W271-2 – Spring 2016 – **Lab 2**

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Question 6: CLM 3

Your analytics team has been tasked with analyzing aggregate revenue, cost and sales data, which have been provided to you in the R workspace/data frame `retailSales.Rdata`.

Your task is two fold. First, your team is to develop a model for predicting (forecasting) revenues. Part of the model development documentation is a backtesting exercise where you train your model using data from the first two years and evaluate the model's forecasts using the last two years of data.

Second, management is equally interested in understanding variables that might affect revenues in support of management adjustments to operations and revenue forecasts. You are also to identify factors that affect revenues, and discuss how useful management's planned revenue is for forecasting revenues.

Your analysis should address the following:

- **Exploratory Data Analysis: focus on bivariate and multivariate relationships.**

First we explore the whole dataset.

```
load("retailSales.Rdata")
data <- retailSales; rm(retailSales)
summary(data)
```

```
##       Year                         Product.line
##  Min.   :2004   Camping Equipment       :24108
##  1st Qu.:2005   Golf Equipment          : 8820
##  Median :2006   Mountaineering Equipment:12348
##  Mean   :2006   Outdoor Protection      : 8820
##  3rd Qu.:2006   Personal Accessories    :30576
##  Max.   :2007
##
##               Product.type                   Product
##  Eyewear             : 9408   Aloe Relief       :  588
##  Watches             : 7644   Astro Pilot       :  588
##  Lanterns            : 7056   Auto Pilot        :  588
##  Cooking Gear        : 5880   Bear Edge         :  588
##  Navigation          : 5880   Bear Survival Edge:  588
##  Climbing Accessories: 4116   Bella             :  588
##  (Other)             :44688   (Other)           :81144
##    Order.method.type  Retailer.country    Revenue
##  E-mail     :12096   Australia: 4032   Min.   :       0
##  Fax        :12096   Austria  : 4032   1st Qu.:   18579
##  Mail       :12096   Belgium  : 4032   Median :   59867
##  Sales visit:12096   Brazil   : 4032   Mean   :  189418
##  Special    :12096   Canada   : 4032   3rd Qu.:  190193
##  Telephone  :12096   China    : 4032   Max.   :10054289
##  Web        :12096   (Other)  :60480   NA's   :59929
##  Planned.revenue     Product.cost        Quantity        Unit.cost
##  Min.   :      16   Min.   :      6   Min.   :    1   Min.   :  0.85
##  1st Qu.:   19557   1st Qu.:   9432   1st Qu.:  328   1st Qu.: 11.43
##  Median :   63907   Median :  32784   Median : 1043   Median : 36.83
##  Mean   :  198818   Mean   : 111625   Mean   : 3607   Mean   : 84.89
```

```
##  3rd Qu.:  203996   3rd Qu.: 111371   3rd Qu.:  3288   3rd Qu.: 80.00
##  Max.   :10054289   Max.   :6756853   Max.   :313628   Max.   :690.00
##  NA's   :59929      NA's   :59929     NA's   :59929    NA's   :59929
##    Unit.price       Gross.profit     Unit.sale.price
##  Min.   :   2.06   Min.   : -18160   Min.   :   0.00
##  1st Qu.:  23.00   1st Qu.:   8333   1st Qu.:  20.15
##  Median :  66.77   Median :  25794   Median :  62.65
##  Mean   : 155.99   Mean   :  77793   Mean   : 147.23
##  3rd Qu.: 148.30   3rd Qu.:  78254   3rd Qu.: 140.96
##  Max.   :1359.72   Max.   :3521098   Max.   :1307.80
##  NA's   :59929     NA's   :59929     NA's   :59929
```

The dataset contains 84,672 observations of 14 variables. 5 of them are categorical (`Product.line`, `Product.type`, `Product`, `Order.method.type`, `Retailer.country`), and `Year` should also be considered as categorical, since there are data from only 4 years (from 2004 to 2007).

```
data <- data %>%
  mutate(Year = as.factor(Year))
```

We also notice (from the output of `summary`) that some of the variables (all of them numerical) has a high number of `NA`s, the same in all cases (59929, i.e., 70.78% of the total number of observations). Do the `NA`s appear in the same observations for all those variables? Yes, they do.

```
# data_isNA <- as.data.frame(sapply(data, is.na))
data_isNA <- data %>% mutate_each(funs(is.na(.)))
head(data_isNA)
```

```
##    Year Product.line Product.type Product Order.method.type
## 1 FALSE        FALSE        FALSE   FALSE             FALSE
## 2 FALSE        FALSE        FALSE   FALSE             FALSE
## 3 FALSE        FALSE        FALSE   FALSE             FALSE
## 4 FALSE        FALSE        FALSE   FALSE             FALSE
## 5 FALSE        FALSE        FALSE   FALSE             FALSE
## 6 FALSE        FALSE        FALSE   FALSE             FALSE
##   Retailer.country Revenue Planned.revenue Product.cost Quantity Unit.cost
## 1            FALSE   FALSE           FALSE        FALSE    FALSE     FALSE
## 2            FALSE   FALSE           FALSE        FALSE    FALSE     FALSE
## 3            FALSE    TRUE            TRUE         TRUE     TRUE      TRUE
## 4            FALSE    TRUE            TRUE         TRUE     TRUE      TRUE
## 5            FALSE   FALSE           FALSE        FALSE    FALSE     FALSE
## 6            FALSE    TRUE            TRUE         TRUE     TRUE      TRUE
##   Unit.price Gross.profit Unit.sale.price
## 1      FALSE        FALSE           FALSE
## 2      FALSE        FALSE           FALSE
## 3       TRUE         TRUE            TRUE
## 4       TRUE         TRUE            TRUE
## 5      FALSE        FALSE           FALSE
## 6       TRUE         TRUE            TRUE
```

```
# vars_with_NAs <- apply(data_isNA, 2, sum)
vars_with_NAs <- data_isNA %>% summarise_each(funs(sum))
(vars_with_NAs <- names(vars_with_NAs)[vars_with_NAs>0])
```

```
## [1] "Revenue"         "Planned.revenue" "Product.cost"    "Quantity"
## [5] "Unit.cost"       "Unit.price"      "Gross.profit"    "Unit.sale.price"
```

```
sapply(data_isNA[, vars_with_NAs[-1]], identical,
       as.vector(data_isNA[, vars_with_NAs[1]]))
```

```
## Planned.revenue    Product.cost        Quantity       Unit.cost
##            TRUE            TRUE            TRUE            TRUE
##      Unit.price    Gross.profit Unit.sale.price
##            TRUE            TRUE            TRUE
```

