Computer practical 1: Topics in Statistics III/IV, Term 1

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Aim

- To be become familiar with R Notebook.
- To become familiar with Iterative Proportional Fitting (IPF) method
- Apply IPF method to produce MLE for the Log Linear models
- To learn how to solve systems of noon-linear equations via Newton method
- Apply Newton method to produce MLE for the Log Linear models
- Extensions of Newton method, and IPF method to to produce MLEs for 4-way and higher order tables

About R Markdown Notebook

What it is

R Markdown Notebook:

- creates documents that contain explanatory text, mathematical equations, live code, and visualizations.
- produces fully interactive documents allowing the readers to change the parameters underlying the analysis, and see the results immediately.
- produces interactive statistical reports that include data analysis, code, and results.

An R Notebook demo:

In what follows, we provide a simple demo to help you familiarise yourselves with the R Markdown Notebook environment.

This is an R Markdown Notebook. When you execute code within the Notebook, the results appear beneath the code.

Try executing this chunk by clicking the Run button within the chunk or by placing your cursor inside it and pressing Ctrl+Shift+Enter.

summary(cars)

speed		dist	
Min.	: 4.0	Min. :	2.00
1st Qu	.:12.0	1st Qu.:	26.00
Median	:15.0	Median :	36.00
Mean	:15.4	Mean :	42.98
3rd Qu	.:19.0	3rd Qu.:	56.00
Max.	:25.0	Max. :1	20.00

plot(cars)

How it works (Skip it)

Creating documents with R Markdown Notebook, requires the user to create a .Rmd (script) file that contains a combination of Markdown code (that produced the explanatory text) and R code chunks (that produce plots, and data analysis outputs). Then the .Rmd file is processed automatically by the software in order to generate a document in a format such as: HTML (web page), PDF, MS Word document, slide show, handout, book, dashboard, package vignette, etc.

In this practical, we will not go into details about Markdown coding, although it is has a super simple syntax. We recommend the interested student to read the nice cheat-sheet available from [here].

How to tune presentation (Skip it)

The user to specify how the chunk will be executed, or how its output will be presented, by setting the appropriate flags inside $\{r, \ldots\}$. If time permits, use the following flags in the previous chuck. What is their effect?

- eval: (TRUE; logical) whether to evaluate the code chunk; it can also be a numeric vector to select which R expression(s) to evaluate, e.g. eval=c(1, 3, 4) or eval=-(4:5)
- echo: (TRUE; logical or numeric) whether to include R source code in the output file. Besides TRUE/FALSE which completely turns on/off the source code, we can also use a numeric vector to select which R expression(s) to echo in a chunk, e.g. echo=2:3 means only echo the 2nd and 3rd expressions, and echo=-4 means to exclude the 4th expression.
- results: ('markup'; character) takes these values
 - hold: hold all the output pieces and push them to the end of a chunk
 - hide: hide results; this option only applies to normal R output (not warnings, messages or errors)
 - markup: mark up the results using the output hook, e.g. put results in a special LaTeX environment
- collapse: (FALSE; logical; applies to Markdown output only) whether to, if possible, collapse all the source and output blocks from one code chunk into a single block (by default, they are written to separate blocks)

More options can be found at https://yihui.name/knitr/options/.

You can use inline R code inside a sentence. For example you can say that the average speed of the car is 15.4, with standard error 0.1057529. Now see the output document.

Do the following:

- (... below the enumerated list)
 - 1. Add a new chunk by clicking the Insert Chunk button on the toolbar or by pressing Ctrl+Alt+I.
 - 2. Write a simple R command inside this chunk, just to experiment; E.g. write down hist(cars\$speed).
 - 3. Run this R chunk as described earlier.

Produce the document:

The document will be saved in the working directory.

- To produce and save the document as a Notebook: click the *Preview* button (or *Knit* button) or press Ctrl+Shift+K to preview the HTML file.
 - When you save the notebook, an HTML file containing the code and output will be saved alongside it.

