Rahul Narvekar | ECON 573 | Problem Set 1

Part 1: Ex 1, 2, 4, 5, 6 from Chapter 2 of ISL.

1. For each of parts (a) through (d), indicate whether we would generally expect the performance of a flexible statistical learning method to be better or worse than an inflexible method. Justify your answer.
(a) The sample size n is extremely large, and the number of predictors p is small.

- In this situation a flexible method will be better because it will more close fit the data and since the sample size is large

(b) The number of predictors p is extremely large, and the number of observations n is small.

- In this situation a flexible method will be worse, as it would not fit well to smaller number of observations

(c) The relationship between the predictors and response is highly non-linear.

- A flexible method will fit the data better

(d) The variance of the error terms, i.e. $\sigma 2 = \text{Var}(\varo)$, is extremely high.

- Since the error term has a lot of variance, a flexible method would be worse than an inflexible one

2. Explain whether each scenario is a classification or regression problem, and indicate whether we are most interested in inference or prediction. Finally, provide n and p.
(a) We collect a set of data on the top 500 firms in the US. For each firm we record profit, number of employees, industry and the CEO salary. We are interested in understanding which factors affect CEO salary.

- n = 500
- p = 3
- regression
- inference

(b) We are considering launching a new product and wish to know whether it will be a success or a failure. We collect data on 20 similar products that were previously launched. For each product we have recorded whether it was a success or failure, price charged for the product, marketing budget, competition price, and ten other variables.

- n = 20
- p = 14
- classification
- prediction

(c) We are interest in predicting the ed % change in the USD/Euro exchange rate in relation to the weekly changes in the world stock markets. Hence we collect weekly data for all of 2012. For each week we record the % change in the USD/Euro, the % change in the US market, the % change in the British market, and the % change in the German market.

- n = 52, for 52 weeks in a year
- p = 4
- regression
- prediction

4. You will now think of some real-life applications for statistical learning.
(a) Describe three real-life applications in which classification might be useful. Describe the response, as well as the predictors. Is the goal of each application inference or prediction? Explain your answer.

- Will an online training model for onboarding new employees work?
    - Response: Training works or doesn't
    - Predictors:
        - Num of modules
        - Length
        - Assessments in the training
    - Prediction
- Should Toyota create a new crossover for the north America market?
    - Response: Should or shouldn't create the crossover
    - Predictors
        - Costs
        - Sale Price
        - MPG
        - Competitors

    - Prediction
- Should Apple create a new MacBook with a screen an inch bigger than the current one?
    - Response: should or shouldn't create the MacBook
    - Predictors:
        - Price
        - Manufacturing costs
        - Distribution
        - Competitors
    - Prediction of whether the product should be created or not

(b) Describe three real-life applications in which regression might be useful. Describe the response, as well as the predictors. Is the goal of each application inference or prediction? Explain your answer.

- How much will a car be worth n years from now?
    - Response: an estimations of the cars price
    - Predictors
        - Miles
        - Mpg
        - Body condition
        - Previous owners
        - Accidents
    - Prediction of car price
- How does college years of education compare with salary in first job
    - Response: salary amount after education amount
    - predictors
        - Years of education
        - Certifications
        - Prior experience or internships
    - Prediction of salary
- How much will a plant grow in a certain amount of days?
    - Response: heigh of the plant
    - Predictors
        - Fertilizer
        - Water
        - Sunlight
        - Soil conditions
    - Prediction of height

(c) Describe three real-life applications in which cluster analysis might be useful.

- Separating groups of people into tax brackets based on their income
    - Response: groups of tax brackets
    - Predictors
        - Salary
        - Number of children
        - Marital status
    - Prediction of tax bracket
- Separating students based on their grade
    - Response: group of students based on letter grade
    - Predictors:
        - Grade
    - Prediction of letter grade
- Separating cars into budget, mistier, and luxury brands
    - Response: classification of cars by quality
    - Predictors:
        - Types of materials
        - Brand prestige
        - Car horsepower and torque
    - Prediction of quality

5. What are the advantages and disadvantages of a very flexible (versus a less flexible) approach for regression or classification? Under what circumstances might a more flexible approach be preferred to a less flexible approach? When might a less flexible approach be preferred?

- Advantages
    - Good for large population sizes
    - If the model is non-linear
- Disadvantages
    - If there are a lot of predictors, variance could be very high
    - Could lead to an overfit of the data
- You should use a flexible approach when there are not a lot of predictors and the general population size is large

6. Describe the differences between a parametric and a non-parametric statistical learning approach. What are the advantages of a parametric approach to regression or classification (as opposed to a nonparametric approach)? What are its disadvantages?

- Parametric
    - Takes an assumption about the functional form
    - Once a model is found the data is fit
    - Advantages
        - Very simple to estimate the model
        - Don’t need as large of a sample size
    - Disadvantages
        - Maybe using the wrong model to estimate
        - An overfit may occur if an overly flexible model is used
- Non-Parametric
    - Do not make explicit assumptions about the functional form
    - Estimate the model to get as close the data points as possible

ECON 573 Problem Set 1 Part 2 and 3

Part 2

8a) Use the read.csv() function to read the data into R. Call the loaded data college. Make sure that you have the directory set to the correct location for the data.

```
college = read.csv("College.csv")
```

8b) Look at the data using the fix() function. You should notice that the first column is just the name of each university.We don't really want R to treat this as data. However, it may be handy to have these names for later. Try the following commands:

```
rownames(college) = college[,1]
college = fix(college)
college = college [,-1]
college = fix(college)
```

8ci) Use the summary() function to produce a numerical summary of the variables in the data set.

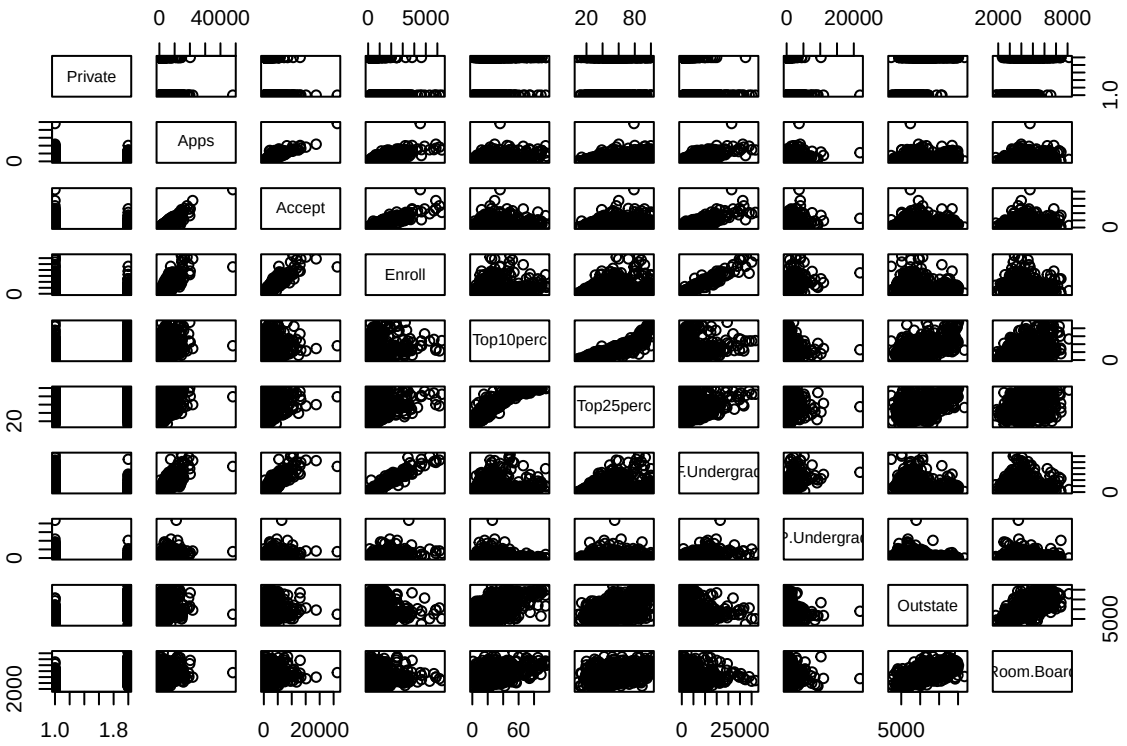
```
summary(college)
```

```
##    Private                 Apps           Accept          Enroll
##  Length:777         Min.   :   81   Min.   :   72   Min.   :  35
##  Class :character   1st Qu.:  776   1st Qu.:  604   1st Qu.: 242
##  Mode  :character   Median : 1558   Median : 1110   Median : 434
##                     Mean   : 3002   Mean   : 2019   Mean   : 780
##                     3rd Qu.: 3624   3rd Qu.: 2424   3rd Qu.: 902
##                     Max.   :48094   Max.   :26330   Max.   :6392
##    Top10perc       Top25perc      F.Undergrad     P.Undergrad
##  Min.   : 1.00   Min.   :  9.0   Min.   :  139   Min.   :    1.0
##  1st Qu.:15.00   1st Qu.: 41.0   1st Qu.:  992   1st Qu.:   95.0
##  Median :23.00   Median : 54.0   Median : 1707   Median :  353.0
##  Mean   :27.56   Mean   : 55.8   Mean   : 3700   Mean   :  855.3
##  3rd Qu.:35.00   3rd Qu.: 69.0   3rd Qu.: 4005   3rd Qu.:  967.0
##  Max.   :96.00   Max.   :100.0   Max.   :31643   Max.   :21836.0
##     Outstate       Room.Board       Books           Personal
##  Min.   : 2340   Min.   :1780   Min.   :  96.0   Min.   : 250
##  1st Qu.: 7320   1st Qu.:3597   1st Qu.: 470.0   1st Qu.: 850
##  Median : 9990   Median :4200   Median : 500.0   Median :1200
##  Mean   :10441   Mean   :4358   Mean   : 549.4   Mean   :1341
##  3rd Qu.:12925   3rd Qu.:5050   3rd Qu.: 600.0   3rd Qu.:1700
##  Max.   :21700   Max.   :8124   Max.   :2340.0   Max.   :6800
##       PhD            Terminal       S.F.Ratio      perc.alumni
##  Min.   :  8.00   Min.   : 24.0   Min.   : 2.50   Min.   : 0.00
##  1st Qu.: 62.00   1st Qu.: 71.0   1st Qu.:11.50   1st Qu.:13.00
```

```
##  Median : 75.00   Median : 82.0   Median :13.60   Median :21.00
##  Mean   : 72.66   Mean   : 79.7   Mean   :14.09   Mean   :22.74
##  3rd Qu.: 85.00   3rd Qu.: 92.0   3rd Qu.:16.50   3rd Qu.:31.00
##  Max.   :103.00   Max.   :100.0   Max.   :39.80   Max.   :64.00
##      Expend        Grad.Rate
##  Min.   : 3186   Min.   : 10.00
##  1st Qu.: 6751   1st Qu.: 53.00
##  Median : 8377   Median : 65.00
##  Mean   : 9660   Mean   : 65.46
##  3rd Qu.:10830   3rd Qu.: 78.00
##  Max.   :56233   Max.   :118.00
```

