Log 708 - Chapter 8 Solutions

Halvard Arntzen

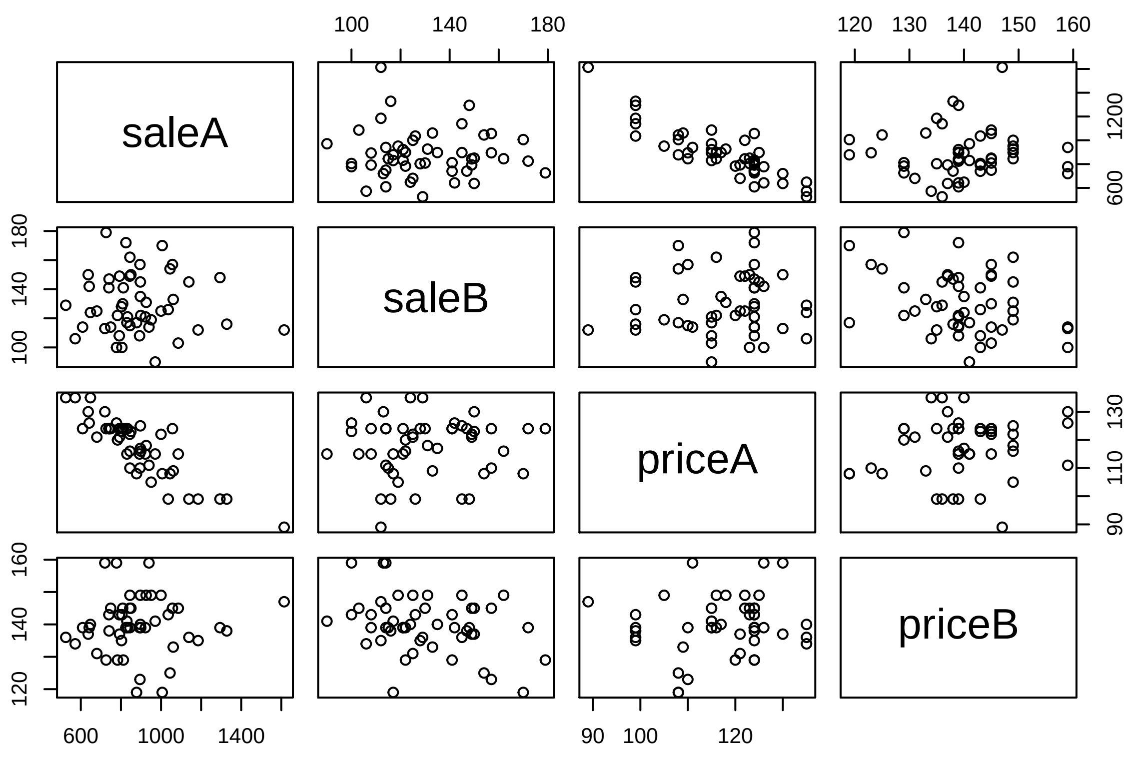
8.1 Not this year

8.2

a. The expression should be decreasing as a function of x_A and increasing as a function of x_B, so we should have $\alpha_A < 0$,$\alpha_B > 0$. If $\alpha_B = 0$, the term relating to brand B becomes $x_B^0 = 1$, so the price of brand B does not affect the sale of brand A if this is the case.

It is always a good idea to have a look at the data:

```
meatdata <- read.csv("M:/Undervisning/Undervisningh21/Data/meat_brands.csv")
#make a matrix plot of all variables
plot(meatdata)
```



```r
summary(meatdata)
```

```
##      saleA            saleB            priceA           priceB     
##  Min.   : 525.0   Min.   : 90.0   Min.   : 89.0   Min.   :119.0  
##  1st Qu.: 779.2   1st Qu.:114.2   1st Qu.:110.2   1st Qu.:136.0  
##  Median : 845.0   Median :125.5   Median :121.0   Median :139.0  
##  Mean   : 883.1   Mean   :130.2   Mean   :117.5   Mean   :139.7  
##  3rd Qu.: 966.0   3rd Qu.:146.5   3rd Qu.:124.0   3rd Qu.:145.0  
##  Max.   :1614.0   Max.   :179.0   Max.   :135.0   Max.   :159.0
```

