
Writing custom scripts & running R batch mode analysis

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The R scripting language

Scripting

- A script is a series of instructions that when executed sequentially automates a task
 - A script is a good solution to a repetitive problem
- The art of good script writing is
 - understanding exactly what you want to do
 - expressing the steps as concisely as possible
 - making use of error checking
 - including descriptive comments
- R is a powerful scripting language, and embodies aspects found in most standard programming environments
 - procedural statements
 - loops
 - functions
 - conditional branching
- Scripts may be written in any standard text editor, e.g. notepad, gedit, kate
 - RGui (Mac and Windows) has a built-in text editor

An example script

Scripting

- Colony forming assays provide a measure of cellular proliferation. They are used as read outs for various biological systems
 - A well controlled study may involve multiple samples, treatments and controls (probably replicated).
 - This produces a lot of 'count' data, ideally suited to routine script processing
- Encapsulating the analysis into an R script requires a clear understanding of the problem and data structure

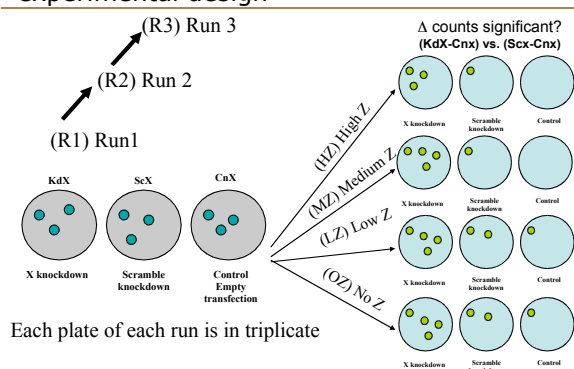
CFA experimental design

Scripting

- Expression of gene X may prevent cells from proliferating in high concentrations of compound Z. The theory is tested by knocking down gene X and growing cells in varying concentrations of compound Z.
 - Three repeat runs (same cell line)
 - Gene X knockdown --> KdX
 - Scramble gene X knockdown control --> ScX
 - Control (transfect empty vector) --> CnX
 - 4 concentrations of compound Z
 - High (HZ), Medium (MZ), Low (LZ), None (OZ)
 - The experiment is replicated over 3 successive weeks
 - Run1 (R1), Run2 (R2) and Run3 (R3)
 - 108 counts in total

Colony forming assay

experimental design



Preparing the calculation(s)

Scripting

- We need to make barplots of counts for the KDX-CNX and SCX-CNX for each concentration of Z.
- We will group the repeat runs & replicates, and take an average.
- A Wilcoxon Rank Sum test will tell us whether there is a significant level of protection for KDX in concentrations of Z
- We'll add in some data quality checks
 - Boxplots of repeat runs
 - Variance within replicates

We can copy & paste lines of code into a blank text document, try them out and keep the ones that work!

Importing data

Scripting

	R1						R2						R3					
Plate	KDX			SCX			CNX			KDX			SCX			CNX		
Replicate	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3	1	2	3
OZ																		
LZ																		
MZ																		
HZ																		