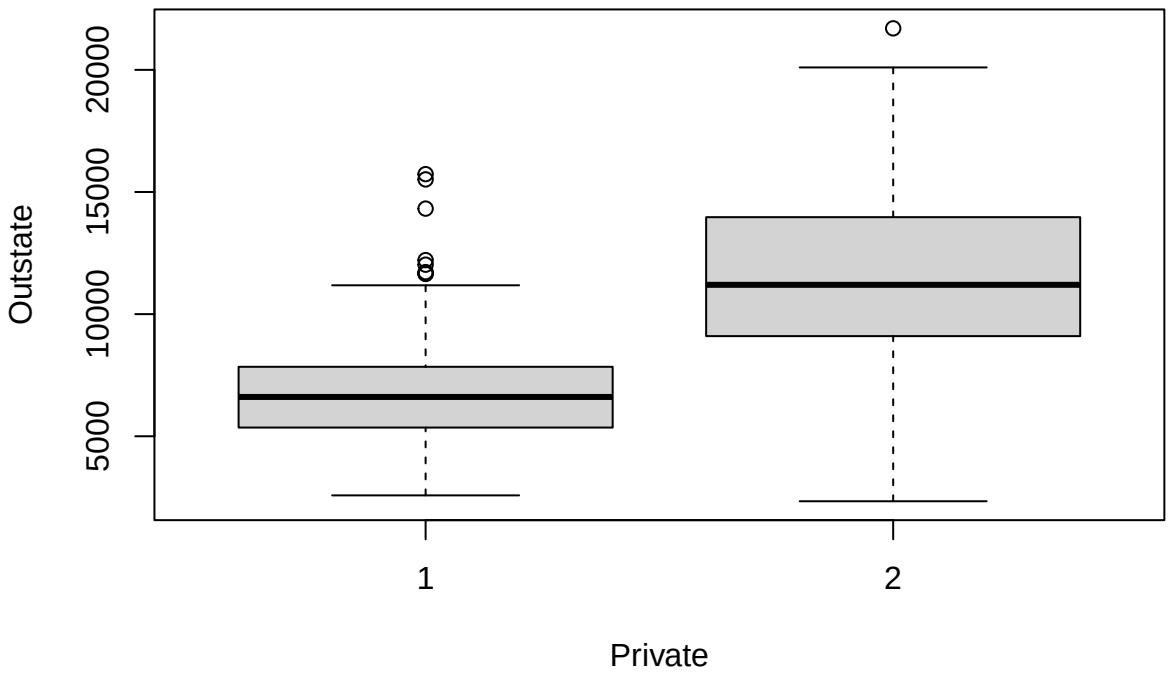
8cii). Use the pairs() function to produce a scatterplot matrix of the first ten columns or variables of the data. Recall that you can reference the first ten columns of a matrix A using A[,1:10].

```
college[,1] = as.numeric(factor(college[,1]))
pairs(college[, 1:10])
```



8ciii) Use the plot() function to produce side-by-side boxplots of Outstate versus Private.

```
attach(college)
boxplot(Outstate ~ Private, xlab = "Private", ylab = "Outstate")
```



8civ) Create a new qualitative variable, called Elite, by binning the Top10perc variable. We are going to divide universities into two groups based on whether or not the proportion of students coming from the top 10% of their high school classes exceeds 50%.

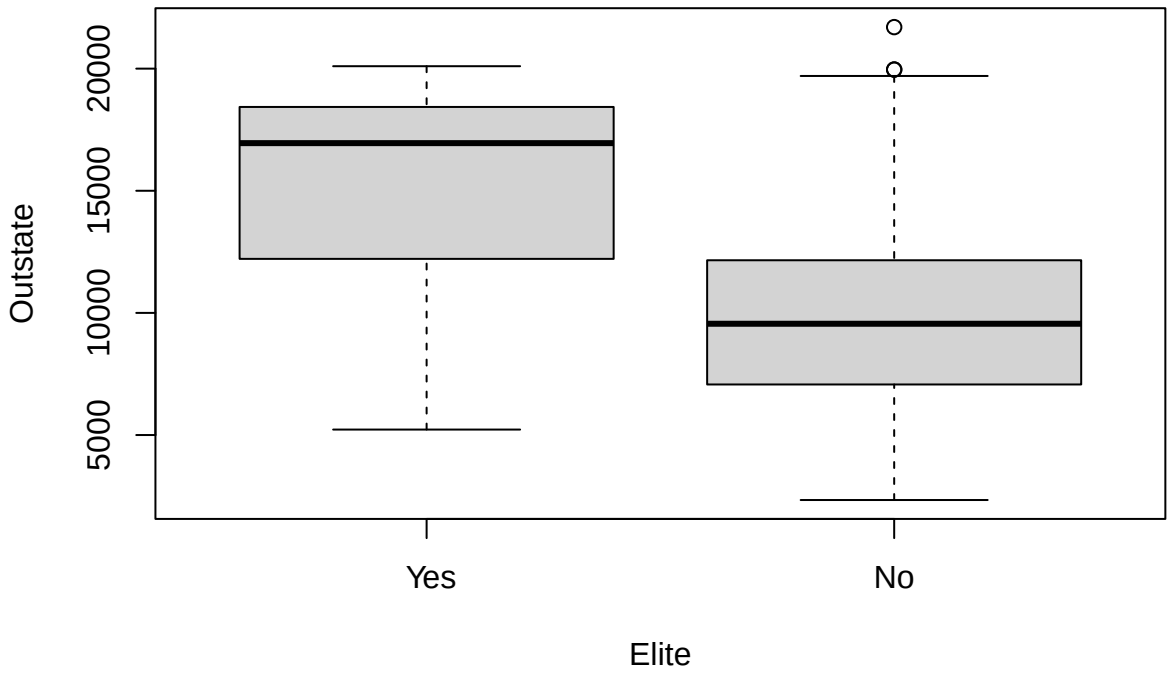
```
Elite = rep("No",nrow(college ))
Elite [college$Top10perc >50]=" Yes"
Elite = as.factor (Elite)
college = data.frame(college ,Elite)
```

Use the summary() function to see how many elite universities there are. Now use the plot() function toproduce side-by-side boxplots of Outstate versus Elite.

```
summary(college$Elite)
```

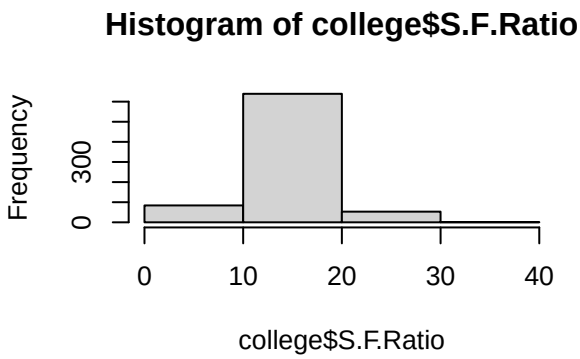
```
##  Yes   No
##   78  699
```

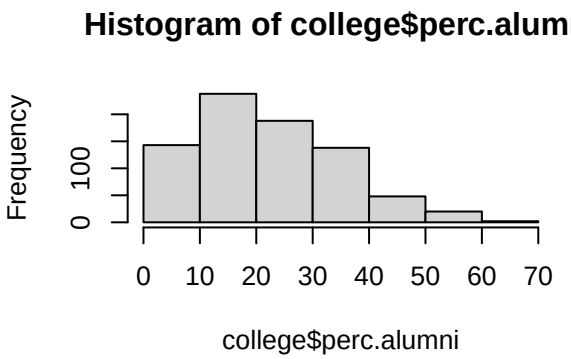
```
boxplot(college$Outstate ~ college$Elite, xlab = "Elite", ylab = "Outstate")
```

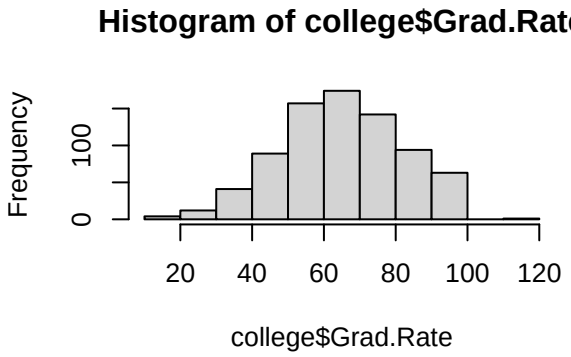


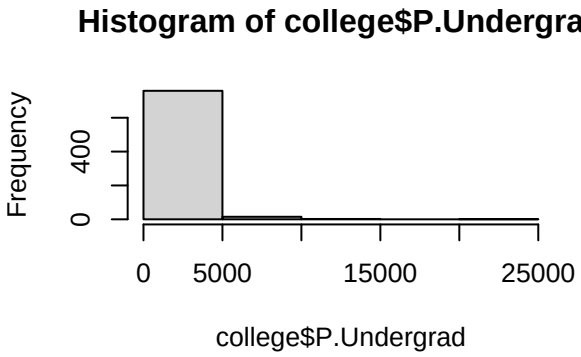
8cv) Use the hist() function to produce some histograms with differing numbers of bins for a few of the quantitative variables. You may find the command par(mfrow=c(2,2)) useful: it will divide the print window into four regions so that four plots can be made simultaneously. Modifying the arguments to this function will divide the screen in other ways.

```
par(mfrow=c(2,2))
hist(college$S.F.Ratio, breaks = 5)
hist(college$perc.alumni, breaks = 6)
hist(college$Grad.Rate, breaks = 8)
hist(college$P.Undergrad, breaks = 4)
```









8cvi) Continue exploring the data, and provide a brief summary of what you discover.