We see larger sales of brand A in general, and somewhat higher prices in general for brand B. From the various scatterplot only the sale vs price relation for brand A is very clear. No other effects appear visually as very strong. (That does not mean there *are* no other effects, as we will see.) There are no "dangerous" outlier data points, so it looks good for a regression analysis.

b. Ok, doing a few initial experiments show that while saleA is affected by both prices, the saleB is not significantly affected by priceA, so we can consider the following three models.

```r
library(stargazer)


#brand A sales full model
regA <- lm(log(saleA) ~ log(priceA) + log(priceB), data = meatdata)

#same for B
regB <- lm(log(saleB) ~ log(priceA) + log(priceB), data = meatdata)

#reduced model for saleB
regB2 <- update(regB, . ~ . - log(priceA))
regB2 <- stargazer(regA, regB, regB2,
          type = "text",
          keep.stat=c("n", "rsq"),
          model.numbers=FALSE,
          column.labels = c("A", "B", "B2"))
```

```
## 
## ==========================================
##                    Dependent variable:    
##               ----------------------------
##               log(saleA)     log(saleB)   
##                   A          B        B2  
## ------------------------------------------
## log(priceA)   -2.077***    0.179          
##                (0.164)    (0.234)
```

```
##
## log(priceB)    0.589**   -0.861** -0.823**
##                (0.238)   (0.339)  (0.334)
##
## Constant      13.744***  8.254*** 8.921***
##                (1.315)   (1.874)  (1.652)
##
## -----------------------------------------
## Observations     50         50       50
## R2              0.773     0.123    0.112
## =========================================
## Note:          *p<0.1; **p<0.05; ***p<0.01
```

c. We can read somehting like this:

- For the sale of brand A:
  - if priceA increases by 1%, the sale will drop (expected) by about 2.1%
  - if priceB increases by 1%, the sale will go up by (expected) about 0.59%
- For the sale of brand B:
  - if priceB increases by 1%, the sale will drop (expected) by about 0.82%
  - the sale is not significantly related to priceA. (I.e. we can not reject the null hypothesis $\beta_A = 0$.)

This can be interpreted as follows. Typical buyers of brand A are quite price sensitive, if the price goes up, they tend to stop buying, and they do not generally switch to brand B (because price A is largely unrelated to sale B).

Typical buyers of brand B are much less price sensitive. If the price B goes up, some sale of B is lost, but at the same time we see sale A going up, so we can interpret this as customers swithcing to brand A when brand B is getting more expensive.

We can note in connection with this, that in practice, we often think about say 10 or 20% price jumps, and in this case we just multiply up the effect, so for example a 10% higher price A would lead to about 21% lost sales for A. Or we can think oppositely: A 10% drop in price B would increase the sale of B by about 8%.

d. Briefly: Widely advertised low price campaigns for meat A could have at least two effects:

1. Customers who usually shops elsewhere are attracted by the offer, so the *size* of the market temporarily changes. The constant c_A in the model describes a fixed market size where prices are known to all. We may need to model changes in c_A that may occur in campaign weeks.

2. Since people have freezers, many would buy lots of meat in campaign weeks and store at home. That would possibly "dry-out" the market in subsequent weeks. Again, the number of potential buyers (size of market) of meat A may vary from week to week. The supermarket should be prepared to order less meat in weeks following a substantial low price campaign.

Without going into any detail, clearly modifications to such models are possible. Regarding point 1, dummy variables indicating extra advertising/campaign weeks could be included in a sensible way. For point 2, the *time order* of weeks seems to matter. One could have dummies indicating one, two, three weeks after campaigns. It would be possible to model changes in market size with this.