- To produce and save the document in HTML, PDF or MS Word formats: select the option *Knit to HTML* (or PDF, or Word) available in the menu that appears when you click the little black arrow next to the *Preview* button (or *Knit* button).
 - This will produce the document in more standard / less functional formats.

Contigency table: data manipulation

Below we load a table where refers to a 1992 survey by the Wright State University School of Medicine and the United Health Services in Dayton, Ohio. The survey asked 2276 students in their final year of high school in a nonurban area near Dayton, Ohio whether they had ever used alcohol, cigarettes, or marijuana. Denote the variables in this $2 \times 2 \times 2$ table by A for alcohol use, C for cigarette use, and M for marijuana use.

Load the observed counts in a data frame obs.frame and print the result. Use commands:

- data.frame(): as in SC2
- factor(): to encode a vector as a factor (aka category)
- expand.grid(): to produce all combinations of the supplied vectors or factors.

Create 3 dimentional contingency table from obs.frame. Use command:

• xtabs(), to create a contingency table from cross-classifying factors in a dara.frame

```
No 456 538
Yes 44 911
```

Create a contigency table which contains the row, column, layer, etc...margins.

- Use command addmargins() with obs.xtabs
- Save it in obs.addmargins

#

Compute the marginal contigency table of marijuana and cigarette.

- Use command margin.table(, margin =) and obs.xtabs.
- Save it in obs.mc.xtabs.

#

Compute the (joint) sampling proportions.

- Use command prop.table() with obs.xtabs.
- Save it in obs.prop.table.

#

Create a data.frame of proportions.

- Use the command as.data.frame() with obs.prop.table
- Save it as obs.prop.frame

#

As a homework, you can further experiment with commands

- margin.table: computing marginal tables
- prop.table: computing proportions
- addmargins : putting margins on tables;
 - e.g., obs.prop.margin <- addmargins(prop.table(obs.xtabs))</pre>

Odds ratio calculations

Code an R function, named 'odds.ratio' with:

- Inputs:
 - x : a 2 by 2 matrix whose elements are the observed counts of a 2 by 2 contigency table
 - conf. level : with default input value 0.95 representing the confidence level
 - theta0: with default value 1 representing a null hypothesis value of the odds ratio test
- Outputs:
 - estimator : representing mle of odds satio
 - log.estimator : representing the mle of log odds ratio

- asympt.SE : representing the standard error / standard deviation of the mle of odds ratio
- conf.interval: representing confidence interval of mle of odds ratio at sig level conf.level (from the inputs)
- conf.level =representing confidence level
- Ztest: representing the test statistic for the odds ratio test (2 tails)
- p.value : representing the p value of the odds ratio test (2 tails)
- log.conf.interval : representing in log scale the confidence interval of mle of odds ratio at sig level conf.level (from the inputs)

```
odds.ratio <- function(x,conf.level=0.95,theta0=1)
{
    #
    #
}</pre>
```

For the marginal contigency table of marijuana and cigarette, * compute the mle of the marginal odds ratio of marijuana and cigarette * computet the 95% Confidence Interval of the marginal odds ratio of marijuana and cigarette * perform a statiastical hypothesis test that marijuana and cigarette are independent at sig level 0.05

```
obs.xtabs <- xtabs(count ~ marijuana+cigarette+alcohol, data=obs.frame)
obs.mc.xtabs <- margin.table(obs.xtabs, margin=c(1,2))</pre>
```

Fourfold Plots

You can draw Fourfold Plots

Tables 2 x 2

It is a graphical expression visualizing the odds ratio

$$\theta = \frac{n_{11}n_{22}}{n_{12}n_{21}}$$

in 2 x 2 contingency tables.

It shows the departure from independence as measured by the sample odds ratio,

Each cell n_{ij} is represented as a quarter-circle with radius proportional to $\sqrt{n_{ij}}$ and area proportional to n_{ij} .