9) This exercise involves the Auto data set studied in the lab. Make sure that the missing values have been removed from the data.

```
auto = read.csv("Auto.csv")
auto = na.omit(auto)
detach(college)
attach(auto)
```

9a) Which of the predictors are quantitative, and which are qualitative?

```
sapply(auto, class)
```

```
##          mpg    cylinders displacement   horsepower       weight acceleration
##    "numeric"    "integer"    "numeric"  "character"    "integer"    "numeric"
##         year       origin         name
##    "integer"    "integer"  "character"
```

From the output of the command it seems as if name is the only qualitative variable

9b) What is the range of each quantitative predictor? You can answer this using the range() function.

```
apply(auto[,1:7], 2, range)
```

```
##      mpg    cylinders displacement horsepower weight acceleration year
## [1,] " 9.0" "3"       " 68.0"      "?"        "1613" " 8.0"       "70"
## [2,] "46.6" "8"       "455.0"      "98"       "5140" "24.8"       "82"
```

9c) What is the mean and standard deviation of each quantitative predictor?

```
sapply(auto[,1:7], mean, na.rm = TRUE)
```

```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA
```

```
##          mpg    cylinders displacement   horsepower       weight acceleration
##    23.515869     5.458438   193.532746           NA  2970.261965    15.555668
##         year
##    75.994962
```

```
sapply(auto[,1:7], sd, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm =
## na.rm): NAs introduced by coercion
```

```
##          mpg    cylinders displacement   horsepower       weight acceleration
##     7.825804     1.701577   104.379583    38.491160   847.904119     2.749995
##         year
##     3.690005
```

9d) Now remove the 10th through 85th observations. What is the range, mean, and standard deviation of each predictor in the subset of the data that remains?

```
sapply(auto[-c(10:85),1:7], range, na.rm = TRUE)
```

```
##      mpg    cylinders displacement horsepower weight acceleration year
## [1,] "11"   "3"       "68"         "?"        "1649" "8.5"        "70"
## [2,] "46.6" "8"       "455"        "98"       "4997" "24.8"       "82"
```

```
sapply(auto[-c(10:85),1:7], mean, na.rm = TRUE)
```

```
## Warning in mean.default(X[[i]], ...): argument is not numeric or logical:
## returning NA
```

```
##          mpg    cylinders displacement   horsepower       weight acceleration
##    24.438629     5.370717   187.049844           NA  2933.962617    15.723053
##         year
##    77.152648
```

```
sapply(auto[-c(10:85),1:7], sd, na.rm = TRUE)
```

```
## Warning in var(if (is.vector(x) || is.factor(x)) x else as.double(x), na.rm =
## na.rm): NAs introduced by coercion
```

```
##          mpg    cylinders displacement   horsepower       weight acceleration
##     7.908184     1.653486    99.635385    35.895567   810.642938     2.680514
##         year
##     3.111230
```

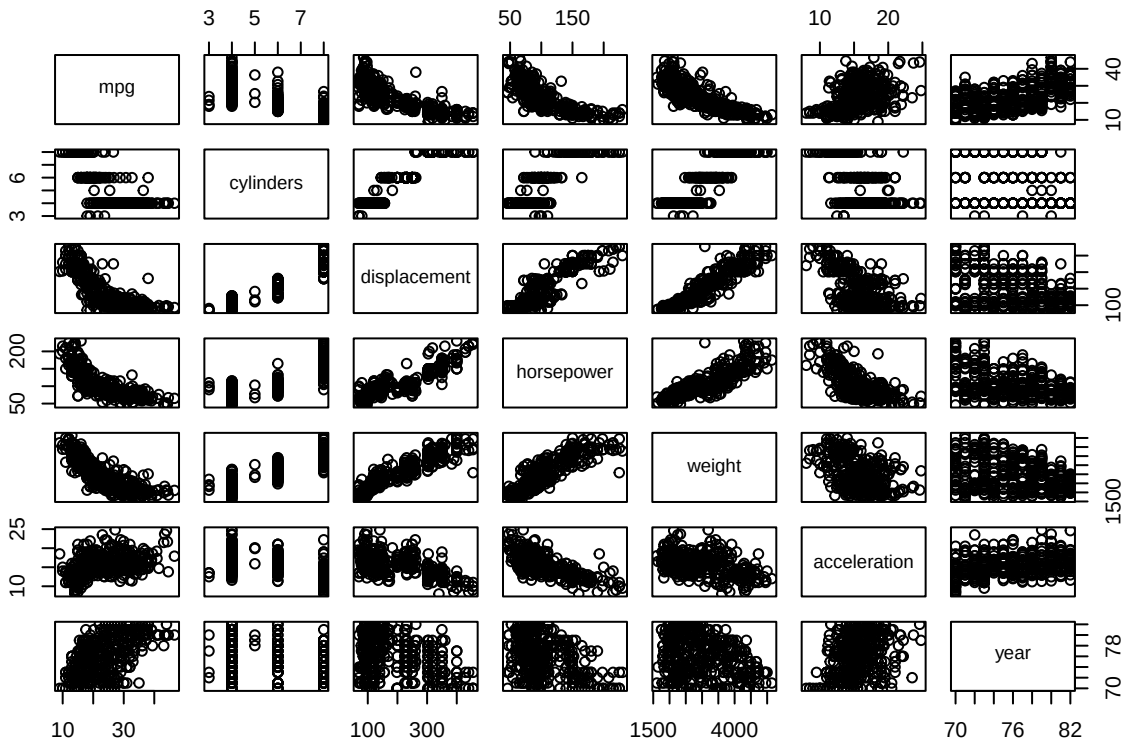
9e) Using the full data set, investigate the predictors graphically, using scatterplots or other tools of your choice. Create some plots highlighting the relationships among the predictors. Comment on your findings.

```
auto$horsepower <- as.numeric(type.convert(auto$horsepower))
```

```
## Warning in type.convert.default(auto$horsepower): 'as.is' should be specified by
## the caller; using TRUE
```

```
## Warning: NAs introduced by coercion
```

```
pairs(auto[,1:7])
```



9f) Suppose that we wish to predict gas mileage (mpg) on the basis of the other variables. Do your plots suggest that any of the other variables might be useful in predicting mpg? Justify your answer.

```
regression = lm(mpg ~ cylinders+year+weight+horsepower+displacement+acceleration+origin, data= auto)
regression
```

```
##
## Call:
## lm(formula = mpg ~ cylinders + year + weight + horsepower + displacement +
##     acceleration + origin, data = auto)
##
## Coefficients:
##  (Intercept)     cylinders          year        weight    horsepower
##   -17.218435     -0.493376      0.750773     -0.006474     -0.016951
## displacement  acceleration        origin
##     0.019896      0.080576      1.426140
```

10) This exercise involves the Boston housing data set.

```
library(MASS)
data(Boston)
```

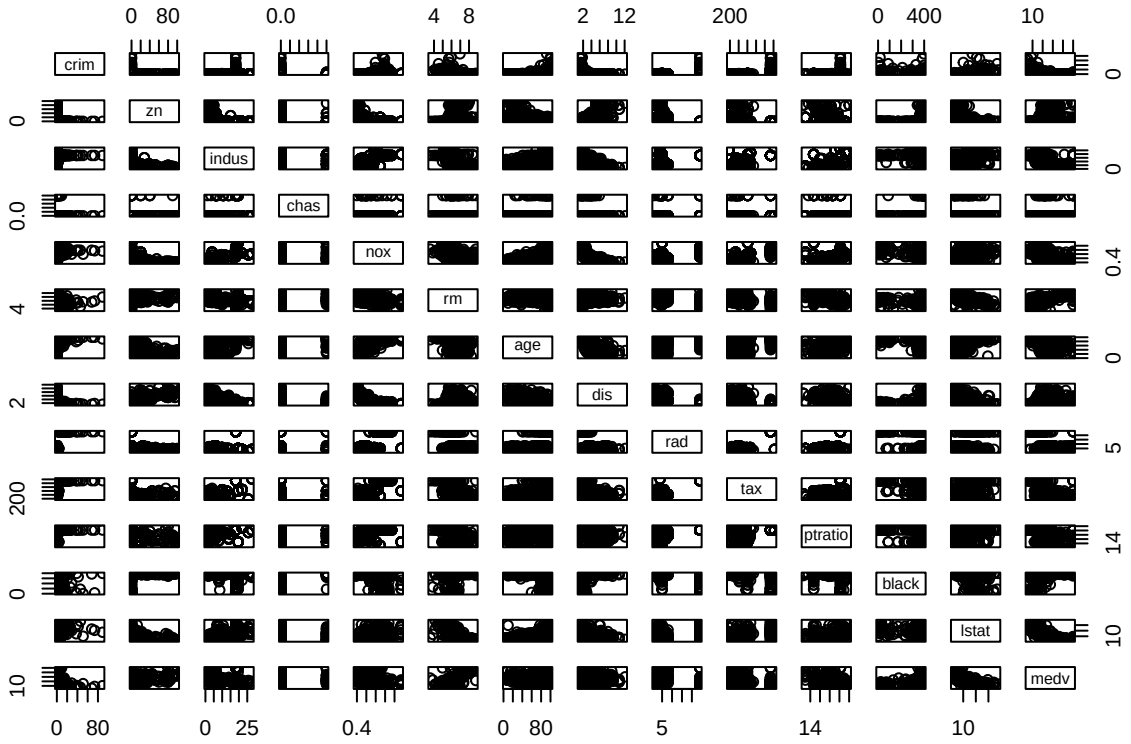
10a) How many rows are in this data set? How many columns? What do the rows and columns represent?
506 rows, 14 columns

```
dim(Boston)
```

```
## [1] 506  14
```

