A collector of antique grandfather clocks knows that the price received for the clocks increases linearly with the age of the clocks. Moreover, the collector hypothesizes that the auction price of the clocks will increase linearly as the number of bidders increases. Thus, the following first-order model is hypothesized:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \varepsilon$$

where

Y = Auction price (dollars)

 $X_1 = Age of clock (years)$

 $X_2 =$ Number of bidders

A sample of 32 auction prices of grandfather clocks, along with their age and the number of bidders, is given in the table below.

Age, X ₁	Number of Bidders, X ₂	Auction Price, Y	Age, X ₁	Number of Bidders, X ₂	Auction Price, Y
127	13	1,235	170	14	2,131
115	12	1,080	182	8	1,550
127	7	845	162	11	1,884
150	9	1,522	184	10	2,041
156	6	1,047	143	6	845
182	11	1,979	159	9	1,483
156	12	1,822	108	14	1,055
132	10	1,253	175	8	1,545
137	9	1,297	108	6	729
113	9	946	179	9	1,792
137	15	1,713	111	15	1,175
117	11	1,024	187	8	1,593
137	8	1,147	111	7	785
153	6	1,092	115	7	744
117	13	1,152	194	5	1,356
126	10	1,336	168	7	1,262

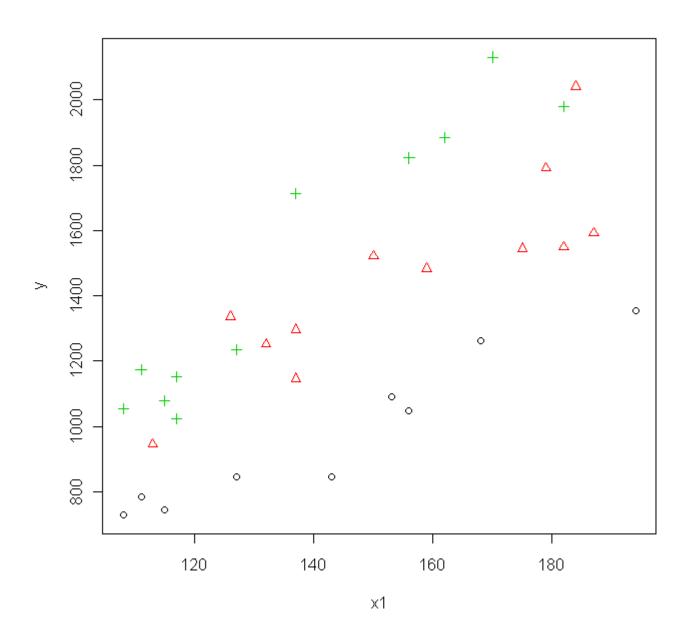
```
> clocks.dat = read.table(" ... /clocks.csv",sep=",",header=T)
> clocks.fit1 = lm(y ~ x1 + x2, data=clocks.dat)
> summary(clocks.fit1)
Call:
lm(formula = y \sim x1 + x2, data = clocks.dat)
Residuals:
   Min 1Q Median 3Q
-206.48 -117.34 16.66 102.55 213.50
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -1338.9513 173.8095 -7.704 1.71e-08 ***
              12.7406 0.9047 14.082 1.69e-14 ***
85.9530 8.7285 9.847 9.34e-11 ***
x1
x2
Signif. codes: 0 '*** 0.001 '** 0.01 '* 0.05 '.' 0.1 ' ' 1
Residual standard error: 133.5 on 29 degrees of freedom
Multiple R-Squared: 0.8923, Adjusted R-squared: 0.8849
F-statistic: 120.2 on 2 and 29 DF, p-value: 9.216e-15
```

Suppose the collector of grandfather clocks, having observed many auctions, believes that the *rate of increase* of the auction price with age will be driven upward by a large number of bidders. Consequently, the interaction model is proposed:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \varepsilon$$

```
> clocks.dat$x1x2 = clocks.dat$x1 * clocks.dat$x2
> clocks.fit2 = lm(y \sim x1 + x2 + x1x2, data=clocks.dat)
> summary(clocks.fit2)
Call:
lm(formula = y \sim x1 + x2 + x1x2, data = clocks.dat)
Residuals:
    Min 1Q Median 3Q
                                      Max
-154.995 -70.431 2.069 47.880 202.259
Coefficients:
           Estimate Std. Error t value Pr(>|t|)
(Intercept) 320.4580 295.1413 1.086 0.28684
            0.8781
                       2.0322 0.432 0.66896
x1
           -93.2648 29.8916 -3.120 0.00416 **
1.2978 0.2123 6.112 1 35e-06 **
x2
                       0.2123 6.112 1.35e-06 ***
x1x2
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
Residual standard error: 88.91 on 28 degrees of freedom
Multiple R-Squared: 0.9539, Adjusted R-squared: 0.9489
F-statistic: 193 on 3 and 28 DF, p-value: < 2.2e-16
```

```
> gr = rep(1,32)
>
> for (i in 1:32) {
+ if (x2[i]>7) {gr[i]=gr[i]+1}
+ if (x2[i]>10) {gr[i]=gr[i]+1}
+ }
>
> plot(x1,y,pch=gr,col=gr)
```