- If there is no association $\theta = 1$ between classification variables, the quarter-circles should form a circle.
- If there is positive association $\theta > 1$ between classification variables, the diagonal areas are greater than the off-diagonal areas
- If there is negative association $\theta < 1$ between classification variables, the diagonal areas are smaller than the off-diagonal areas

R provides a function to draw this kind of plots by using the function fourfoldplot' from the packageved'

• Install 'vcd' package and load it

```
# install.packages('vcd') # uncomment it if you have not installed package vcd
library(vcd)
```

Check in help the function fourfoldplot by usign the command '?fourfoldplot'

- Draw a Fourfold Plot for the marginal contigency table of marijuana and cigarette.
- Discuss what you can see

```
#
#
#
```

Note that:

- * The area of each shaded quadrant shows the observed counts.
- * Circular arcs show the limits of confidence interval for the odds ratio.

Tables 2 x 2 x K

Fourfold Plots can be also used for 2 x 2 x K contigancy tables

- Draw a Fourfold Plot for the contigency table of marijuana cigarette, and alcohol by controlling on the alcohol levels.
- inspect the plots

```
#
#
#
```

Mosaic plot

Mosaic plot display graphically the cells of a contingency table as rectangular areas of size proportional to the corresponding observed frequencies.

When the classification variables are independent the areas tend to be perfectly aligned in rows and columns.

The greater the deviation is, the worse the aforesaid alignment is.

Furthermore, specific locations of the table that deviate from independence the most can be identified and thus the pattern of underlying association can be explained.

The strength of individual cells contribution to divergence from independence as well as the direction of the divergence are reflected in the magnitude and sign of the corresponding independence model's residuals that can be incorporated in a mosaic plot.

R provides a function to draw this kind of plots by using the function mosaic' from the packageved'

• Install 'vcd' package and load it

```
#install.packages('vcd') # uncomment it if you have not installed package vcd
library(vcd)
```

• Check the command mosaic' in help by typing?mosaic'

For the I x J case: * Draw a Mosaic Plot for the marginal contigency table of marijuana cigarette. * in particular use use mosaic(x,residuals_type="deviance",gp=shading_hcl) where x is the contigency table of interest

* Interpretet the plots

For the I x J x K case: * Draw a Mosaic Plot for the contigency table of marijuana cigarette and alcohol. * Interpretet the plots

#

The Iterative Proportions Fitting method

The iterative proportional fitting (IPF) algorithm is a simple method for calculating μ_{ijk} for log-linear models. The main idea of the procedure is the following:

- Start with $\mu_{ijk...}^{(0)}$ satisfying a model no more complex than the one being fitted. E.g., $\mu_{ijk...}^{(0)} = 1.0$ should be ok.
- For t = 1, ...,
 - adjust $\mu_{ijk}^{(t)}$ to match by multiplying each marginal table in the set of minimal sufficient statistics, by appropriate factors
 - escape the loop, when the maximum difference between the sufficient statistics and their fitted values is sufficiently close to zero.

Illustration:

Consider 3-way, $I \times J \times K$ tables, and with classifiers X, Y, Z.

Given the model (XY, XZ, YZ) design a IPF recursion producing estimates for μ_{ijk} 's Steps:

- Compute the minimal sufficient statistics are $\{n_{ij+}\}, \{n_{i+k}\}, \{n_{+jk}\}.$
- Assume that the approximated μ_{ijk} 's from the (t-1)-th cycle is $\mu_{ijk}^{(t-1)}$.
- Then the t-th cycle of the IPF algorithm has the following steps:

- Set
$$m_{ijk}^{(0)} = \mu_{ijk}^{(t-1)}$$

- Compute

$$m_{ijk}^{(1)} = m_{ijk}^{(0)} \frac{n_{ij+}}{m_{ij+}^{(0)}}; \forall i, j, k$$

$$m_{ijk}^{(2)} = m_{ijk}^{(1)} \frac{n_{i+k}}{m_{i+k}^{(1)}}; \forall i, j, k$$

$$m_{ijk}^{(3)} = m_{ijk}^{(2)} \frac{n_{+jk}}{m_{+jk}^{(2)}}; \forall i, j, k$$

- Set
$$\mu_{ijk}^{(t)} = m_{ijk}^{(3)}, \forall i, j, k$$

...and produces $\mu_{ijk}^{(t)}$ as approximation.