10b) Make some pairwise scatterplots of the predictors (columns) in this data set. Describe your findings.
looking att the pairs theres a large jumble of data, some of the variable are definitely coorelated while others seem to show nothing at all

```
pairs(Boston)
```



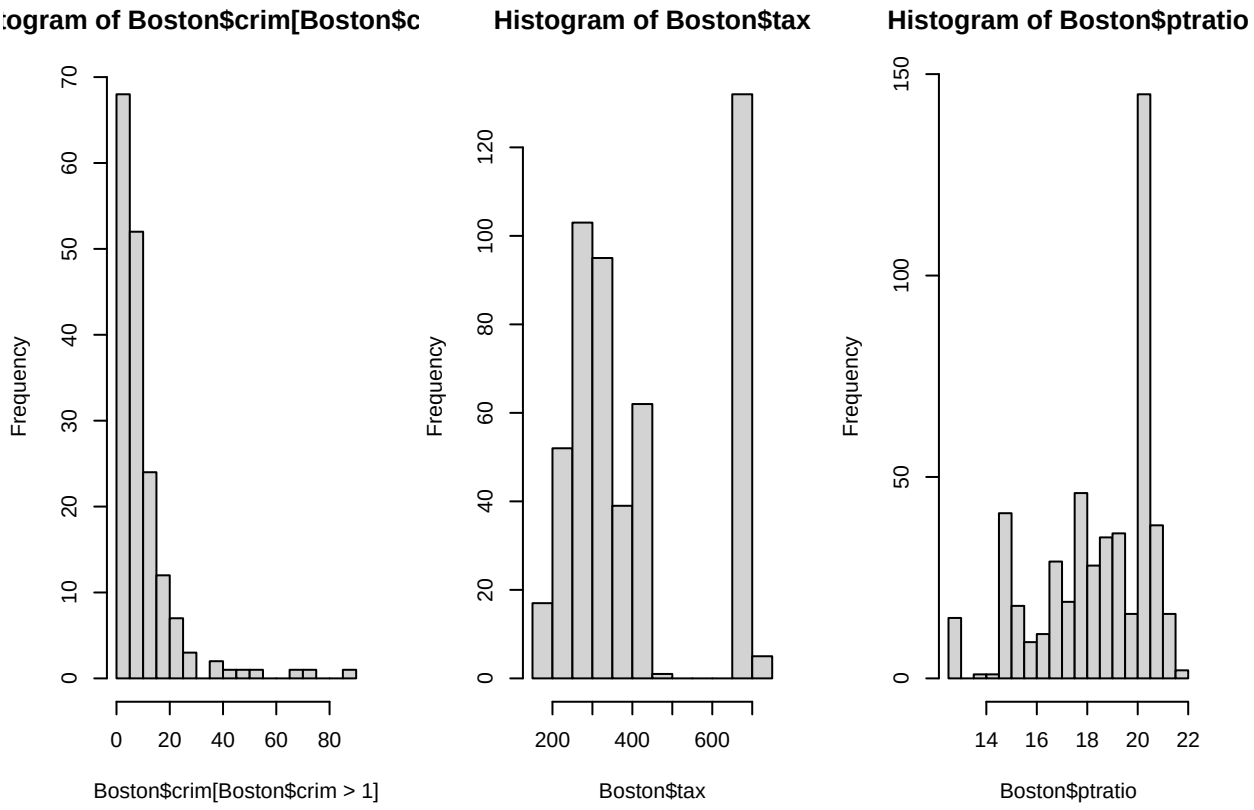
10c) Are any of the predictors associated with per capita crime rate? If so, explain the relationship. It seems that variables with the strongest correlation coefficient are possitive

```
Boston.corr.crim = cor(Boston)[-1,1]
print(Boston.corr.crim[order(abs(Boston.corr.crim))])
```

```
##        chas          zn          rm     ptratio         age         dis
## -0.05589158 -0.20046922 -0.21924670  0.28994558  0.35273425 -0.37967009
##       black        medv       indus         nox       lstat         tax
## -0.38506394 -0.38830461  0.40658341  0.42097171  0.45562148  0.58276431
##         rad
##  0.62550515
```

10d) Do any of the suburbs of Boston appear to have particularly high crime rates? Tax rates? Pupil-teacher ratios? Comment on the range of each predictor. -About 15 sububurs have high crime rates -There seems to be one outlier in the data, but otherwise tax is uniform -There seems to be higher skew in teacher ratios

```
par(mfrow=c(1,3))
hist(Boston$crim[Boston$crim > 1], breaks=15)
hist(Boston$tax, breaks=15)
hist(Boston$ptratio, breaks=15)
```



10e) How many of the suburbs in this data set bound the Charles river?

```
sum(Boston$chas == 1)
```

```
## [1] 35
```

10f) What is the median pupil-teacher ratio among the towns in this data set?

```
median(Boston$ptratio)
```

```
## [1] 19.05
```

10g) Which suburb of Boston has lowest median value of owneroccupied homes? What are the values of the other predictors for that suburb, and how do those values compare to the overall ranges for those predictors? Comment on your findings.

```
t(subset(Boston, medv == min(medv)))
```

```
##             399      406
## crim     38.3518  67.9208
## zn        0.0000   0.0000
## indus    18.1000  18.1000
## chas      0.0000   0.0000
## nox       0.6930   0.6930
```

```
## rm        5.4530   5.6830
## age     100.0000 100.0000
## dis       1.4896   1.4254
## rad      24.0000  24.0000
## tax     666.0000 666.0000
## ptratio  20.2000  20.2000
## black   396.9000 384.9700
## lstat    30.5900  22.9800
## medv      5.0000   5.0000
```

10h) In this data set, how many of the suburbs average more than seven rooms per dwelling? More than eight rooms per dwelling? Comment on the suburbs that average more than eight rooms per dwelling.

```
sum(Boston$rm > 7)
```

```
## [1] 64
```

```
sum(Boston$rm > 8)
```

```
## [1] 13
```

```
summary(subset(Boston, rm > 8))
```

```
##       crim                zn             indus              chas        
##  Min.   :0.02009   Min.   : 0.00   Min.   : 2.680   Min.   :0.0000  
##  1st Qu.:0.33147   1st Qu.: 0.00   1st Qu.: 3.970   1st Qu.:0.0000  
##  Median :0.52014   Median : 0.00   Median : 6.200   Median :0.0000  
##  Mean   :0.71879   Mean   :13.62   Mean   : 7.078   Mean   :0.1538  
##  3rd Qu.:0.57834   3rd Qu.:20.00   3rd Qu.: 6.200   3rd Qu.:0.0000  
##  Max.   :3.47428   Max.   :95.00   Max.   :19.580   Max.   :1.0000  
##       nox               rm             age              dis        
##  Min.   :0.4161   Min.   :8.034   Min.   : 8.40   Min.   :1.801  
##  1st Qu.:0.5040   1st Qu.:8.247   1st Qu.:70.40   1st Qu.:2.288  
##  Median :0.5070   Median :8.297   Median :78.30   Median :2.894  
##  Mean   :0.5392   Mean   :8.349   Mean   :71.54   Mean   :3.430  
##  3rd Qu.:0.6050   3rd Qu.:8.398   3rd Qu.:86.50   3rd Qu.:3.652  
##  Max.   :0.7180   Max.   :8.780   Max.   :93.90   Max.   :8.907  
##       rad              tax           ptratio          black       
##  Min.   : 2.000   Min.   :224.0   Min.   :13.00   Min.   :354.6  
##  1st Qu.: 5.000   1st Qu.:264.0   1st Qu.:14.70   1st Qu.:384.5  
##  Median : 7.000   Median :307.0   Median :17.40   Median :386.9  
##  Mean   : 7.462   Mean   :325.1   Mean   :16.36   Mean   :385.2  
##  3rd Qu.: 8.000   3rd Qu.:307.0   3rd Qu.:17.40   3rd Qu.:389.7  
##  Max.   :24.000   Max.   :666.0   Max.   :20.20   Max.   :396.9  
##      lstat           medv      
##  Min.   :2.47   Min.   :21.9  
##  1st Qu.:3.32   1st Qu.:41.7  
##  Median :4.14   Median :48.3  
##  Mean   :4.31   Mean   :44.2  
##  3rd Qu.:5.12   3rd Qu.:50.0  
##  Max.   :7.44   Max.   :50.0
```

Part 3

These lines of code are from the starter file!