Fine for humans, bad for R

Run	Plate	Treatment	Replicate	Count
Run1	Plate1	Treatment1	Rep1	100
Run1	Plate1	Treatment1	Rep2	100
Run1	Plate1	Treatment1	Rep3	100
Run1	Plate1	Treatment1	Rep4	100
Run1	Plate1	Treatment1	Rep5	100
Run1	Plate1	Treatment1	Rep6	100
Run1	Plate1	Treatment1	Rep7	100
Run1	Plate1	Treatment1	Rep8	100
Run1	Plate1	Treatment1	Rep9	100
Run1	Plate1	Treatment1	Rep10	100
Run1	Plate1	Treatment1	Rep11	100
Run1	Plate1	Treatment1	Rep12	100
Run1	Plate1	Treatment1	Rep13	100
Run1	Plate1	Treatment1	Rep14	100
Run1	Plate1	Treatment1	Rep15	100
Run1	Plate1	Treatment1	Rep16	100
Run1	Plate1	Treatment1	Rep17	100
Run1	Plate1	Treatment1	Rep18	100
Run1	Plate1	Treatment1	Rep19	100
Run1	Plate1	Treatment1	Rep20	100
Run1	Plate1	Treatment1	Rep21	100
Run1	Plate1	Treatment1	Rep22	100
Run1	Plate1	Treatment1	Rep23	100
Run1	Plate1	Treatment1	Rep24	100
Run1	Plate1	Treatment1	Rep25	100
Run1	Plate1	Treatment1	Rep26	100
Run1	Plate1	Treatment1	Rep27	100
Run1	Plate1	Treatment1	Rep28	100
Run1	Plate1	Treatment1	Rep29	100
Run1	Plate1	Treatment1	Rep30	100
Run1	Plate1	Treatment1	Rep31	100
Run1	Plate1	Treatment1	Rep32	100
Run1	Plate1	Treatment1	Rep33	100
Run1	Plate1	Treatment1	Rep34	100
Run1	Plate1	Treatment1	Rep35	100
Run1	Plate1	Treatment1	Rep36	100
Run1	Plate1	Treatment1	Rep37	100
Run1	Plate1	Treatment1	Rep38	100
Run1	Plate1	Treatment1	Rep39	100
Run1	Plate1	Treatment1	Rep40	100
Run1	Plate1	Treatment1	Rep41	100
Run1	Plate1	Treatment1	Rep42	100
Run1	Plate1	Treatment1	Rep43	100
Run1	Plate1	Treatment1	Rep44	100
Run1	Plate1	Treatment1	Rep45	100
Run1	Plate1	Treatment1	Rep46	100
Run1	Plate1	Treatment1	Rep47	100
Run1	Plate1	Treatment1	Rep48	100
Run1	Plate1	Treatment1	Rep49	100
Run1	Plate1	Treatment1	Rep50	100
Run1	Plate1	Treatment1	Rep51	100
Run1	Plate1	Treatment1	Rep52	100
Run1	Plate1	Treatment1	Rep53	100
Run1	Plate1	Treatment1	Rep54	100
Run1	Plate1	Treatment1	Rep55	100
Run1	Plate1	Treatment1	Rep56	100
Run1	Plate1	Treatment1	Rep57	100
Run1	Plate1	Treatment1	Rep58	100
Run1	Plate1	Treatment1	Rep59	100
Run1	Plate1	Treatment1	Rep60	100
Run1	Plate1	Treatment1	Rep61	100
Run1	Plate1	Treatment1	Rep62	100
Run1	Plate1	Treatment1	Rep63	100
Run1	Plate1	Treatment1	Rep64	100
Run1	Plate1	Treatment1	Rep65	100
Run1	Plate1	Treatment1	Rep66	100
Run1	Plate1	Treatment1	Rep67	100
Run1	Plate1	Treatment1	Rep68	100
Run1	Plate1	Treatment1	Rep69	100
Run1	Plate1	Treatment1	Rep70	100
Run1	Plate1	Treatment1	Rep71	100
Run1	Plate1	Treatment1	Rep72	100
Run1	Plate1	Treatment1	Rep73	100
Run1	Plate1	Treatment1	Rep74	100
Run1	Plate1	Treatment1	Rep75	100
Run1	Plate1	Treatment1	Rep76	100
Run1	Plate1	Treatment1	Rep77	100
Run1	Plate1	Treatment1	Rep78	100
Run1	Plate1	Treatment1	Rep79	100
Run1	Plate1	Treatment1	Rep80	100
Run1	Plate1	Treatment1	Rep81	100
Run1	Plate1	Treatment1	Rep82	100
Run1	Plate1	Treatment1	Rep83	100
Run1	Plate1	Treatment1	Rep84	100
Run1	Plate1	Treatment1	Rep85	100
Run1	Plate1	Treatment1	Rep86	100
Run1	Plate1	Treatment1	Rep87	100
Run1	Plate1	Treatment1	Rep88	100
Run1	Plate1	Treatment1	Rep89	100
Run1	Plate1	Treatment1	Rep90	100
Run1	Plate1	Treatment1	Rep91	100
Run1	Plate1	Treatment1	Rep92	100
Run1	Plate1	Treatment1	Rep93	100
Run1	Plate1	Treatment1	Rep94	100
Run1	Plate1	Treatment1	Rep95	100
Run1	Plate1	Treatment1	Rep96	100
Run1	Plate1	Treatment1	Rep97	100
Run1	Plate1	Treatment1	Rep98	100
Run1	Plate1	Treatment1	Rep99	100
Run1	Plate1	Treatment1	Rep100	100

We will create a data frame of factors comprising Run, Plate, Treatment, Replicate
The response variable is counts.

