Advanced Data Analysis HW4

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1.

(a)

Answer:

I expect there's a positive correlation between sales of cigarettes and Age, because the people with higher ages tend to smoke more cigarettes, the proportion of people smoking within young people is relatively small.
I expect there's a negative correlation between sales of cigarettes and HS, because people with higher education are more aware of the harm of smoking and are tend to somke less.
I expect there's a positive correlation between sales of cigarettes and Income, because with more money, people can afford more cigarettes.
I don't expect there's a correlation between sales of cigarettes and Black, because there's no supporting evidence that black people are mode likely to smoke more than others.
I expect there's a negative correlation between sales of cigarettes and Female, because there are a lot more men smoking than women, the higher the proportion of the women, the less the proportion of people smoking.
I expect there's a negative correlation between sales of cigarettes and Price, the less the price is, the more people can afford the cigarettes.

(b)

Answer:

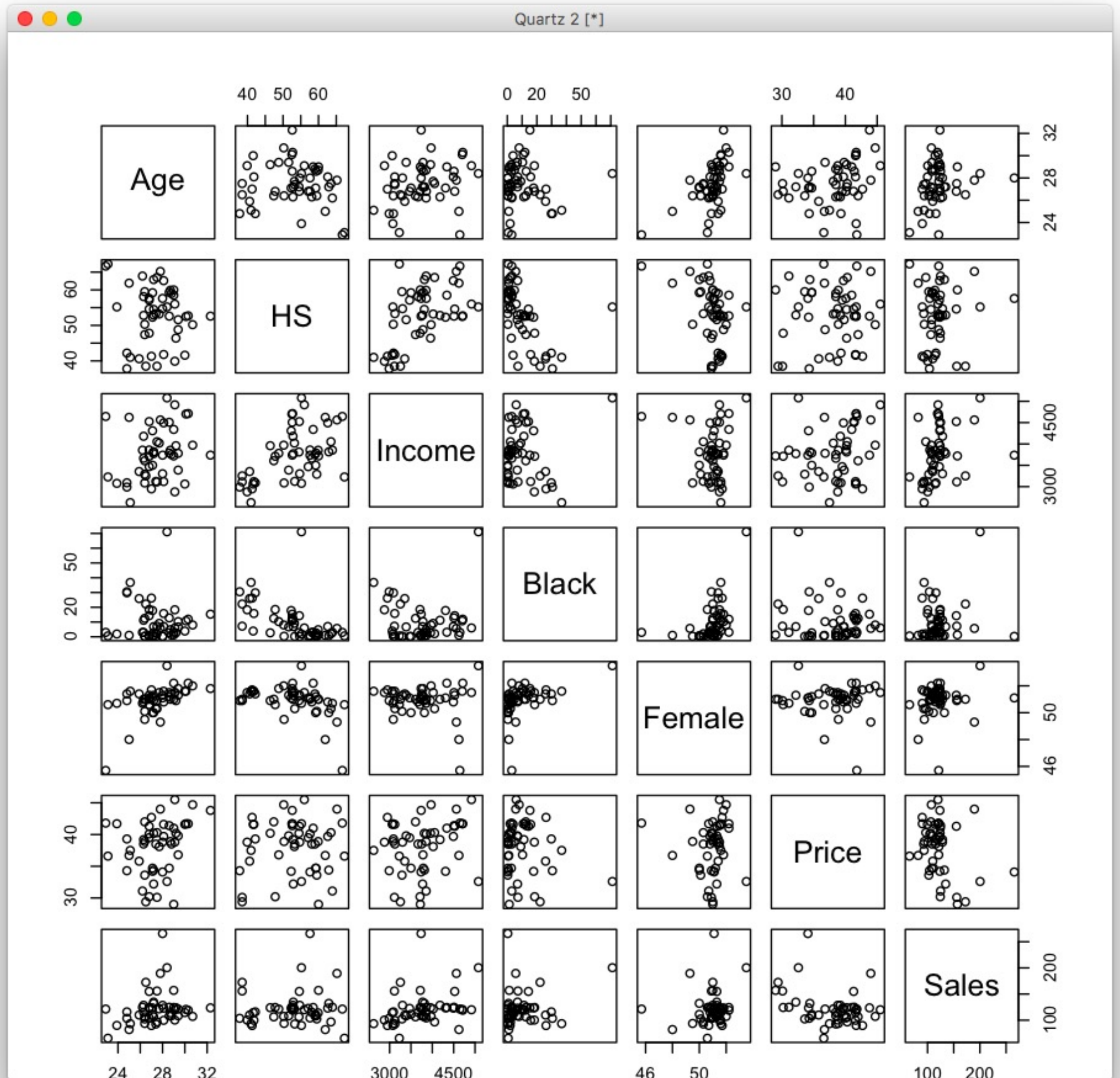
```
> data = read.table("DATACIGARETTE.txt", header = TRUE)
> mat.data <- data.matrix(data[,2:8])
> cor((mat.data))
```