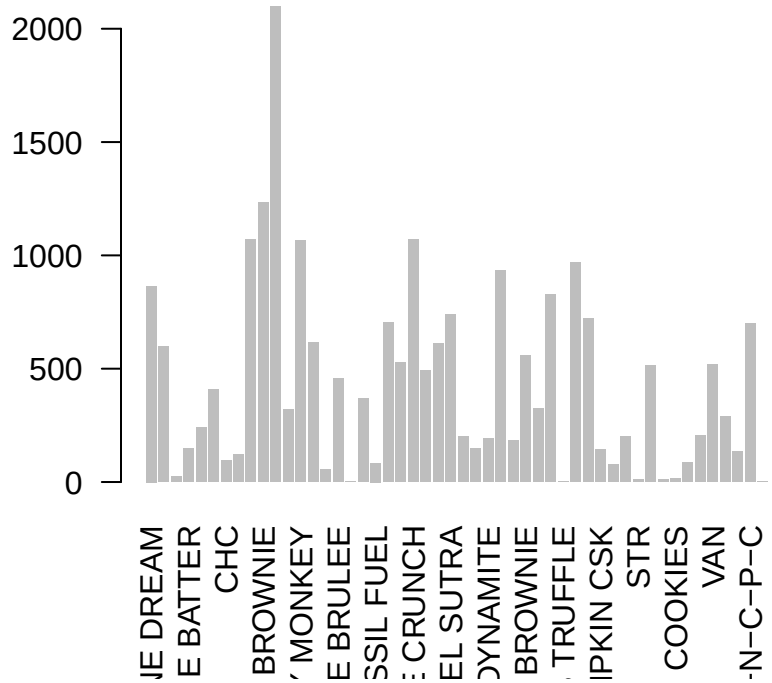
```
benjer = read.csv("BenAndJerry.csv")
names(benjer)
```

```
##  [1] "quantity"                      "price_paid_deal"
##  [3] "price_paid_non_deal"           "coupon_value"
##  [5] "promotion_type"                "total_spent"
##  [7] "size1_descr"                   "flavor_descr"
##  [9] "formula_descr"                 "household_id"
## [11] "household_size"                "household_income"
## [13] "age_of_female_head"            "age_of_male_head"
## [15] "age_and_presence_of_children"  "male_head_employment"
## [17] "female_head_employment"        "male_head_education"
## [19] "female_head_education"         "marital_status"
## [21] "male_head_occupation"          "female_head_occupation"
## [23] "household_composition"         "race"
## [25] "hispanic_origin"               "region"
## [27] "scantrack_market_identifier"   "projection_factor"
## [29] "fips_state_code"               "fips_county_code"
## [31] "census_tract_county_code"      "type_of_residence"
## [33] "kitchen_appliances"            "tv_items"
## [35] "female_head_birth"             "male_head_birth"
## [37] "household_internet_connection"
```

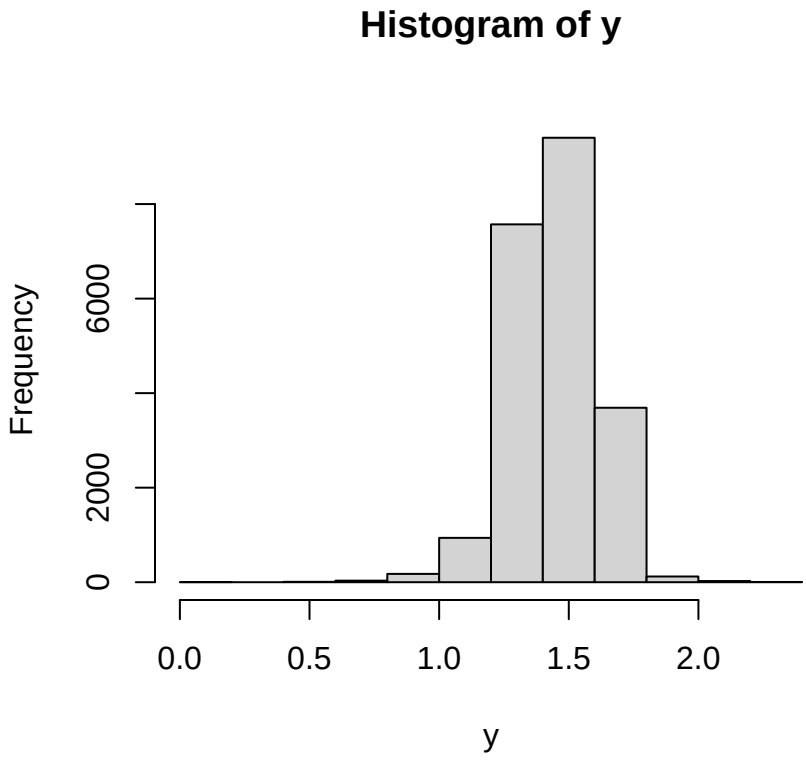
```
priceper1 = (benjer$price_paid_deal + benjer$price_paid_non_deal)/benjer$quantity
y <- log(1+priceper1)
x <- benjer[,c("flavor_descr","size1_descr",
    "household_income","household_size")]
x$flavor_descr <- relevel(factor(x$flavor_descr),"VAN")
x$usecoup = factor(benjer$coupon_value>0)
x$couponper1 <- benjer$coupon_value/benjer$quantity
x$region <- factor(benjer$region,
    levels=1:4, labels=c("East","Central","South","West"))
x$married <- factor(benjer$marital_status==1)
x$race <- factor(benjer$race,
    levels=1:4,labels=c("white","black","asian","other"))
x$hispanic_origin <- benjer$hispanic_origin==1
x$microwave <- benjer$kitchen_appliances %in% c(1,4,5,7)
x$dishwasher <- benjer$kitchen_appliances %in% c(2,4,6,7)
x$sfh <- benjer$type_of_residence==1
x$internet <- benjer$household_internet_connection==1
x$tvcable <- benjer$tv_items>1
fit <- glm(y~., data=x)
pvals <- summary(fit)$coef[-1,4]
par(mfrow=c(1,1))
par(mar=c(5,10,5,5))
barplot(table(benjer$flavor),border=NA, las=2)
class(benjer$promotion_type)
```

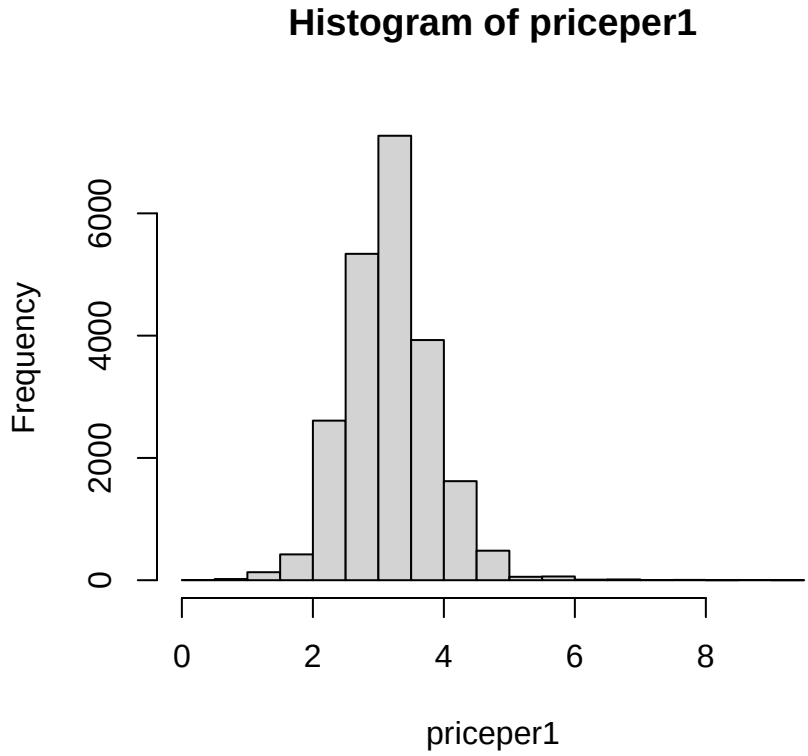
```
## [1] "integer"
```

```
barplot(table(benjer$flavor),border=NA, las=2)
```