And the amount of NAs per category is roughly the same for all categorical values (or at least there are non-missing data for all categories; below we just show the percentage per category for three of the numerical variables).

```
data_categorical <- data %>%
  select(which(names(data) %in% names(data)[sapply(data, is.factor)])) %>%
  mutate_each(funs(as.character(.))) %>% mutate(Revenue = data$Revenue)
data_categorical %>%
  select(Revenue, Year) %>%
  group_by(Year) %>%
  summarise_each(funs(100*mean(is.na(.)))) %>%
  rename("% of NAs in numerical variables" = Revenue)
```

```
## Source: local data frame [4 x 2]
##
##    Year % of NAs in numerical variables
##   (chr)                           (dbl)
## 1  2004                        67.95163
## 2  2005                        65.49981
## 3  2006                        71.70257
## 4  2007                        77.95729
```

```
data_categorical %>%
  select(Revenue, Product.line) %>%
  group_by(Product.line) %>%
  summarise_each(funs(100*mean(is.na(.)))) %>%
  rename("% of NAs in numerical variables" = Revenue)
```

```
## Source: local data frame [5 x 2]
##
##               Product.line % of NAs in numerical variables
##                      (chr)                           (dbl)
## 1        Camping Equipment                        65.26049
## 2           Golf Equipment                        68.67347
## 3 Mountaineering Equipment                        76.13379
## 4       Outdoor Protection                        66.62132
## 5     Personal Accessories                        74.77106
```

```
## Source: local data frame [21 x 2]
##
```

```
##    Retailer.country % of NAs in numerical variables
##               (chr)                           (dbl)
## 1         Australia                        77.15774
## 2           Austria                        72.44544
## 3           Belgium                        75.99206
## 4            Brazil                        81.49802
## 5            Canada                        57.66369
## 6             China                        77.33135
## 7           Denmark                        80.28274
## 8           Finland                        79.46429
## 9            France                        60.49107
## 10          Germany                        59.37500
## 11            Italy                        69.07242
## 12            Japan                        58.60615
## 13            Korea                        74.47917
## 14           Mexico                        73.36310
## 15      Netherlands                        70.03968
## 16        Singapore                        70.70933
## 17            Spain                        71.55258
## 18           Sweden                        74.25595
## 19      Switzerland                        80.03472
## 20   United Kingdom                        70.23810
## 21    United States                        52.28175
```

So we can ommit all those missing observations (reducing our sample size to 24743), and continue with a further analysis of the numerical variables:

```
data <- data %>% na.omit()
data_categorical <- data %>%
  select(which(names(data) %in% names(data)[sapply(data, is.factor)]))
data_non_categorical <- data %>%
  select(which(names(data) %in% names(data)[!sapply(data, is.factor)]))
round(stat.desc(data_non_categorical, desc = TRUE, basic = TRUE), 2)
```

```
##                   Revenue Planned.revenue Product.cost    Quantity
## nbr.val      2.474300e+04    2.474300e+04 2.474300e+04    24743.00
## nbr.null     7.600000e+01    0.000000e+00 0.000000e+00        0.00
## nbr.na       0.000000e+00    0.000000e+00 0.000000e+00        0.00
## min          0.000000e+00    1.569000e+01 5.760000e+00        1.00
## max          1.005429e+07    1.005429e+07 6.756853e+06   313628.00
## range        1.005429e+07    1.005427e+07 6.756847e+06   313627.00
## sum          4.686776e+09    4.919342e+09 2.761941e+09 89237091.00
## median       5.986727e+04    6.390684e+04 3.278372e+04     1043.00
## mean         1.894182e+05    1.988175e+05 1.116251e+05     3606.56
## SE.mean      2.484130e+03    2.559050e+03 1.515680e+03       55.80
## CI.mean.0.95 4.869040e+03    5.015880e+03 2.970830e+03      109.38
## var          1.526863e+11    1.620349e+11 5.684198e+10 77048387.56
## std.dev      3.907509e+05    4.025355e+05 2.384156e+05     8777.72
## coef.var     2.060000e+00    2.020000e+00 2.140000e+00        2.43
##              Unit.cost Unit.price  Gross.profit Unit.sale.price
## nbr.val       24743.00   24743.00  2.474300e+04        24743.00
## nbr.null          0.00       0.00  0.000000e+00           76.00
## nbr.na            0.00       0.00  0.000000e+00            0.00
```

```
## min                 0.85       2.06 -1.815960e+04          0.00
## max               690.00    1359.72  3.521098e+06       1307.80
## range             689.15    1357.66  3.539257e+06       1307.80
## sum           2100344.99 3859701.42  1.924835e+09    3642909.71
## median             36.83      66.77  2.579376e+04         62.65
## mean               84.89     155.99  7.779311e+04        147.23
## SE.mean             0.83       1.57  1.005230e+03          1.48
## CI.mean.0.95        1.63       3.08  1.970320e+03          2.89
## var             17190.71   60912.60  2.500267e+10      53846.65
## std.dev           131.11     246.80  1.581223e+05        232.05
## coef.var            1.54       1.58  2.030000e+00          1.58
```

All numerical variables are right-skewed, with long right tails (i.e., with several observations more than 2 standard deviations far from the mean), especially the ones corresponding to aggregate—non-unit—results.