We have 3 spreadsheets of data
Run1counts.csv
Run2counts.csv
Run3counts.csv

We will need to write a procedure that reads in the data
Note that our script will require a consistent data format

Factors

Response

Prepare for raw data

Script walkthrough 1

- Open a blank text document, and prepare to write this script
 - The data is contained in three files:
 - 11_CFA_Run1Counts.csv
 - 11_CFA_Run2Counts.csv
 - 11_CFA_Run3Counts.csv
 - Load in the data and concatenate it into a single data frame

```
# load in the data from the three runs into three separate data frames t1,
t2, t3
t1 = read.csv("11_CFA_Run1Counts.csv")
t2 = read.csv("11_CFA_Run2Counts.csv")
t3 = read.csv("11_CFA_Run3Counts.csv")

# concatenate the three data frames into a single data frame
colony = rbind(t1, t2, t3)

# (or use one of the loops from yesterday...)
```

Example code:
11_CFAcountData.R

Import raw data

Script walkthrough 2

- Data is by default read in as factors, i.e. all input strings are enumerated and stored as numbers
- The three separate data frame have no indication of which number they came from. We will add a column indicating this:

```
# add the missing Run column - factors are stored as numbers !
runNum <- factor( rep( 1:3, each=36 ), labels=c("Run1","Run2","Run3") )
colony <- cbind( "Run" = runNum, colony )

# reorder factor levels in their natural order (instead of alphabetical)
colony$Treatment <- factor(colony$Treatment, c("OZ", "LZ", "MZ", "HZ"))
colony$Plate <- factor(colony$Plate, c("KDX","SCX","CNX"))

# show the full table
colony
```

The tapply function a brief digression

- Assume we have the following data for heights of 5 males and females:

```
data <- data.frame(gender=c("Male", "Male", "Female",  
                             "Female", "Female"), height=c(6, 6.1, 5.8, 6, 5.95))
```

gender	height
1 Male	6.00
2 Male	6.10
3 Female	5.80
4 Female	6.00
5 Female	5.95
- By calling `mean()` on the height column we can get the average of all 5 people, but how do we get average separately for males and females?
- `tapply()` lets us do exactly this
 - It applies a function to grouped data:
- `tapply(data$height, data$gender, mean)`
 data groups function

Undertake data analysis Script walkthrough 3

- We need the means of the triplicate counts for each Run
 - Broken down by plate type (KDX,SCX,CNX) and Z treatment concentration (OZ,LZ,MZ,HZ)

```
### Part 2. Investigating data ###  
tapply(colony$Count, list(colony$Run, colony$Plate,  
colony$Treatment), mean)
```

We can plot a graph of this. It gives us the variation in counts per run

```
par(mfrow=c(4,2,2,2))  
boxplot(Count~Run*Plate*Treatment, las=2, cex=0.2,  
data=colony)
```

Better still, lets plot a grouped bar chart of mean counts per plate type per Z treatment

```
barplot(tapply(colony$Count, list(colony$Plate,  
colony$Treatment), mean), beside=T)
```

```
## OZ  
Run1 98.33333 129.6667 108.3333  
Run2 180.33333 206.0000 188.6667  
Run3 282.33333 288.6667 265.6667  
  
## LZ  
Run1 75.0000 53.0000 21.66667  
Run2 136.3333 103.6667 32.00000  
Run3 157.0000 180.6667 46.66667  
  
## MZ  
Run1 29.66667 6.333333 0.3333333  
Run2 47.00000 11.66667 2.0000000  
Run3 73.00000 17.33333 3.666667  
  
## HZ  
Run1 6.333333 1.333333 0.3333333  
Run2 12.00000 0.333333 0.0000000  
Run3 18.66667 0.333333 0.0000000
```

Summarize & save the analysis Script walkthrough 4

- we need a reshaped, background corrected, table of results on which to perform our tests
- for clarity where possible use dollar (\$) notation (work only with data frames)

```
### Part 3. Summarizing data ###  
result <- tapply(colony$Count, list(colony$Treatment, colony$Plate), mean)  
result <- data.frame(result) # result of tapply is matrix, convert to dataframe  
result
```

```
# calculate kdx and scx values after background correction  
kdx = result$KDX - result$CNX  
scx = result$SCX - result$CNX
```

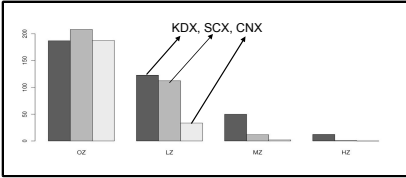
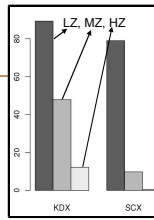
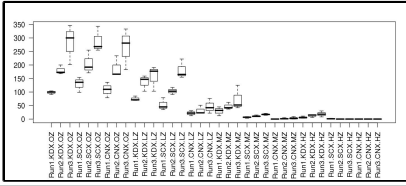
```
result <- cbind(kdx, scx)  
# remove the OZ entry  
result <- result[-1,]  
barplot(result, beside=T)
```