Example

We use the Alcohol, Cigarette, and Marijuana data-set

```
# I will do this for you
## load the data
obs.frame<-data.frame(count=c(911,538,44,456,3,43,2,279),
                      expand.grid(
 marijuana=factor(c("Yes","No"),levels=c("No","Yes")),
  cigarette=factor(c("Yes","No"),levels=c("No","Yes")),
  alcohol=factor(c("Yes","No"),levels=c("No","Yes")))
## orint the obs.frame
obs.frame
```

- Consider the Log-linear model describing a homogeneous association between each pair of variables at each level of the third one; i.e. [XY, XZ, YZ]
- Find the fitted values for $\mu_{i,j,k}$, by using your own code
- Check your results with R function 'loglin{stats}'

Solution

```
# Step 1 : compute and save the minimal statistics
# Step 2: Create a seed for the fitted mu's
# Step 3: Perform the loop to approximate the mu's
```

Present the fitted μ 's as a data frame

#

You can double check your result with the output of the R package

```
obs.xtab <- xtabs(obs.frame)</pre>
library(MASS)
fitAC.AM.CM<-loglm(count~alcohol*cigarette+alcohol*marijuana+cigarette*marijuana,
              data=obs.xtab,
              param=T,
              fit=T)
fit.array<- fitted(fitAC.AM.CM)</pre>
fit.array
```

```
, , alcohol = No
         cigarette
```

Example

- Consider the Log-linear model describing mutual independence; i.e. [X, Y, Z]
- Find the fitted values for $\mu_{i,j,k}$

Solution

```
#
#
```

Example (Homework)

The table below, summarises summarizes observations of 68,694 passengers in autos and light trucks involved in accidents in the state of Maine in 1991. The table classifies passengers by gender (G) location of accident (Z), seat-belt use (S), and injury (I). The Table reports the sample proportion of passengers who were injured. For each GL combination, the proportion of injuries was about halved for passengers wearing seat belts.

```
# load dataset
obs.frame.accident<-data.frame(
    expand.grid(
        belt=c("No","Yes"),
        location=c("Urban","Rural"),
        gender=c("Female","Male"),
        injury=c("No","Yes")),
    count=c(7287,11587,3246,6134,10381,10969,6123, 6693,996, 759, 973, 757, 812, 380, 1084, 513))
#print dataset
obs.frame.accident</pre>
```

Consider the Homogeneity association model (GZ, GS, GI, ZS, ZI, SI),

- 1. Write your own code to compute the fitted values for $\mu_{i,j,k,c}$
- 2. Check your ewsults with the R command 'loglin{stats}'

Solution

```
#
# CHECK WITH COMMAND loglin
#
#
```

Consider the 3 way interaction model (GLI, GSI, LSI, GLS).

- 1. Write your own code to compute the fitted values for $\mu_{i,j,k,c}$
- 2. Check your ewsults with the R command 'loglin{stats}'

Solution

```
#
#
# CHECK WITH COMMAND loglin
#
#
```

Consider the independent model (G, S, L, I)

- 1. compute the fitted values for $\mu_{i,j,k,c}$, by using your own code
- 2. check your resutls with 'loglin{stats}'

Solution

```
# # # CHECK WITH COMMAND loglin # # #
```

Newton Method

Newton's method is a general purpose procedure to compute numerically the solution of a system of non-linear equations given that a number of assumptions are satisfied.

In general.