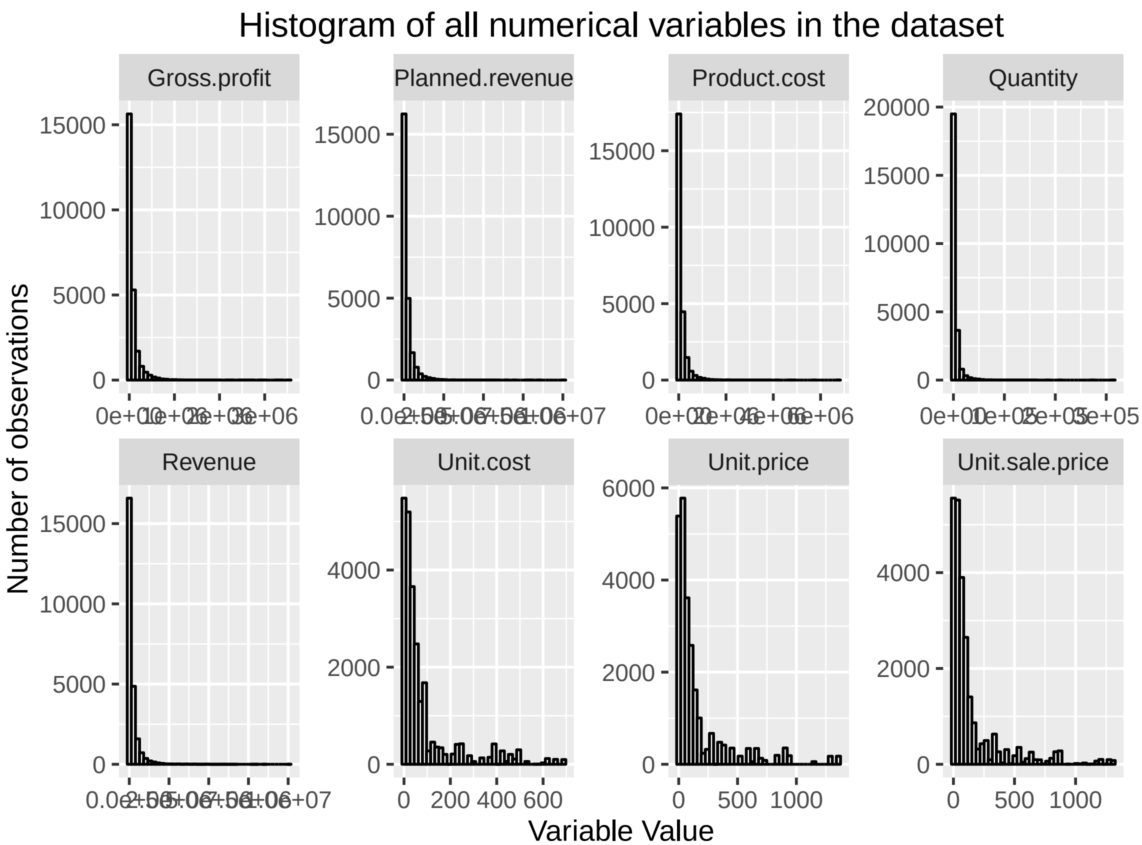


Figure 1: Histogram of all non-categorical variables in the dataset

Below we show the correlation matrix of the numerical variables, as well as two different representations of the scatterplot matrix (where we've used a sample of the data of size 500 because the plotting functions consume a lot of resources; that's why the correlations shown in the second Figure, only approximate, differ from the ones shown right below). As we might have expected, the correlations between `Revenue`, `Planned.revenue`, `Product.cost`, and `Gross.profit` (i.e., the aggregate values), as well as those between `Unit.cost`, `Unit.price`, and `Unit.sale.price` (i.e., the values per unit), are positive and very high. `Quantity` is negatively correlated with the unitary variables (but that correlation is negligible in absolute value), and is moderately correlated ($\rho \simeq 0.5$) with the aggregate values.

```r
cor(data_non_categorical)
```

```
##                  Revenue Planned.revenue Product.cost   Quantity
## Revenue        1.0000000       0.9990586    0.9903575  0.5055979
## Planned.revenue 0.9990586       1.0000000    0.9895792  0.4994770
## Product.cost    0.9903575       0.9895792    1.0000000  0.5061298
## Quantity        0.5055979       0.4994770    0.5061298  1.0000000
## Unit.cost       0.2463441       0.2550054    0.2415089 -0.1687497
## Unit.price      0.2332806       0.2421026    0.2194407 -0.1677662
## Gross.profit    0.9779407       0.9767878    0.9395732  0.4862920
## Unit.sale.price 0.2360448       0.2444078    0.2220105 -0.1674531
##                 Unit.cost Unit.price Gross.profit Unit.sale.price
## Revenue          0.2463441  0.2332806    0.9779407       0.2360448
## Planned.revenue  0.2550054  0.2421026    0.9767878       0.2444078
## Product.cost     0.2415089  0.2194407    0.9395732       0.2220105
## Quantity        -0.1687497 -0.1677662    0.4862920      -0.1674531
## Unit.cost        1.0000000  0.9886870    0.2446187       0.9889263
## Unit.price       0.9886870  1.0000000    0.2456107       0.9992750
## Gross.profit     0.2446187  0.2456107    1.0000000       0.2485667
## Unit.sale.price  0.9889263  0.9992750    0.2485667       1.0000000
```

```
##
## t test of coefficients:
##
##                   Estimate  Std. Error t value  Pr(>|t|)
## (Intercept)     -3.3970e+03  3.0377e+02 -11.183 < 2.2e-16 ***
## Planned.revenue  9.6981e-01  1.8151e-03 534.297 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Linear hypothesis test
##
## Hypothesis:
## Planned.revenue = 0.95
##
## Model 1: restricted model
## Model 2: Revenue ~ Planned.revenue
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df      F    Pr(>F)
## 1  24742
## 2  24741  1 119.12 < 2.2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Linear hypothesis test
##
## Hypothesis:
## Planned.revenue = 0.969810179080499
##
## Model 1: restricted model
```