so the pairwise correlation coefficient matrix is:

```
            Age         HS          Income      Black       Female      Price       Sales
 Age 1.00000000  -0.09891626 0.25658098  -0.04033021 0.55303189  0.24775673
   0.22655492
 HS  -0.09891626 1.00000000  0.53400534  -0.50171191 -0.41737794 0.05697473
   0.06669476
 Income  0.25658098  0.53400534  1.00000000  0.01728756  -0.06882666 0.21455717
   0.32606789
 Black  -0.04033021 -0.50171191 0.01728756  1.00000000  0.45089974  -0.14777619
   0.18959037
 Female  0.55303189  -0.41737794 -0.06882666 0.45089974  1.00000000  0.02247351
   0.14622124
 Price 0.24775673  0.05697473  0.21455717  -0.14777619 0.02247351  1.00000000
   -0.30062263
 Sales 0.22655492  0.06669476  0.32606789  0.18959037  0.14622124  -0.30062263
   1.00000000
```

```
> pairs(data[,2:8])
```

The corresponding scatter plot is:



(c)

Answer:

```
> results = lm(Sales ~ Age+HS+Income+Black+Female+Price , data=data)
# install.packages('car')
> library(car)
> vif(results)
```

The VIF for 6 variables are:

```
   Age         HS     Income     Black    Female     Price
2.300617 2.676465 2.325164 2.392152 2.406417 1.142181
```

(d)

Answer:

Yes, there are outlying Sales observations in the regression model relating Sales to the six predictors.

```
> r = rstudent(results)
> data[abs(r)>3,]
```

```
   State  Age  HS   Income  Black  Female  Price  Sales
29  NV    27.8  65.2  4563   5.7   49.3    44.0   189.5
30  NH    28.0  57.6  3737   0.3   51.1    34.1   265.7
```

As we can see from the result, NV and NH are the two states that have outlying Sales observations in the regression model relating Sales to the six predictors.

(e)

Answer:

```
> results = lm(Sales ~ Age+HS+Income+Black+Female+Price , data=data)
> lev = hat(model.matrix(results))
> lev
```

```
  0.148834504030601  0.580160351053579  0.0496985364502016  0.13709423363853
   0.0601062187168606  0.130138939805311  0.174671432351856  0.109964259157845
   0.719712840922186  0.2984807799694  0.0992462576906176  0.216903455841289
   0.092060813754798  0.078138923121058  0.0863031077553889  0.0600834204236368
   0.0600531614367214  0.229271714316211  0.147216983914844  0.0592277100717082
   0.082438148474407  0.111768500306865  0.0788600537461464  0.0595424855799236
   0.220268293959589  0.0538126742130819  0.07535749988127  0.0713061951148198
   0.171156408722539  0.0663450574293963  0.112543589203342  0.205163482615724
   0.125210794051503  0.189612219012305  0.0977942068782977  0.0427023659576899
   0.0747312407280888  0.194824611487451  0.110848283936785  0.107728709447137
   0.157387827636549  0.0702636797470909  0.0861059621640753  0.073209300335295
   0.310573704010913  0.0646432821046025  0.121378178796484  0.06441386857486
   0.139413729014416  0.0386706972156815  0.0845573052310269
```