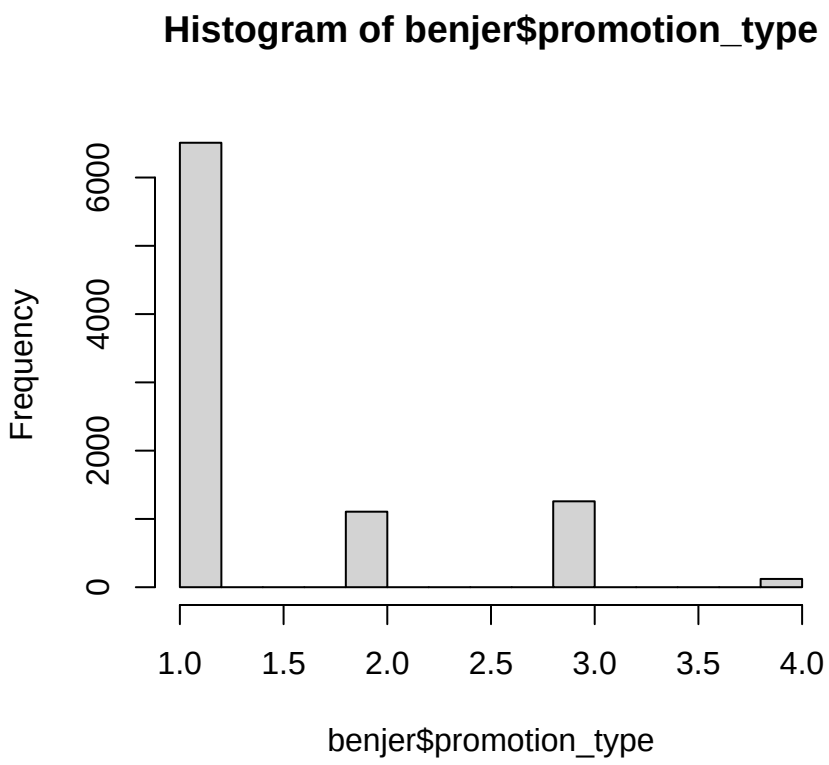



```
hist(y); hist(priceper1);
```

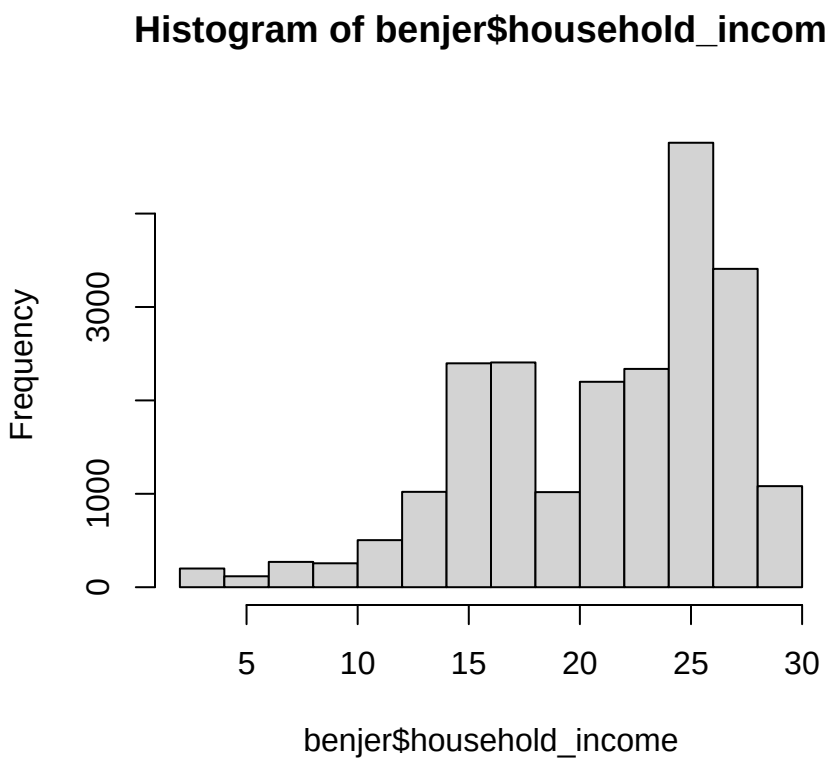

Histogram of y
Frequency
0
2000
6000
0.0
0.5
1.0
1.5
2.0
y



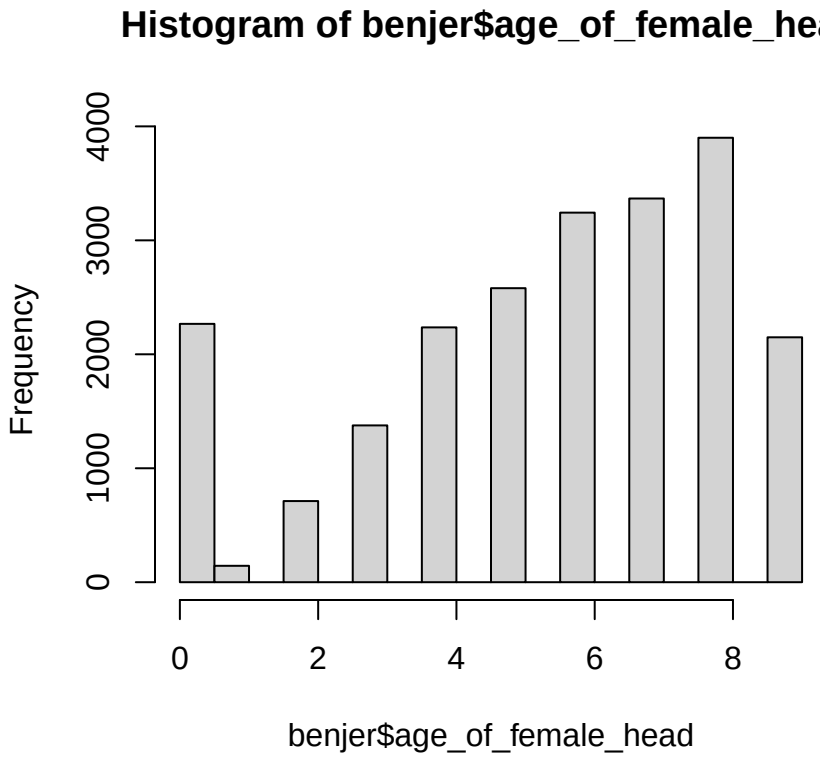

```
hist(benjer$promotion_type)
```



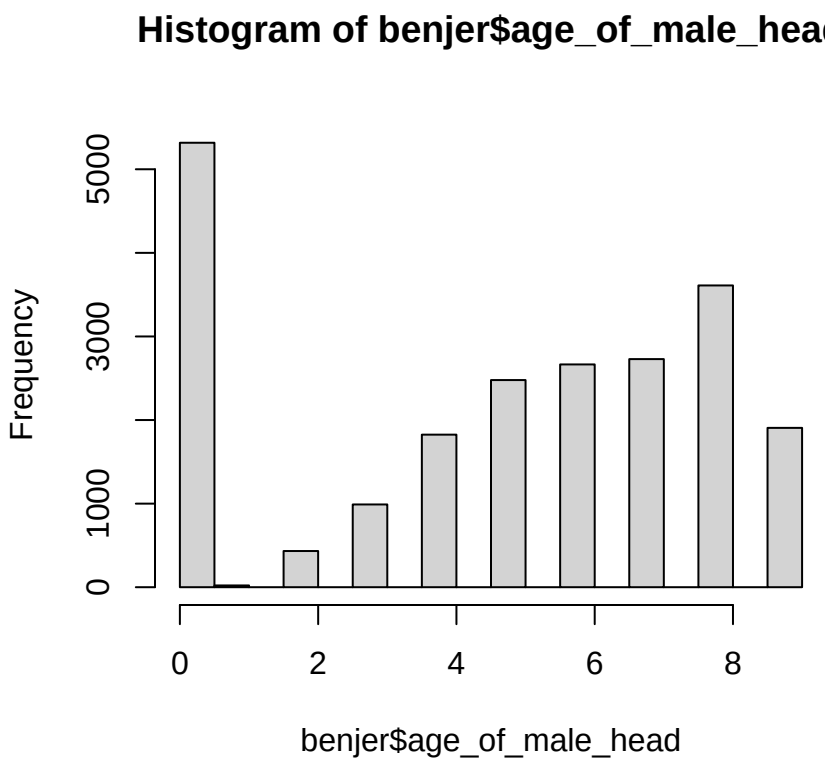

```
hist(benjer$household_income)
```



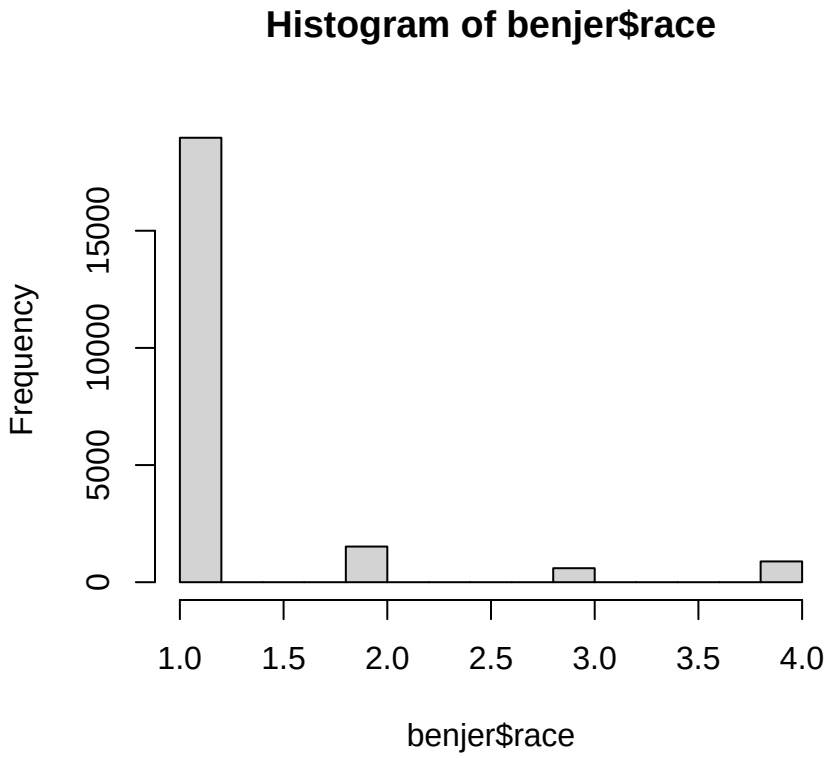

```
hist(benjer$age_of_female_head)
```