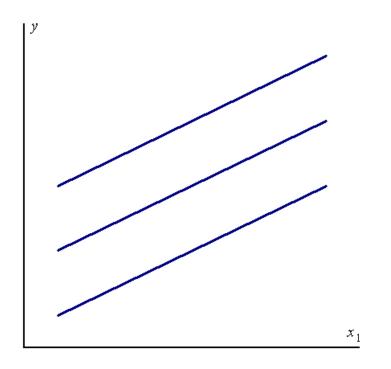
An Interaction Model Relating Y to Two Quantitative Independent Variables

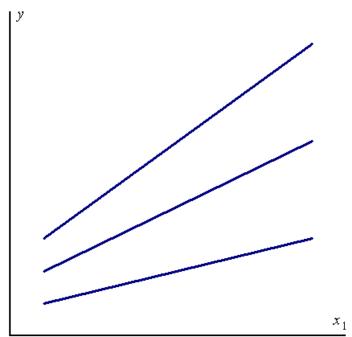
$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \varepsilon$$

where

 $(\beta_1 + \beta_3 x_2)$ represents the change in E(Y) for every 1-unit increase in x_1 , holding x_2 fixed.

 $(\beta_2 + \beta_3 x_1)$ represents the change in E(Y) for every 1-unit increase in x_2 , holding x_1 fixed.





No interaction between x_1 and x_2

Interaction between x_1 and x_2

Estimate the change in auction price of a 170-year-old grandfather clock, y, for each additional bidder.

$$\hat{\beta}_2 \approx 85.95$$

We estimate that the auction price of a grandfather clock will increase by about \$85.95 for every additional bidder.

$$\hat{\beta}_2 + \hat{\beta}_3 x_1 \approx -93.265 + 1.2978 \cdot 170 \approx 127.36$$

We estimate that the auction price of a 170-year-old clock will increase by about \$127.36 for every additional bidder.

```
> clocks.dat$y[17] = 1131
                                                  - creating an outlier
  > clocks.fit3 = lm(y \sim x1 + x2 + x1x2, data=clocks.dat)
  > summary(clocks.fit3)
  lm(formula = y \sim x1 + x2 + x1x2, data = clocks.dat)
  Residuals:
             1Q Median
                               3Q
      Min
  -783.43 -75.51 -11.01 125.33 285.70
  Coefficients:
               Estimate Std. Error t value Pr(>|t|)
  (Intercept) -512.8102 665.8601 -0.770 0.4477
                8.1651
                           4.5847 1.781 0.0858 .
  x1
                          67.4376 0.295 0.7702
                19.8877
  x2
  x1x2
                 0.3196
                           0.4790 0.667 0.5101
  Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
  Residual standard error: 200.6 on 28 degrees of freedom
  Multiple R-Squared: 0.7292, Adjusted R-squared: 0.7002
  F-statistic: 25.13 on 3 and 28 DF, p-value: 4.277e-08
> X = cbind(rep(1,32),clocks.dat$x1,clocks.dat$x2,clocks.dat$x1*clocks.dat$x2)
> ## the hat-matrix
> H = X %*% solve(t(X)%*%X) %*% t(X)
> ## leverages
> lev = rep(0,32)
> for (i in 1:32) {lev[i] = H[i,i]}
> lev
 [1] 0.08744552 0.09588217 0.09284425 0.03427419 0.09043677 0.17071980
 [7] 0.09518823 0.03923118 0.03787039 0.08540308 0.15283620 0.07005945
[13] 0.04868743 0.08641369 0.12081830 0.04687672 <mark>0.33847490</mark> 0.09805986
[19] \quad 0.08064726 \quad 0.12424110 \quad 0.08628552 \quad 0.04090267 \quad 0.23824594 \quad 0.07618809
[25] 0.24675474 0.08234239 0.28575991 0.11688367 0.16245986 0.14159717
[31] 0.44331534 0.08285421
                                     OR
> influence(clocks.fit2)$hat
         1
                   2
                               3
                                         4
                                                     5
                                                                6
0.08744552\ 0.09588217\ 0.09284425\ 0.03427419\ 0.09043677\ 0.17071980\ 0.09518823
                   9
                              10
                                        11
                                                   12
                                                              1.3
0.03923118 0.03787039 0.08540308 0.15283620 0.07005945 0.04868743 0.08641369
                              17
                                                   19
        1.5
                  16
                                        18
                                                              2.0
0.12081830 0.04687672 0.33847490 0.09805986 0.08064726 0.12424110 0.08628552
        2.2
                  23
                              24
                                        25
                                            26
                                                       27
0.04090267 \ 0.23824594 \ 0.07618809 \ 0.24675474 \ 0.08234239 \ 0.28575991 \ 0.11688367
        29
                   30
                             31
                                        32
0.16245986 0.14159717 0.44331534 0.08285421
```