According to the common rule we will flag any observation whose leverage value satisfies

$$h_{ii} > \frac{2p}{n} = \frac{12}{51}$$

```
> data[which(lev>12/51),1]
> lev[lev>12/51]
```

```
AK DC FL UT
0.580160351053579  0.719712840922186  0.2984807799694  0.310573704010913
```

Thus, according to the rule above, we get 4 states who have high leverage: AK, DC, FL, UT.

(f)

Answer:

Typically, points with Cook's distance greater than 1 are classified as being influential, so we calculate Cook's distance for every state's data:

```
> cook = cooks.distance(results)
> cook
```

Then we get the 51 Cook's distance:

```
0.000872312260768373 0.11046568368098 0.000231406438616766 0.00533644985289951
    0.00087184813943891 0.00487422897991362 0.000903689085754166 0.0247623942663158
    0.272772360871267 0.00031718427842994 0.00228486844474409 0.149108047215374
    0.00577305260600313 0.000515725336002152 0.000235292422912618 0.0022195814166927
    0.0011742764662855 0.0293108038740074 0.0091907941594545 0.0046197884422297
    0.00853949173434342 5.43666855436729e-05 0.000993543307494363
    0.000416583654710988 0.00357717450931961 0.00181158830548335 0.00222167629931825
    0.0106704252779454 0.226884733564416 0.243073931655456 0.00865807771956428
    0.00862556323250348 0.0128750489379433 0.0514726373485391 0.000694147592466878
    0.000198786969647856 0.000926126973805015 0.000632210801320141
    0.00231792501997608 3.5406858359337e-07 0.00559710600247828 0.0021868920733631
    0.000167678660476866 0.000276633855805063 0.0861896935150744 0.00441253690931487
    0.0144781318896138 0.00554156138259945 0.00241683043673791 0.000216940322227759
    6.00182901861485e-05
```

No one is greater than 1, so there's no influential points according to the rule of Cook's distance.

(g)

Answer:

```
> results = lm(log(Sales) ~ Age+HS+Income+Black+Female+Price, data=data)
> r = rstudent(results)
> data[abs(r)>3,]
```

```
   State  Age  HS   Income  Black  Female  Price  Sales
29  NV   27.8  65.2  4563   5.7   49.3   44.0   189.5
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As we can see from the result, NV and NH are the two states that have outlying Sales observations in the regression model relating Sales to the six predictors.

```
> lev = hat(model.matrix(results))
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```

```
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    0.0601062187168606 0.130138939805311 0.174671432351856 0.109964259157845
    0.719712840922186 0.2984807799694 0.0992462576906176 0.216903455841289
    0.092060813754798 0.078138923121058 0.0863031077553889 0.0600834204236368
    0.0600531614367214 0.229271714316211 0.147216983914844 0.0592277100717082
    0.082438148474407 0.111768500306865 0.0788600537461464 0.0595424855799236
    0.220268293959589 0.0538126742130819 0.07535749988127 0.0713061951148198
    0.171156408722539 0.0663450574293963 0.112543589203342 0.205163482615724
    0.125210794051503 0.189612219012305 0.0977942068782977 0.0427023659576899
    0.0747312407280888 0.194824611487451 0.110848283936785 0.107728709447137
    0.157387827636549 0.0702636797470909 0.0861059621640753 0.073209300335295
    0.310573704010913 0.0646432821046025 0.121378178796484 0.06441386857486
    0.139413729014416 0.0386706972156815 0.0845573052310269
```

According to the common rule we will flag any observation whose leverage value satisfies

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```
> data[which(lev>12/51),1]
> lev[lev>12/51]
```