- Let function $f: \mathbb{R}^n \to \mathbb{R}^n$.
- Assume you need to find the solution x^* of the equation

$$f(x^*) = 0 (1)$$

• Newtons's method for solving the system (1) is the recursion

$$x^{(t+1)} = x^{(t)} - [\nabla_x f(x^{(t)})]^{-1} f(x^{(t)})$$
(2)

for $t \in \mathbb{N}$ and for a pre-specified seed value $x^{(0)} \in \mathbb{R}^n$.

• In theory, Newton's method converges to the solution quadratically; i.e.

$$\lim_{t \to \infty} \frac{|x^{(t+1)} - x^*|_{\infty}}{|x^{(t)} - x^*|_{\infty}^2} = 0$$

under regularity conditions discussed in (Numerical analysis / R. L. Burden, J. D. Faires.)

• In practice, we run Newton's recursion several times starting from a different seed each time.

An intuitive explanation why it works

• From the Taylor expansion, and assuming that $\nabla_x^2 f(x)$ is continuous, I get

$$f(x_{t+1}) = f(x_t) + \nabla_x f(x_t)(x_{t+1} - x_t) + O(|x_{t+1} - x_t|^2)$$

and by ignoring the error term and rearranging the quantities I get

$$x_{t+1} \sim x_t + \nabla_x f(x_t) (f(x_{t+1}) - f(x_t))$$

• If x_{t+1} is the solution, or close to that, then $f(x_{t+1}) = 0$, and hence

$$x_{t+1} \sim x_t - \nabla_x f(x_t) f(x_t)$$

- Now, we see that the gradient of f times the values of f at x_t leads the sequence towards locations where f is zero.
- So, eventually, it may work ...

Pseudo-algorithm of Newton's method:

Aim Approximate the solution of f(x) = 0

Input number of equations n; seed $x^{(0)}=(x_1^{(0)},...,x_n^{(0)})\in\mathbb{R}^n$; tolerance τ ; maximum number of iterations TOutput: Approximate solution $x^* \in \mathbb{R}^n$; trace of $x^{(t)}$; trace of relative error $\tau^{(t)} = |x^{(t)} - x^{(t-1)}|_{\infty}$; number of iterations performed t

- 1. Set $x_{\text{opt}} = x^{(0)}$
- 2. Set t = 1
- 3. While $(t \leq T)$ do:

 - i) Compute $n \times 1$ vector $F \in \mathbb{R}^n$ whose i-th element is $F_i = f(x_{\text{opt},i})$ ii) Compute $n \times n$ vector $J \in \mathbb{R}^{n \times n}$ whose (i,j)-th element is $J_{i,j} = \frac{\mathrm{d}}{\mathrm{d}x_j} f_i(x_{\text{opt}})$ for $(i,j) \in \{1,...,n\}^2$
 - iii) Solve the $n \times n$ linear system Jy = -F and compute $y \in \mathbb{R}^n$
 - iv) Update $x_{\text{opt}} = x_{\text{opt}} + y$
 - v) Compute $\epsilon^* = |y|_{\infty}$
 - vi) If $\epsilon^* < \tau$, then escape from the loop
 - vii) Increase the time step t = t + 1
- 4. Set $x^* = x_{\text{opt}}$
- 5. Return as output: Return as output: x^* , t^* , and ϵ^* .

Example

Solve the system of non-linear equations

$$\begin{cases}
\cos(x_2 x_3) + \frac{1}{2} &= 3x_1 \\
81(x_2 + 0.1)^2 &= x_1^2 + (x_3 + 0.1)^2 + \sin(x_3) + 1.06 \\
-\frac{10\pi - 3}{3} &= \exp(-x_1 x_2) + 20x_3
\end{cases}$$