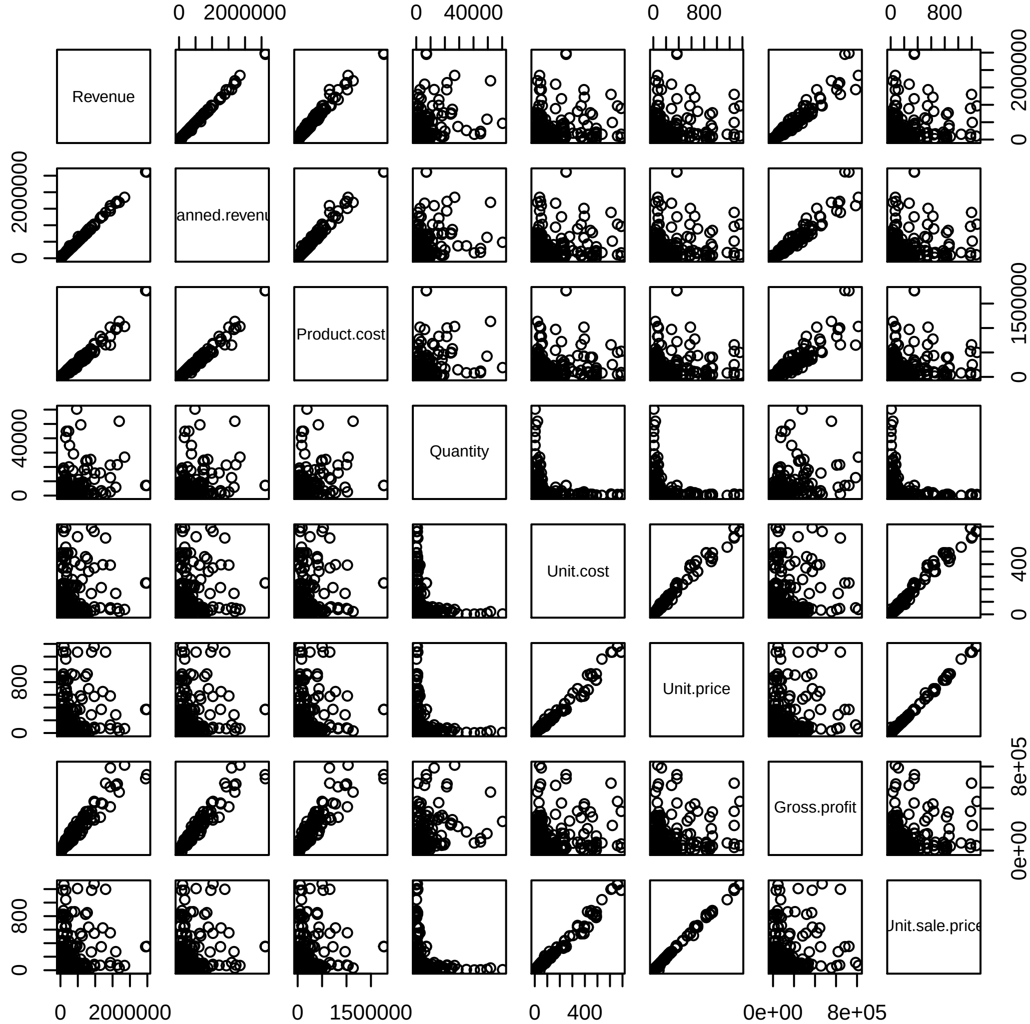


Figure 2: Scatterplot matrix of a sample of the dataset