```
AK DC FL UT
0.580160351053579 0.719712840922186 0.2984807799694 0.310573704010913
```

Thus, according to the rule above, we get 4 states who have high leverage: AK, DC, FL, UT. Typically, points with Cook's distance greater than 1 are classified as being influential, so we calculate Cook's distance for every state's data:

```
> cook = cooks.distance(results)
> cook
```

Then we get the 51 Cook's distance:

```
0.00359045513224516 0.240240855616072 0.00121318532616218 0.00940000348486041
    0.000293993996183841 0.000845445364141786 0.00157627217231795 0.0336654337125128
    0.14134926250704 4.17359595508581e-08 0.00203727701223271 0.270758042867878
    0.00458499785548776 0.000451889520957869 9.31888737750166e-06 0.00184184619189831
     0.000560973161470141 0.0319246707978281 0.0204097590400288 0.00921415105332014
    0.00810736995024783 7.12278615229615e-05 0.00254520116778151 0.0002981214100366
    0.00317957208142376 0.00184483532854467 0.00116873114507587 0.0108404640748746
    0.242062092944229 0.161220045757967 0.0123781360184546 0.0103388197355609
    0.0176912765990876 0.0540788613509783 0.00205060932036119 4.12952664005199e-05
    0.000879330434682632 0.0030802159952135 0.00441873438600284 8.57636871488496e-05
    0.005679380081201 0.00398597075671328 0.000654080555535082 0.00040384707347726
    0.238154414273449 0.00956732233083818 0.0132426216290245 0.00700748304948474
    0.00221365370129141 0.000195642965139178 0.00154531793916012
```

No one is greater than 1, so there's no influential points according to the rule of Cook's distance.

2.

(a)

Answer:

In order to test the hypothesis, we have a full model:

$$y_{ijk} = \mu + \alpha_B D_{i,B} + \alpha_C D_{i,C} + \beta_N D_{j,N} + \beta_O D_{j,O} + \beta_P D_{j,P} + \epsilon_{ij,k}$$

and a reduced model:

$$y_{ijk} = \mu + \beta_N D_{j,N} + \beta_O D_{j,O} + \beta_P D_{j,P} + \epsilon_{ij,k}$$

We will reject the Null Hypothesis if the two models are different:

```
> data = read.csv("/Users/lleiou/Google Drive/      Courses/4th term/Advanced-Data-
    Analysis/HW/Question/HW4/Oildata.csv")
> colnames(data)
> full = lm(Mileage ~ factor(Rgasoline) + factor(GasolineAd), data = data)
> reduce1 = lm(Mileage ~ factor(GasolineAd), data = data)
> anova(reduce1, full)
```

```
Res.Df  RSS       Df  Sum of Sq  F          Pr(>F)
37      3496.295  NA  NA         NA         NA
35      3466.153  2   30.14234   0.1521834  0.859396
```

Since the p-value of the test is $0.859396 > \alpha = 0.05$, we cannot reject the Null Hypothesis that $\alpha_B = \alpha_C = 0$

(b)

Answer:

In order to test the hypothesis, we have a full model:

$$y_{ijk} = \mu + \alpha_B D_{i,B} + \alpha_C D_{i,C} + \beta_N D_{j,N} + \beta_O D_{j,O} + \beta_P D_{j,P} + \epsilon_{ij,k}$$

and a reduced model:

$$y_{ijk} = \mu + \alpha_B D_{i,B} + \alpha_C D_{i,C} + \epsilon_{ij,k}$$

We will reject the Null Hypothesis if the two models are different:

```
> full = lm(Mileage ~ factor(Rgasoline) + factor(GasolineAd), data = data)
> reduce2 = lm(Mileage ~ factor(Rgasoline), data = data)
> anova(reduce2, full)
```

```
Res.Df RSS       Df  Sum of Sq  F          Pr(>F)
38     3592.151  NA  NA         NA         NA
35     3466.153  3   125.9986   0.4240966  0.736912
```

Since the p-value of the test is $0.736912 > \alpha = 0.05$, we cannot reject the Null Hypothesis that $\beta_N = \beta_O = \beta_P = 0$