5208    5190    5474    6343    6437
## adjCV    4450    4876    5153    5137    5416    6266    6358
##      14 comps 15 comps
## CV       6417    6403
## adjCV    6339    6326
##
## TRAINING: % variance explained
##      1 comps  2 comps  3 comps  4 comps  5 comps  6 comps  7 comps  8 comps
## X       47.32   67.78   73.14   77.87   84.81   89.60   92.93   94.71
## price   70.47   82.18   92.06   93.32   93.46   93.64   93.84   94.07
##      9 comps 10 comps 11 comps 12 comps 13 comps 14 comps 15 comps
```

## X	96.58	98.07	98.84	99.09	99.78	99.87	100.00
## price	94.17	94.21	94.26	94.34	94.35	94.36	94.36

```
plot(RMSEP(modele6), legendpos = "topright")
```



```
plot(modele6, plottype = "coef", ncomp=4, xaxt='n')
axis(1, at=1:15, labels=colnames(vehicles)[-13], las = 2)
```