-ve subsctrpts
mean 'delete'

```
wilcox.test(result[,1], result[,2], paired=T)  
cor.test(result[,1], result[,2], paired=T)  
write.csv(result, "CPAresults.csv")
```

We can plot the results as a barchart, and undertake an appropriate two sample classical test

We find that the difference in means is not significant (would expect observation to occur 1:4 times), and that the scramble and knockdown counts have a 90% correlation



Bar chart shows run average counts of various plate types in different Z treatments. KDX is the only plate type that had growth in high Z.

```
> wilcox.test(result[,1],result[,2],paired=TRUE)

Wilcoxon signed rank test

data: result[, 1] and result[, 2]
V = 6, p-value = 0.25
alternative hypothesis: true location shift is not equal to 0
```

```
> cor.test(result[,1],result[,2],paired=TRUE)

Pearson's product-moment correlation

data: result[, 1] and result[, 2]
t = 2.5584, df = 1, p-value = 0.2372
alternative hypothesis: true correlation is not equal to 0
sample estimates:
cor
0.9313792
```

Would expect to see trend 1 in 4 times. There is a 93% correlation between the knockdown of gene X and scramble control and cell counts response when grown in compound Z.

Script steps review

Script walkthrough 5

- Excel formatted data needs to be exported as comma separated values text (or tab!)
- Get the data into R
 - `read.csv()` ... to assign the data to an object
- Produce exploratory plots
 - `boxplot()`
 - `barplot()`
- Undertake statistical tests
 - `cor.test()`
 - Spearman's rank correlation test
 - `wilcox.test()`
 - Wilcoxon test with two sets of paired data ... Mann-Whitney U test
- Write out the results
 - `write.csv()`
 - exports data as comma separated list
 - `save.image()`
 - could also save the R environment after analysis (we didn't do this)

Exercise

Colony forming assay script

- Enter the text of the count data script, and save the file.
 - To run the count data script in R, type
 - `source("filename")` # the script is available as `l1_countData.R`
- Each step of the script is executed, and the results displayed.
- We need to export the graphical output to a file, and the R objects also need to be saved.
 - Modify the script as follows:
Section 3, line directly after ***tapply*** command insert:

```
jpeg(file="fig1.jpg",width=1600,height=800,res=150)
par(mar=c(4,2,2,2))
-- <boxplot commands in middle> ...
dev.off()
jpeg(file="fig2.jpg",width=675,height=900,res=150)
-- <barplot commands in middle> ...
dev.off()
```


Section 4, line directly after ***result*** command insert:

```
jpeg(file="fig3.jpg",width=1600,height=800,res=150)
-- <barplot commands in middle> ...
dev.off()
```

Batch processing R scripts

Scripting

- Scripts can be run without ever launching R, using R CMD batch mode.

quit R and type the following in a linux terminal

```
R CMD BATCH --no-restore l1_CFAcountData.R
```

or if you write all of graphical output to files:

```
Rscript l1_CFAcountData.R (works only with recent R versions)
```

Advanced example: multiple file handling

Reading files using loops and regular expressions

- Earlier we read in each of the three colony files one-by-one
- Yesterday, we saw how to load files using a loop
- But what if we didn't know how many files we had?
- We can use a regular expression to look up the list of available files

```
# look for patterns like 'Counts.csv'
this.pattern <- ".*Counts.csv"

# find all filenames in the current directory containing this pattern
matching.filenames <- dir(pattern=glob2rx(this.pattern))

# see what has been found
matching.filenames

[1] "l1_CFA_Run1Counts.csv" "l1_CFA_Run2Counts.csv" "l1_CFA_Run3Counts.csv"
```

Advanced example: multiple file handling

Reading files using loops and regular expressions

- Using '*' in the pattern is a 'wild card' – means we search for anything that ends in 'Counts.csv'
- glob2rx() is a function which translates this pattern into something the file system can recognise
- Now loop through the matching filenames and open each in turn

```
# start with an empty data frame
colony <- data.frame()

# loop through vector of file names
for(filename in matching_filenames){
  # open each file
  t <- read.csv(matching_filename)
  # append rows
  colony <- rbind(colony, t)
}
```
