

Advanced data processing

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Combining data from multiple sources *Gene clustering example*

- R has powerful functions to combine heterogeneous data into a single data set
- Gene clustering example data:
 - five sets of differentially expressed genes from various experimental conditions
 - file with names of experimentally verified genes
- Gene clustering exercise:
 - 1.combine this dataset into a single table and cluster to see which conditions are similar
 - 2.repeat the clustering but only on a subset of experimentally verified genes

Combining gene tables

- input files have two columns: gene names and fold change
- we want to combine all five tables into a single table, with 0 for missing values

LpR2	3.5795	Psa	3.8529	Iola	3.0121	Iola	3.3019	brat	5.2812
fts1Yh	3.1376	vmd	3.6457	CG31368	2.8063	CG6919	2.0965	ct	4.628
CG6954	2.7482	ct	3.201	Kr-h1	2.7262	CG31368	2.817	CG31163	4.3345
Psa	2.7012	fts1Yh	3.1489	svp	2.7055	CG3149	2.7675	LpR2	3.6882
zfh2	2.6247	bld	3.1229	mub	2.6475	Kr-h1	2.7647	vmd	3.6866
Fur1	2.4413	zfh2	2.8421	CG3149	2.5248	TER94	2.6286	zfh2	3.5314
ct	2.3804	RhoB7B	2.6022	run	2.4759	lha	2.5748	pros	3.4307
S	2.3874	pros	2.5678	lha	2.4302	CG11153	2.4785	Psa	3.3998
nux	2.3574	CG1124	2.5475	CG6954	2.4235	run	2.3631	fts1Yh	3.3869
RhoB7B	2.26	S	2.5424	CG11153	2.3045	CG14888	2.0938	CG31241	2.9973
CG14889	2.1730	oc	2.9111	Awd	2.2295	ts	-2.0243	HmgZ	2.9226
oc	2.1421	Fur1	2.43	CG6919	2.1324	nux	-2.0668	Fur1	2.7469
pros	2.0882	PhDP	2.304	CG14888	2.067	oc	-2.3437	RhoB7B	2.7189
Kr-h1	-2.0447	CG31241	2.2802	Psa	-2.0276	corto	-2.5556	oc	2.6543
CG3149	-2.1521	nux	2.2232	nux	-2.093	fts1Yh	-2.6211	Trab-7	2.6161
lha	-2.2102	CG14889	2.1752	fts1Yh	-2.141	brat	-2.9904	nux	2.5975
CG14888	-2.4346	CG31163	2.1808	CG1124	-2.155	ct	-3.3404	CG14889	2.3054
CG31368	-2.4793	HmgZ	2.0795	Fur1	-2.1588	zfh2	-4.4947	S	2.2324
Trim9	-2.616	svp	-2.0404	S	-2.2539	CG1124	2.0218	run	-2.2194
Awd	-3.0595	TER94	-2.1807	corto	-2.2618	CG6954	-4.7244	Kr-h1	-2.1439
		corto	-2.3481	ts	-2.3017			lha	-2.1793
		gff413	-2.4404	CG14889	-2.4393			CG3149	-2.1892
		brat	-2.7256	zfh2	-2.5884			Trim9	-2.251
		CG31368	-2.7293	HmgZ	-3.6328			gff413	-2.3821
		mub	-2.8905	bld	-3.7627			bld	-3.0293
		Awd	-3.1413	brat	-3.7716			CG6919	-3.3719
		Iola	-3.8862						

Script walkthrough 1

Script walkthrough 1

- To make the big table we first need to find out all the genes present in at least one of the files
- Make sure not to use factors in `read.delim()`

```
# start with an empty collection of genes
genes <- c()
for( fileNum in 1:5 ){
  # load in files 13_DiffGenes1.tsv ...
  t <- read.delim(paste("13_DiffGenes", fileNum, ".tsv",
                        sep="", as.is=TRUE, header=FALSE))
  # label the input columns to help code readability
  names(t) <- c("gene", "expression")
  genes <- union(genes, t$gene)
}

# for tidiness order our genes by name
genes <- sort(genes)

genes # show all genes
```

when loading in character data
use **as.is=T** to prevent it being
converted to factors!

union() is a set operation, combines two vectors by eliminating duplicates. There are also **intersect()** and **setdiff()**

Example code:
13_geneClustering.R

[illegible]

Script walkthrough 2

Script walkthrough 2

- Using the complete list of genes, we can create the big table and fill in the values:

```
# make the destination table [rows = unique genes, cols = file numbers]
values <- matrix(0, nrow=length(genes), ncol=5)
rownames(values) <- genes # name the rows with the complete gene names

for(fileNum in 1:5){
  # read in the file again
  t <- read.delim(paste("I3_DiffGenes", fileNum, ".tsv", sep=""),
                 as.is=T, header=F)
  names(t) <- c("gene", "expression")

  # match the names of the genes to the rows in our big table
  index <- match(t$gene, rownames(values))
  # copy the expression levels
  values[index, fileNum] <- t$expression
}
```

match() returns the index of first argument in the second, i.e. index of input file genes in the big table

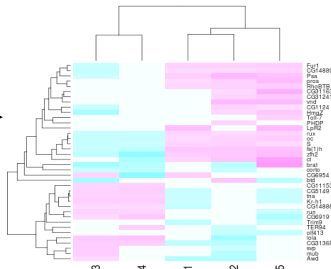
Script walkthrough 3

Script walkthrough 3

- Now we can do hierarchical clustering:

```
heatmap(values, scale="none", col = cm.colors(256))
```

Values from the matrix are colour-coded.
Rows and columns are re-arranged according to similarity



Gene clustering

Script walkthrough 4

- In a second part of our analysis, we want to produce the same heatmap but only based on a list of experimentally verified genes
- The problem is data is not formatted in the most convenient way:

genes	citation
oc,run,RhoBTB,CG5149,CG11153,S,Fur1	Segal et al, Development 2001
tna,Kr-h1,rux	Krejci et al, Development 2002

Gene clustering

Script walkthrough 5

- We load in this table, and only extract the gene names, then we use them to select a subset of **values** matrix

```
# load in the tab-delimited file with genes and citations
t.exp <- read.delim("13_ExperimentalGenes.tsv", as.is=T)
# split all gene names by "," and then flatten it out into a single vector
experim.genes <- unlist( strsplit(t.exp$genes, ",") )
```

↑
unlist() flattens out a nested list into a single vector

↑
strsplit() splits a vector of strings by a custom split character (","), the results is a list of split values for each element of input vector

```
# redo the heatmap by using just the genes in the experimentally verified set
is.experimental <- rownames(values) %in% experim.genes
heatmap(values[ is.experimental, ], scale="none", col = cm.colors(256))
```

Gene clustering review

- We load in the five tables twice - first to collect gene names, then to load expression values
- Based on expression table (**values**) we construct a clustered heatmap first on the whole set of genes, then on a selected subset
- Go through the code, try it out and understand it
- Try answering the following questions:
 - what is **rownames(values)** ?
 - why is **rownames(values)[index]** and **t\$gene** giving the same output?
 - what is a difference between **rownames(values) %in% experim.genes** and **experim.genes %in% rownames(values)**

Example code:
13_geneClustering.R