Solution

This is equivalent to solving the system $f(x_1, x_2, x_3) = 0$ where

$$f(x) = \begin{bmatrix} 3x_1 - \cos(x_2 x_3) - \frac{1}{2} \\ x_1^2 - 81(x_2 + 0.1)^2 + \sin(x_3) + 1.06 \\ \exp(-x_1 x_2) + 20x_3 + \frac{10\pi - 3}{3} \end{bmatrix}$$

with Jacobian

$$\nabla_x f(x) = \begin{bmatrix} 3 & x_3 \sin(x_2 x_3) & x_2 \sin(x_2 x_3) \\ 2x_1 & -162(x_2 + 0.1) & \cos(x_3) \\ -x_2 \exp(-x_1 x_2) & -x_1 \exp(-x_1 x_2) & 20 \end{bmatrix}$$

I need to supply the Newton's algorithm with the quantities above, as well as consider a tolerance, e.g. 1e-4(meaning 10^{-4}), seed value e.g., $x^{(0)} = (0.1, 0.1, -0.1)^T$, etc...

Create a function for f(x), and called my.f()

```
#
```

Create a function for $\nabla_x f(x)$, and call it my.Df

#

Create a function called my.newton.method() which:

- gets as arguments:
 - the function f(x),
 - the gradient $\nabla_x f(x)$,
 - number of equations n;
 - seed $x^{(0)} = (x_1^{(0)}, ..., x_n^{(0)}) \in \mathbb{R}^n$;
 - tolerance τ ;
 - maximum number of iterations T, etc...
- returns:
 - approximate solution $x^* \in \mathbb{R}^n$;
 - the last relative error τ^* ;
 - number of iterations performed t^* , etc...
- use commands
 - solve(): to solve the system Ax = b
 - while () $\{\ldots\}$: to perform the loop
 - break: to escape from the loop

#

Solve the equation by using the function the you created

#

Newton method for the Log linear model

- I wish to solve non-linear equation $X^T n = X^T \hat{\mu}(\beta)$ where matrix X is the design matrix given the non-identifiability constrints, e.g., for the model (XY, XZ, YZ).
- Equivalently, I want to find $\hat{\beta}$ for $f(\hat{\beta}) = 0$, where $f(\hat{\beta}) = X^T(n \mu(\hat{\beta}))$
- The Jacobian is

$$\nabla_{\beta} f(\beta) = \nabla_{\beta} X^{T} (n - \mu(\beta)) = \nabla_{\beta} [X^{T} \mu(\beta)]$$
$$= X^{T} \operatorname{diag}(\mu(\beta)) X$$

Because the (j,k)th element of $\nabla_{\beta}[X^T\mu(\beta)]$ is

$$\begin{split} \left[\nabla_{\beta} [X^{T} \mu(\beta)] \right]_{j,k} &= -\frac{\mathrm{d}}{\mathrm{d}\beta_{k}} \sum_{i} X_{i,j} \exp(\sum_{j} X_{i,j} \beta_{j}) \\ &= -\sum_{i} X_{i,j} \exp(\sum_{j} X_{i,j} \beta_{j}) X_{i,k} \end{split}$$

since $\mu_i(\beta) = \exp(\sum_j X_{i,j}\beta_j)$.

• Then the Newton's recursion (2) becomes

$$\beta_{t+1} = \beta_t + [X^T \operatorname{diag}(\mu(\beta_t))X]^{-1}X^T(n - \mu(\beta_t))$$

• It is proven that $\beta_t \to \hat{\beta}$.

Example (For Homework)

Consider the data-set, Alcohol, Cigarette, and Marijuana

Consider:

- a Log-linear model describing a homogeneous association between each pair of variables at each level of the third one; i.e. [AC, AM, CM]
- as identifiability constraints the corner points where the reference levels are the last levels; namely, 2 (yes), 2 (yes), and 2 (yes) for marijuana, cigarette, and alcohol.

Use Newton method in order to compute λ 's

Estimate the log linear model coefficients

Solution

```
# This is a homework for further practice.
```

Save me

Generate the document as a Notebook, PDF, Word, or HTML by choosing the relevant option (from the pop-up menu next to the Preview button). Then save your Markdown code by choosing the relevant option (from the task bar menu).

Save the *.Rmd script, so that you can edit it later.