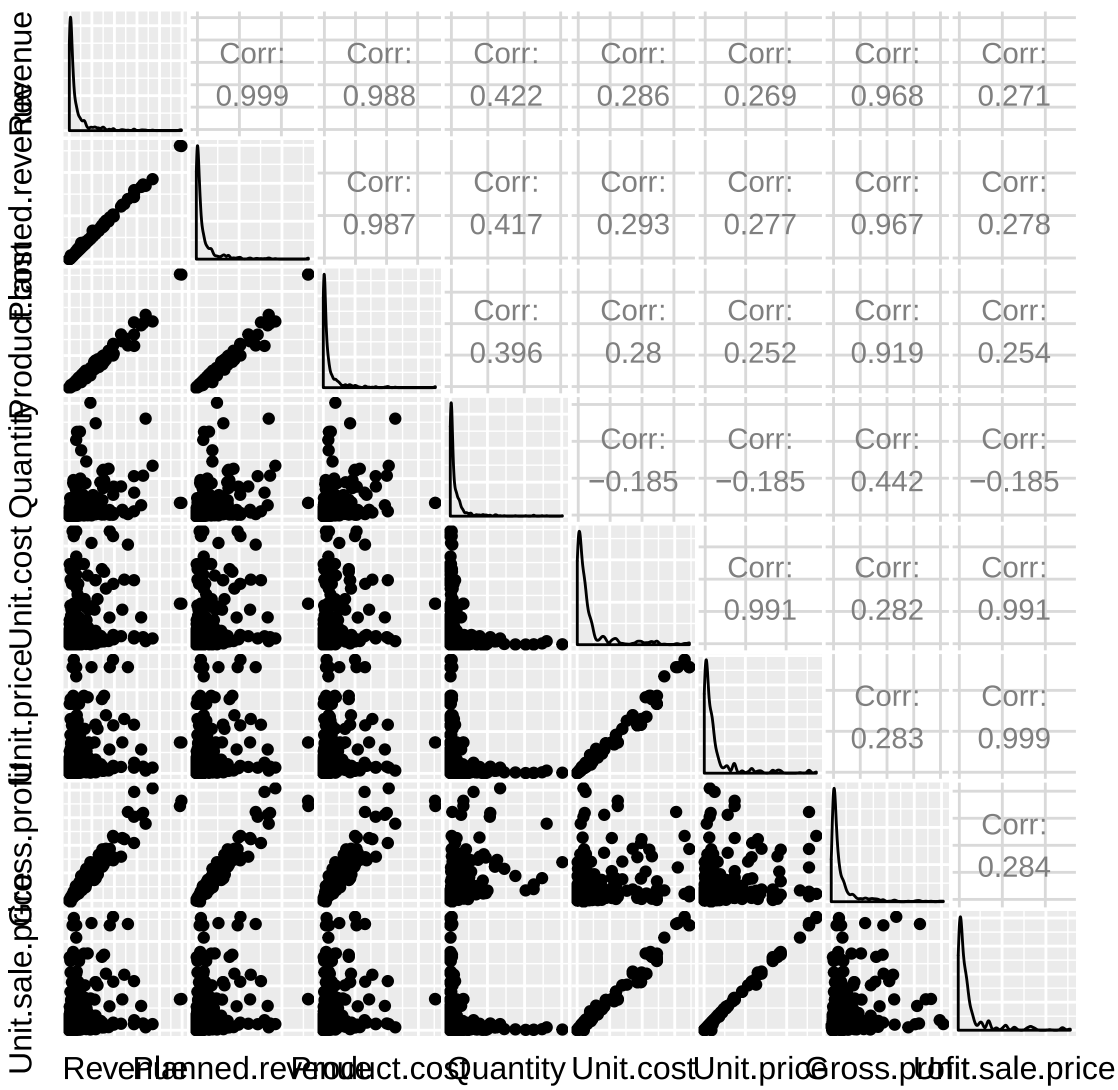
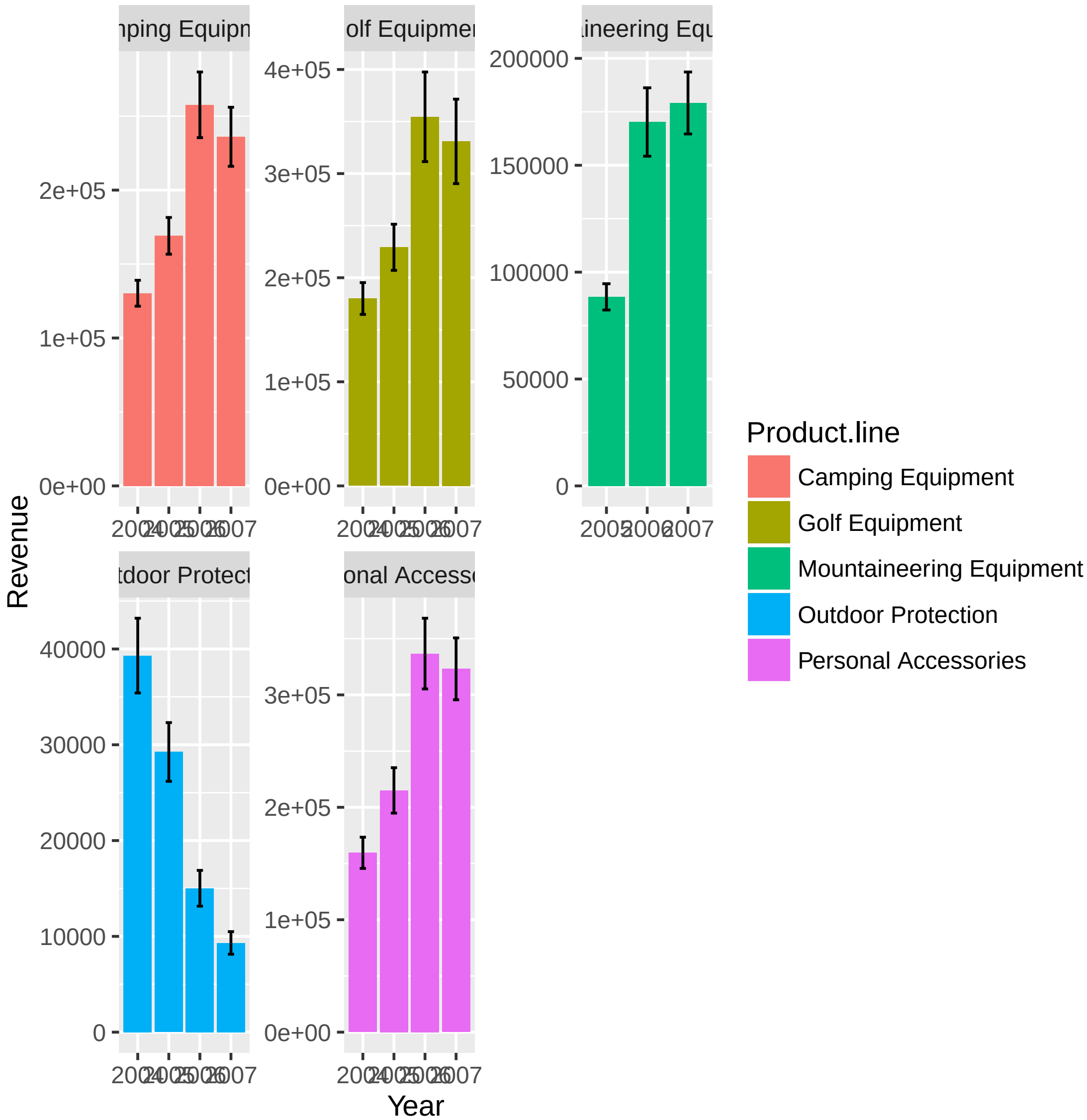