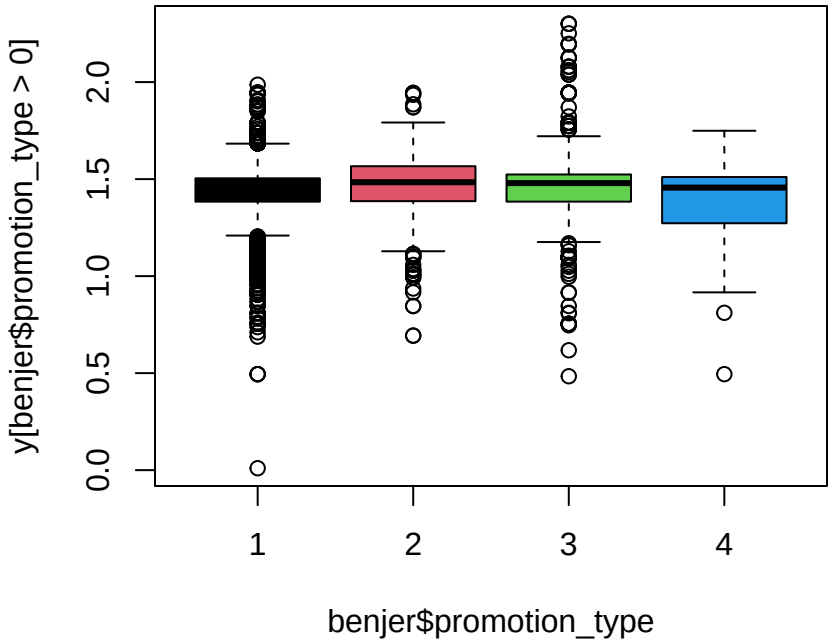

```
hist(benjer$age_of_male_head)
```




```
hist(benjer$race)
```




```
num_cols <- unlist(lapply(benjer, is.numeric))
boxplot(y[benjer$promotion_type>0] ~ benjer$promotion_type, col= levels(factor(benjer$promotion)))
```




```
summary(fit)
```

```
##
## Call:
## glm(formula = y ~ ., data = x)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.45414  -0.06617   0.01078   0.08318   0.64849
##
## Coefficients:
##                                          Estimate Std. Error t value
## (Intercept)                             1.4940011  0.0104454 143.029
## flavor_descrAMERICONE DREAM            -0.0270131  0.0082384  -3.279
## flavor_descrBANANA SPLIT               -0.0408377  0.0088887  -4.594
## flavor_descrBLACK & TAN                -0.0769758  0.0302280  -2.547
## flavor_descrBROWNIE BATTER             -0.0081789  0.0138350  -0.591
## flavor_descrBUTTER PECAN               -0.0130912  0.0115124  -1.137
## flavor_descrCAKE BATTER                -0.0385251  0.0097894  -3.935
## flavor_descrCHC                        -0.0090327  0.0164365  -0.550
## flavor_descrCHC ALMOND NOUGAT          -0.0206583  0.0150504  -1.373
## flavor_descrCHC CHIP C-DH              -0.0235566  0.0079638  -2.958
## flavor_descrCHC FUDGE BROWNIE          -0.0243969  0.0077820  -3.135
## flavor_descrCHERRY GRCA                -0.0310569  0.0072923  -4.259
## flavor_descrCHUBBY HUBBY               -0.0098033  0.0105370  -0.930
```

```
## flavor_descrCHUNKY MONKEY                  -0.0370629  0.0079417  -4.667
## flavor_descrCINNAMON BUNS                  -0.0431549  0.0088415  -4.881
## flavor_descrCOFFEE                          0.0267102  0.0207441   1.288
## flavor_descrCREME BRULEE                   -0.0476383  0.0095128  -5.008
## flavor_descrDOUBLE CHC FUDGE SWR            0.0146750  0.1474511   0.100
## flavor_descrDUBLIN MUDSLIDE                -0.0143134  0.0100695  -1.421
## flavor_descrFOSSIL FUEL                    -0.0495130  0.0173355  -2.856
## flavor_descrHALF BAKED                     -0.0337535  0.0085784  -3.935
## flavor_descrHEATH CANDY EVERYTHING BUT THE -0.0356518  0.0091582  -3.893
## flavor_descrHEATH COFFEE CRUNCH            -0.0215018  0.0079153  -2.716
## flavor_descrHEATH CRUNCH                   -0.0027050  0.0092997  -0.291
## flavor_descrIMAGINE WHIRLED PEACE          -0.0411508  0.0088443  -4.653
## flavor_descrKARAMEL SUTRA                  -0.0316114  0.0084836  -3.726
## flavor_descrMAGIC BROWNIES                 -0.0412340  0.0123096  -3.350
## flavor_descrMINT CHC CHUNK                  0.0127854  0.0138661   0.922
## flavor_descrNEAPOLITAN DYNAMITE            -0.0250128  0.0125600  -1.991
## flavor_descrNEW YORK SUPER FUDGE CHUNK     -0.0331176  0.0081133  -4.082
## flavor_descrOATMEAL COOKIE CHUNK           -0.0230802  0.0126699  -1.822
## flavor_descrONE CSK BROWNIE                -0.0552211  0.0090597  -6.095
## flavor_descrOXFORD MINT CHC COOKIE         -0.0254025  0.0104416  -2.433
## flavor_descrPB CUP                         -0.0273918  0.0082965  -3.302
## flavor_descrPB TRUFFLE                     -0.0585094  0.1474697  -0.397
## flavor_descrPHISH FOOD                     -0.0191778  0.0080634  -2.378
## flavor_descrPISTACHIO PISTACHIO            -0.0273626  0.0085204  -3.211
## flavor_descrPUMPKIN CSK                    -0.0965602  0.0139765  -6.909
## flavor_descrRSP CHC CHUNK                   0.0004508  0.0178187   0.025
## flavor_descrSMORES                          0.0071988  0.0123221   0.584
## flavor_descrSTR                             0.0482053  0.0449004   1.074
## flavor_descrSTR CSK                        -0.0425389  0.0092260  -4.611
## flavor_descrSTRAWBERRIES & CREAM           -0.0193492  0.0413753  -0.468
## flavor_descrSWEET CREAM & COOKIES           0.0342785  0.0363482   0.943
## flavor_descrTRIPLE CARAMEL CHUNK           -0.0404664  0.0170940  -2.367
## flavor_descrTURTLE SOUP                    -0.0541433  0.0122557  -4.418
## flavor_descrVAN CARAMEL FUDGE              -0.0424817  0.0108471  -3.916
## flavor_descrVERMONTY PYTHON                -0.0229930  0.0143106  -1.607
## flavor_descrW-N-C-P-C                      -0.0335837  0.0085858  -3.912
## flavor_descrWHITE RUSSIAN                   0.1962617  0.1474626   1.331
## size1_descr32.0 MLOZ                        0.3108154  0.0080789  38.472
## household_income                            0.0020848  0.0002032  10.262
## household_size                             -0.0040760  0.0008837  -4.612
## usecoupTRUE                                -0.0709608  0.0045418 -15.624
## couponper1                                  0.0683420  0.0027052  25.263
## regionCentral                              -0.0212732  0.0031093  -6.842
## regionSouth                                -0.0247856  0.0029581  -8.379
## regionWest                                 -0.0184250  0.0030072  -6.127
## marriedTRUE                                -0.0113292  0.0025633  -4.420
## raceblack                                   0.0123061  0.0040044   3.073
## raceasian                                  -0.0026165  0.0062476  -0.419
## raceother                                   0.0154499  0.0058016   2.663
## hispanic_originTRUE                        -0.0010270  0.0053361  -0.192
## microwaveTRUE                              -0.0350319  0.0075637  -4.632
## dishwasherTRUE                             -0.0017803  0.0025721  -0.692
## sfhTRUE                                    -0.0091538  0.0024985  -3.664
## internetTRUE                                0.0064933  0.0028001   2.319
```

```
## tvcableTRUE                                  0.0059701  0.0021529   2.773
##                                             Pr(>|t|)
## (Intercept)                                  < 2e-16 ***
## flavor_descrAMERICONE DREAM                 0.001044 **
## flavor_descrBANANA SPLIT                    4.37e-06 ***
## flavor_descrBLACK & TAN                     0.010887 *
## flavor_descrBROWNIE BATTER                  0.554409
## flavor_descrBUTTER PECAN                    0.255492
## flavor_descrCAKE BATTER                     8.33e-05 ***
## flavor_descrCHC                             0.582633
## flavor_descrCHC ALMOND NOUGAT               0.169888
## flavor_descrCHC CHIP C-DH                   0.003100 **
## flavor_descrCHC FUDGE BROWNIE               0.001720 **
## flavor_descrCHERRY GRCA                     2.06e-05 ***
## flavor_descrCHUBBY HUBBY                    0.352189
## flavor_descrCHUNKY MONKEY                   3.08e-06 ***
## flavor_descrCINNAMON BUNS                   1.06e-06 ***
## flavor_descrCOFFEE                          0.197896
## flavor_descrCREME BRULEE                    5.55e-07 ***
## flavor_descrDOUBLE CHC FUDGE SWR            0.920723
## flavor_descrDUBLIN MUDSLIDE                 0.155195
## flavor_descrFOSSIL FUEL                     0.004292 **
## flavor_descrHALF BAKED                      8.36e-05 ***
## flavor_descrHEATH CANDY EVERYTHING BUT THE 9.93e-05 ***
## flavor_descrHEATH COFFEE CRUNCH             0.006603 **
## flavor_descrHEATH CRUNCH                    0.771151
## flavor_descrIMAGINE WHIRLED PEACE           3.29e-06 ***
## flavor_descrKARAMEL SUTRA                   0.000195 ***
## flavor_descrMAGIC BROWNIES                  0.000810 ***
## flavor_descrMINT CHC CHUNK                  0.356509
## flavor_descrNEAPOLITAN DYNAMITE             0.046442 *
## flavor_descrNEW YORK SUPER FUDGE CHUNK      4.48e-05 ***
## flavor_descrOATMEAL COOKIE CHUNK            0.068522 .
## flavor_descrONE CSK BROWNIE                 1.11e-09 ***
## flavor_descrOXFORD MINT CHC COOKIE          0.014989 *
## flavor_descrPB CUP                          0.000963 ***
## flavor_descrPB TRUFFLE                      0.691552
## flavor_descrPHISH FOOD                      0.017398 *
## flavor_descrPISTACHIO PISTACHIO             0.001323 **
## flavor_descrPUMPKIN CSK                     5.02e-12 ***
## flavor_descrRSP CHC CHUNK                   0.979816
## flavor_descrSMORES                          0.559080
## flavor_descrSTR                             0.283012
## flavor_descrSTR CSK                         4.03e-06 ***
## flavor_descrSTRAWBERRIES & CREAM            0.640039
## flavor_descrSWEET CREAM & COOKIES           0.345660
## flavor_descrTRIPLE CARAMEL CHUNK            0.017927 *
## flavor_descrTURTLE SOUP                     1.00e-05 ***
## flavor_descrVAN CARAMEL FUDGE               9.01e-05 ***
## flavor_descrVERMONTY PYTHON                 0.108130
## flavor_descrW-N-C-P-C                       9.20e-05 ***
## flavor_descrWHITE RUSSIAN                   0.183228
## size1_descr32.0 MLOZ                         < 2e-16 ***
## household_income                             < 2e-16 ***
```

```
## household_size                              4.01e-06 ***
## usecoupTRUE                                  < 2e-16 ***
## couponper1                                   < 2e-16 ***
## regionCentral                               8.02e-12 ***
## regionSouth                                  < 2e-16 ***
## regionWest                                  9.11e-10 ***
## marriedTRUE                                 9.93e-06 ***
## raceblack                                   0.002121 **
## raceasian                                   0.675362
## raceother                                   0.007749 **
## hispanic_originTRUE                         0.847390
## microwaveTRUE                               3.65e-06 ***
## dishwasherTRUE                              0.488849
## sfhTRUE                                     0.000249 ***
## internetTRUE                                0.020406 *
## tvcableTRUE                                 0.005559 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.0216865)
##
##     Null deviance: 537.46  on 21939  degrees of freedom
## Residual deviance: 474.33  on 21872  degrees of freedom
##   (34 observations deleted due to missingness)
## AIC: -21721
##
## Number of Fisher Scoring iterations: 2
```

```
fit2 <- glm(y~. - flavor_descr, data=x)
summary(fit2)
```

```
##
## Call:
## glm(formula = y ~ . - flavor_descr, data = x)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.48246  -0.06547   0.01350   0.08183   0.65363
##
## Coefficients:
##                        Estimate Std. Error t value Pr(>|t|)
## (Intercept)           1.4671681  0.0085509 171.581  < 2e-16 ***
## size1_descr32.0 MLOZ  0.3122884  0.0078001  40.037  < 2e-16 ***
## household_income      0.0022125  0.0002024  10.928  < 2e-16 ***
## household_size       -0.0044408  0.0008776  -5.060 4.23e-07 ***
## usecoupTRUE          -0.0700565  0.0045481 -15.404  < 2e-16 ***
## couponper1            0.0687980  0.0027103  25.384  < 2e-16 ***
## regionCentral        -0.0238388  0.0030879  -7.720 1.21e-14 ***
## regionSouth          -0.0272741  0.0029376  -9.285  < 2e-16 ***
## regionWest           -0.0190740  0.0029932  -6.372 1.90e-10 ***
## marriedTRUE          -0.0114444  0.0025625  -4.466 8.00e-06 ***
## raceblack             0.0112838  0.0039853   2.831 0.004639 **
## raceasian            -0.0034105  0.0062424  -0.546 0.584837
## raceother             0.0170006  0.0057942   2.934 0.003349 **
```

```
## hispanic_originTRUE  -0.0009265  0.0053390  -0.174 0.862230
## microwaveTRUE        -0.0378018  0.0075614  -4.999 5.80e-07 ***
## dishwasherTRUE       -0.0008110  0.0025715  -0.315 0.752469
## sfhTRUE              -0.0094224  0.0024914  -3.782 0.000156 ***
## internetTRUE          0.0054607  0.0027974   1.952 0.050949 .
## tvcableTRUE           0.0064237  0.0021490   2.989 0.002801 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02183617)
##
##     Null deviance: 537.46  on 21939  degrees of freedom
## Residual deviance: 478.67  on 21921  degrees of freedom
##   (34 observations deleted due to missingness)
## AIC: -21619
##
## Number of Fisher Scoring iterations: 2
```

```
fit3 <- glm(y~. -flavor_descr -race -dishwasher - hispanic_origin, data=x)
summary(fit3)
```

```
##
## Call:
## glm(formula = y ~ . - flavor_descr - race - dishwasher - hispanic_origin,
##     data = x)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.48390  -0.06576   0.01470   0.08163   0.65247
##
## Coefficients:
##                         Estimate Std. Error t value Pr(>|t|)
## (Intercept)            1.4682779  0.0085423 171.884  < 2e-16 ***
## size1_descr32.0 MLOZ   0.3125617  0.0077985  40.080  < 2e-16 ***
## household_income       0.0021845  0.0001961  11.140  < 2e-16 ***
## household_size        -0.0041371  0.0008737  -4.735 2.20e-06 ***
## usecoupTRUE           -0.0698324  0.0045478 -15.355  < 2e-16 ***
## couponper1             0.0687859  0.0027110  25.373  < 2e-16 ***
## regionCentral         -0.0238157  0.0030865  -7.716 1.25e-14 ***
## regionSouth           -0.0266641  0.0029023  -9.187  < 2e-16 ***
## regionWest            -0.0187114  0.0029605  -6.320 2.66e-10 ***
## marriedTRUE           -0.0119691  0.0025485  -4.697 2.66e-06 ***
## microwaveTRUE         -0.0380804  0.0075199  -5.064 4.14e-07 ***
## sfhTRUE               -0.0098788  0.0024807  -3.982 6.85e-05 ***
## internetTRUE           0.0054916  0.0027912   1.967  0.04915 *
## tvcableTRUE            0.0064773  0.0021471   3.017  0.00256 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02184969)
##
##     Null deviance: 537.46  on 21939  degrees of freedom
## Residual deviance: 479.08  on 21926  degrees of freedom
##   (34 observations deleted due to missingness)
```

```
## AIC: -21610
##
## Number of Fisher Scoring iterations: 2
```

```
fit4 <- glm(y~. -flavor_descr -race -dishwasher - hispanic_origin -internet -tvcable, data=x)
summary(fit4)
```

```
##
## Call:
## glm(formula = y ~ . - flavor_descr - race - dishwasher - hispanic_origin -
##     internet - tvcable, data = x)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -1.48230  -0.06507   0.01479   0.08111   0.65518
##
## Coefficients:
##                          Estimate Std. Error t value Pr(>|t|)
## (Intercept)             1.4741213  0.0083233 177.108  < 2e-16 ***
## size1_descr32.0 MLOZ    0.3121873  0.0077971  40.039  < 2e-16 ***
## household_income        0.0022875  0.0001941  11.783  < 2e-16 ***
## household_size         -0.0039566  0.0008705  -4.545 5.51e-06 ***
## usecoupTRUE            -0.0695301  0.0045478 -15.289  < 2e-16 ***
## couponper1              0.0686635  0.0027115  25.323  < 2e-16 ***
## regionCentral          -0.0246476  0.0030726  -8.022 1.10e-15 ***
## regionSouth            -0.0273725  0.0028818  -9.498  < 2e-16 ***
## regionWest             -0.0197059  0.0029398  -6.703 2.09e-11 ***
## marriedTRUE            -0.0123696  0.0025381  -4.873 1.10e-06 ***
## microwaveTRUE          -0.0359021  0.0074900  -4.793 1.65e-06 ***
## sfhTRUE                -0.0112333  0.0024533  -4.579 4.70e-06 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 0.02186124)
##
##     Null deviance: 537.46  on 21939  degrees of freedom
## Residual deviance: 479.37  on 21928  degrees of freedom
##   (34 observations deleted due to missingness)
## AIC: -21600
##
## Number of Fisher Scoring iterations: 2
```

```
n=nrow(x)
BIC <- c(reg1=extractAIC(fit, k=log(n))[2],
         reg2=extractAIC(fit2, k=log(n))[2],
         reg3=extractAIC(fit3, k=log(n))[2],
         reg4=extractAIC(fit4, k=log(n))[2])
eBIC <- exp(-0.5*(BIC-min(BIC)))
probs <- eBIC/sum(eBIC)
round(probs, 5)
```

```
##    reg1    reg2    reg3    reg4
## 0.00000 0.00000 0.03917 0.96083
```