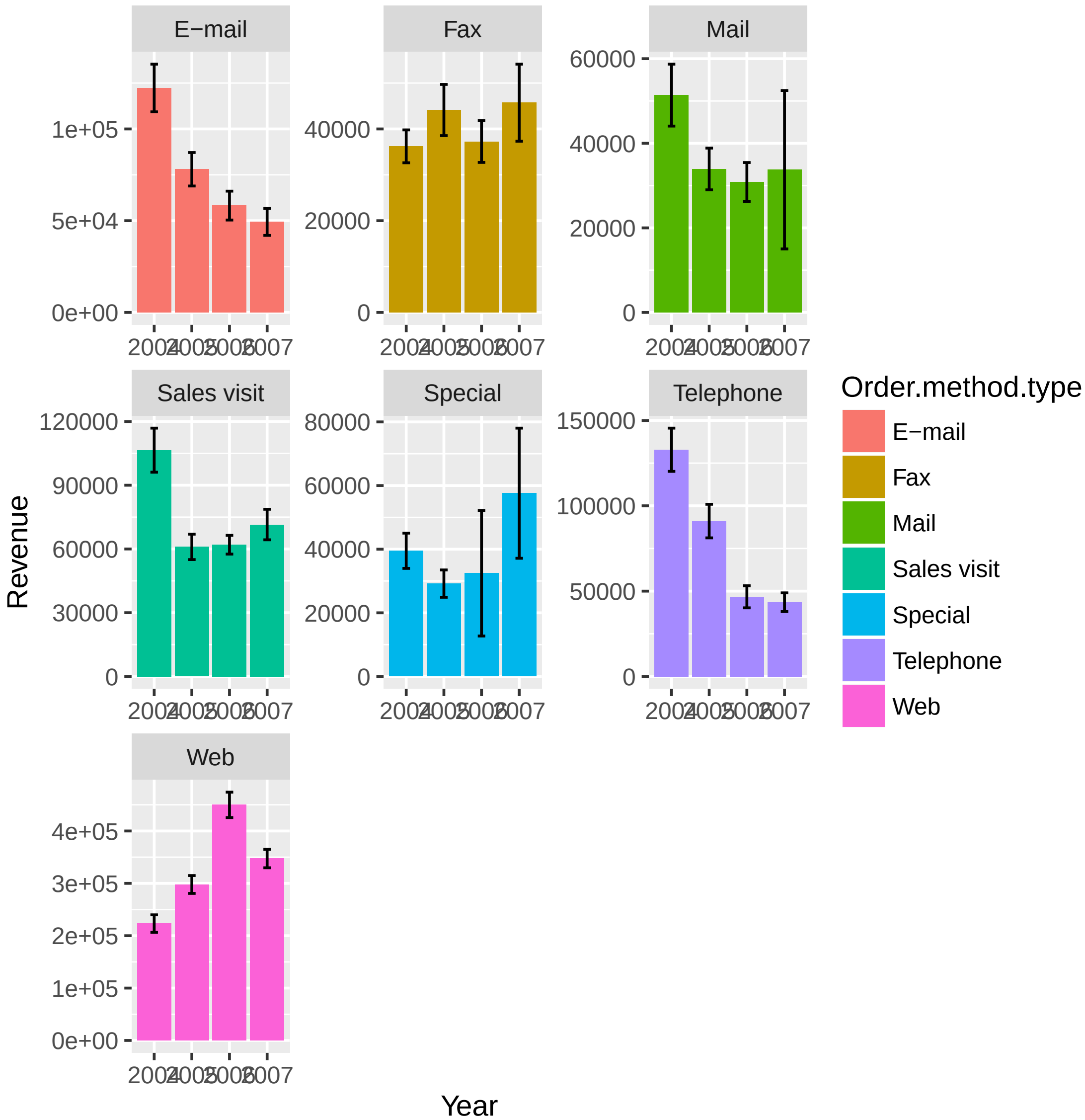
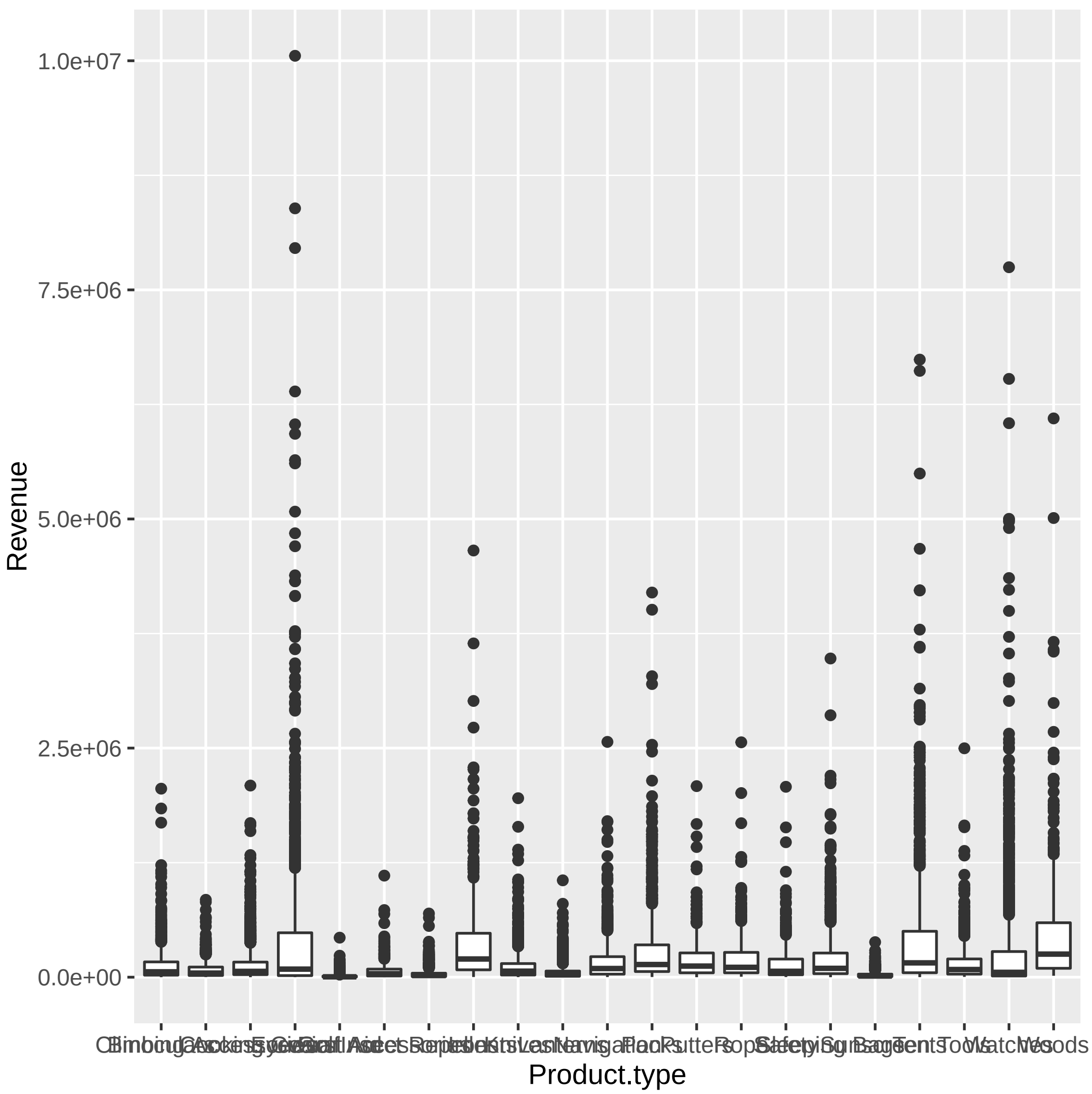


Figure 3: Scatterplot matrix of a sample of the dataset (with correlations)

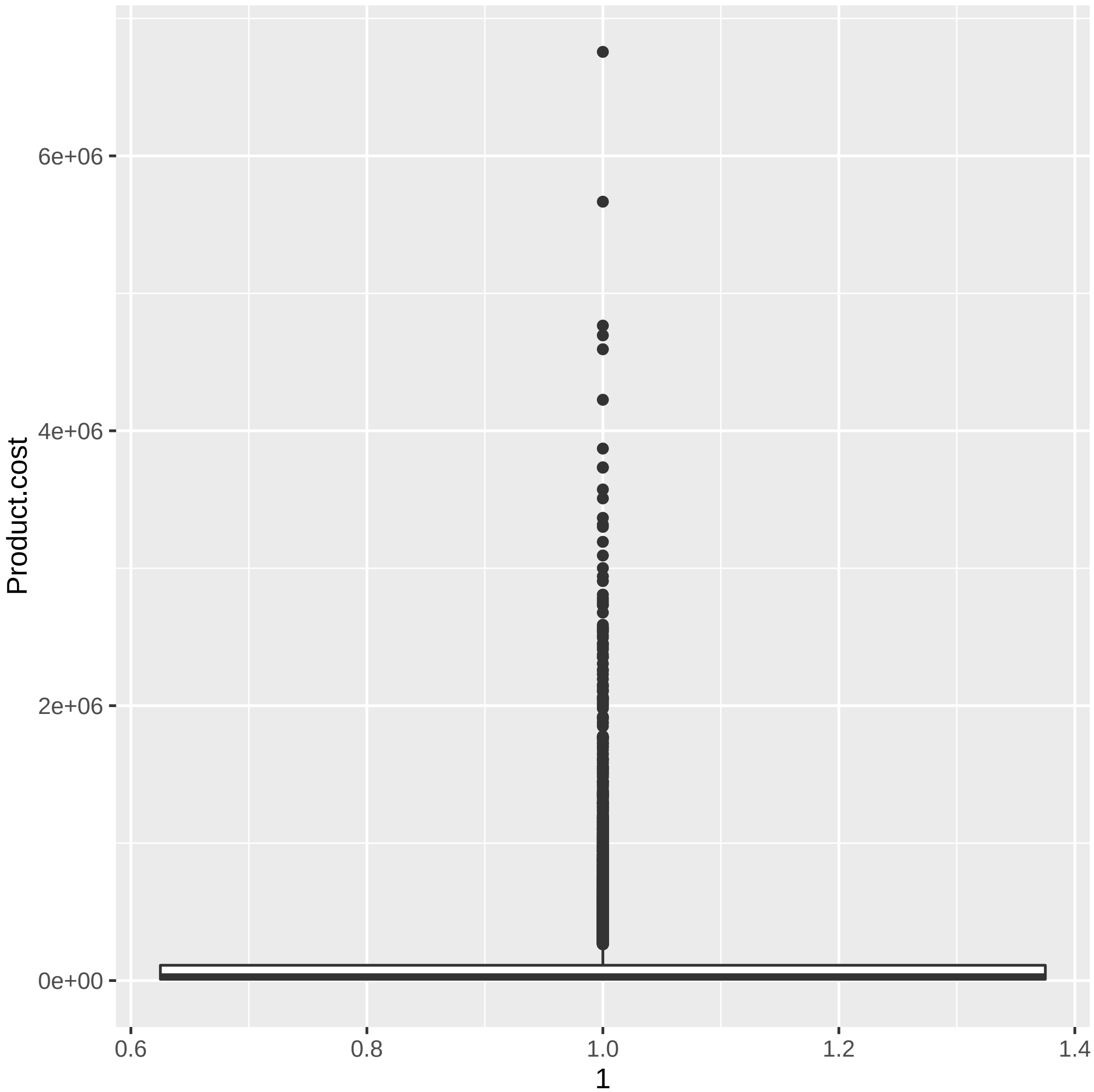
```
## Model 2: Revenue ~ Planned.revenue
##
## Note: Coefficient covariance matrix supplied.
##
##   Res.Df Df  F Pr(>F)
## 1  24742
## 2  24741  1  0      1
```