1. Explore the data and visualize: what variables are interesting? Choose a few, plot them together, and tell a story. As can be seen from the dataset the age of heads seems to have a large significan amount at the younger population as it steadliy increases throughout the age group.Those who do eat at ben and jerry's also tend to have an higher household income. Furthermore the majority of people tend to of race type 1. There also seems to be a higher spread among promotions of type 3

2. Describe the regression model in the code. Improve it? The first model is a baseline in which the log of price per ice cream is regressed against many variables. When the flavor variable was taken out it was found that, asian, hispanic, and dishwashwer, were not significant so they were taken out of the model, which is the third one. Perhaps one way to improve the model is to only include regressors that are significant at the 0.01 alpha level. If this is done, we remove the varialbe internet and tvcable. Doing so will show a higher BIC value for this model. This can be seen in the code by fit4

3. Take the p-values from your regression and look for evidence of association. Relate what you learn to your story from 1. From the p-values it can be seen that all aggressors in fit4 are statistically signifcant at the 0.1 alpha level. Thus the variables of size1_descr32.0 MLOZ 0.3121873 0.0077971 40.039 $<$ 2e-16 *** household_income, household_size, usecoupTRUE, couponper1, regionCentral, regionSouth,regionWest, marriedTRUE, microwaveTRUE, and sfhTRUE do seem to have an association on the log of price.