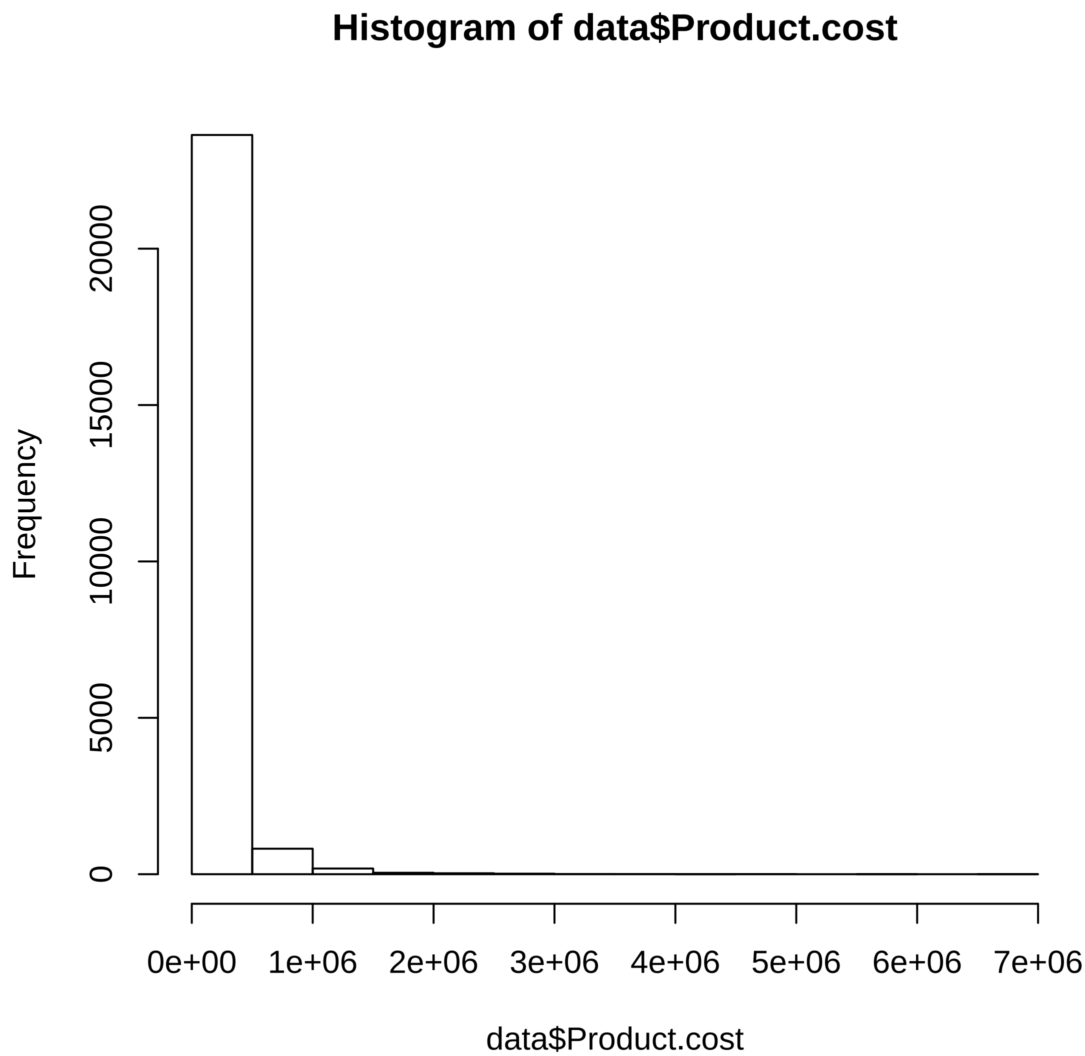



E−mail
Fax
Mail
Sales visit
Special
Telephone
Web
Revenue
Year
Order.method.type
E−mail
Fax
Mail
Sales visit
Special
Telephone
Web




```
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
##        0    18580    59870   189400   190200 10050000
```


Product.cost
6e+06
4e+06
2e+06
0e+00
0.6
0.8
1.0
1.2
1.4
1



- **Be sure to assess conditions and identify unusual observations.**
- **Is the change in the average revenue different from 95 cents when the planned revenue increases by $1?**
- **Explain what interaction terms in your model mean in context supported by data visualizations.**
- **Give two reasons why the OLS model coefficients may be biased and/or not consistent, be specific.**
- **Propose (but do not actually implement) a plan for an IV approach to improve your forecasting model.**