

# Lecture 12

BIOF 339

December 5, 2016

**Bioconductor**

# Bioconductor

Bioconductor provides tools for the analysis and comprehension of high-throughput genomic data, using R.

- 1296 packages
- Covers the bioinformatic pipeline
- Software
- Annotation
- Experiments

Explore Bioconductor  
website

# Installing Bioconductor packages

This is different from the usual `install.packages`

```
source('http://bioconductor.org/biocLite.R')  
biocLite('Biobase', 'limma', 'hgu95av2.db')
```

# Data in Bioconductor

The basic structure in a Bioconductor pipeline is the **ExpressionSet**

```
library(Biobase)
str(sample.ExpressionSet)
```

```
# Formal class 'ExpressionSet' [package "Biobase"] with 7 slots
#   ..@ experimentData  :Formal class 'MIAME' [package "Biobase"] with 13 slots
#   .. ..@ name         : chr "Pierre Fermat"
#   .. ..@ lab          : chr "Francis Galton Lab"
#   .. ..@ contact      : chr "pfermat@lab.not.exist"
#   .. ..@ title        : chr "Smoking-Cancer Experiment"
#   .. ..@ abstract     : chr "An example object of expression set (1)"
#   .. ..@ url          : chr "www.lab.not.exist"
#   .. ..@ pubMedIds    : chr ""
#   .. ..@ samples      : list()
#   .. ..@ hybridizations : list()
#   .. ..@ normControls  : list()
#   .. ..@ preprocessing : list()
```

# Differences with usual R

Instead of storing data in named lists, ExpressionSet objects store data in slots, and we can see what the slots are with `slotNames`:

```
r slotNames(sample.ExpressionSet)

# [1] "experimentData" "assayData" "phenoData" # [4]
"featureData" "annotation" "protocolData" # [7]
"__classVersion__"
```

# Differences with usual R

You can access these slots using @, instead of the usual \$:

```
r sample.ExpressionSet@phenoData
```

```
# An object of class 'AnnotatedDataFrame' #  
sampleNames: A B ... Z (26 total) # varLabels: sex  
type score # varMetadata: labelDescription
```



# Differences with usual R

However, it's much easier to go with the built-in functions

```
pData(sample.ExpressionSet)
```

```
#      sex    type score
# A Female Control 0.75
# B  Male    Case  0.40
# C  Male    Control 0.73
# D  Male    Case  0.42
# E Female    Case  0.93
# F  Male    Control 0.22
# G  Male    Case  0.96
# H  Male    Case  0.79
# I Female    Case  0.37
# J  Male    Control 0.63
# K  Male    Case  0.26
# L Female    Control 0.36
# M  Male    Case  0.41
# N  Male    Case  0.80
```

# Differences with usual R

```
head(exprs(sample.ExpressionSet))
```

#		A	B	C	D	E	F
#	AFFX-MurIL2_at	192.7420	85.75330	176.7570	135.5750	64.49390	76.3569
#	AFFX-MurIL10_at	97.1370	126.19600	77.9216	93.3713	24.39860	85.5088
#	AFFX-MurIL4_at	45.8192	8.83135	33.0632	28.7072	5.94492	28.2925
#	AFFX-MurFAS_at	22.5445	3.60093	14.6883	12.3397	36.86630	11.2568
#	AFFX-BioB-5_at	96.7875	30.43800	46.1271	70.9319	56.17440	42.6756
#	AFFX-BioB-M_at	89.0730	25.84610	57.2033	69.9766	49.58220	26.1262
#		G	H	I	J	K	L
#	AFFX-MurIL2_at	160.5050	65.9631	56.9039	135.60800	63.44320	78.2126
#	AFFX-MurIL10_at	98.9086	81.6932	97.8015	90.48380	70.57330	94.5418
#	AFFX-MurIL4_at	30.9694	14.7923	14.2399	34.48740	20.35210	14.1554
#	AFFX-MurFAS_at	23.0034	16.2134	12.0375	4.54978	8.51782	27.2852
#	AFFX-BioB-5_at	86.5156	30.7927	19.7183	46.35200	39.13260	41.7698
#	AFFX-BioB-M_at	75.0083	42.3352	41.1207	91.53070	39.91360	49.8397
#		M	N	O	P	Q	R
#	AFFX-MurIL2_at	83.0943	89.3372	91.0615	95.9377	179.8450	152.46700/22
#	AFFX-MurIL10_at	75.3455	68.5827	87.4050	84.4581	87.6806	108.0320

# Making a heatmap

# Heatmaps

There are several ways of doing heatmaps in R:

- [http://sebastianraschka.com/Articles/heatmaps\\_in\\_r.html](http://sebastianraschka.com/Articles/heatmaps_in_r.html)
- <https://plot.ly/r/heatmaps/>
- <http://moderndata.plot.ly/interactive-heat-maps-for-r/>
- <http://www.siliconcreek.net/r/simple-heatmap-in-r-with-ggplot2>
- <https://rud.is/b/2016/02/14/making-faceted-heatmaps-with-ggplot2/>

# Some example data

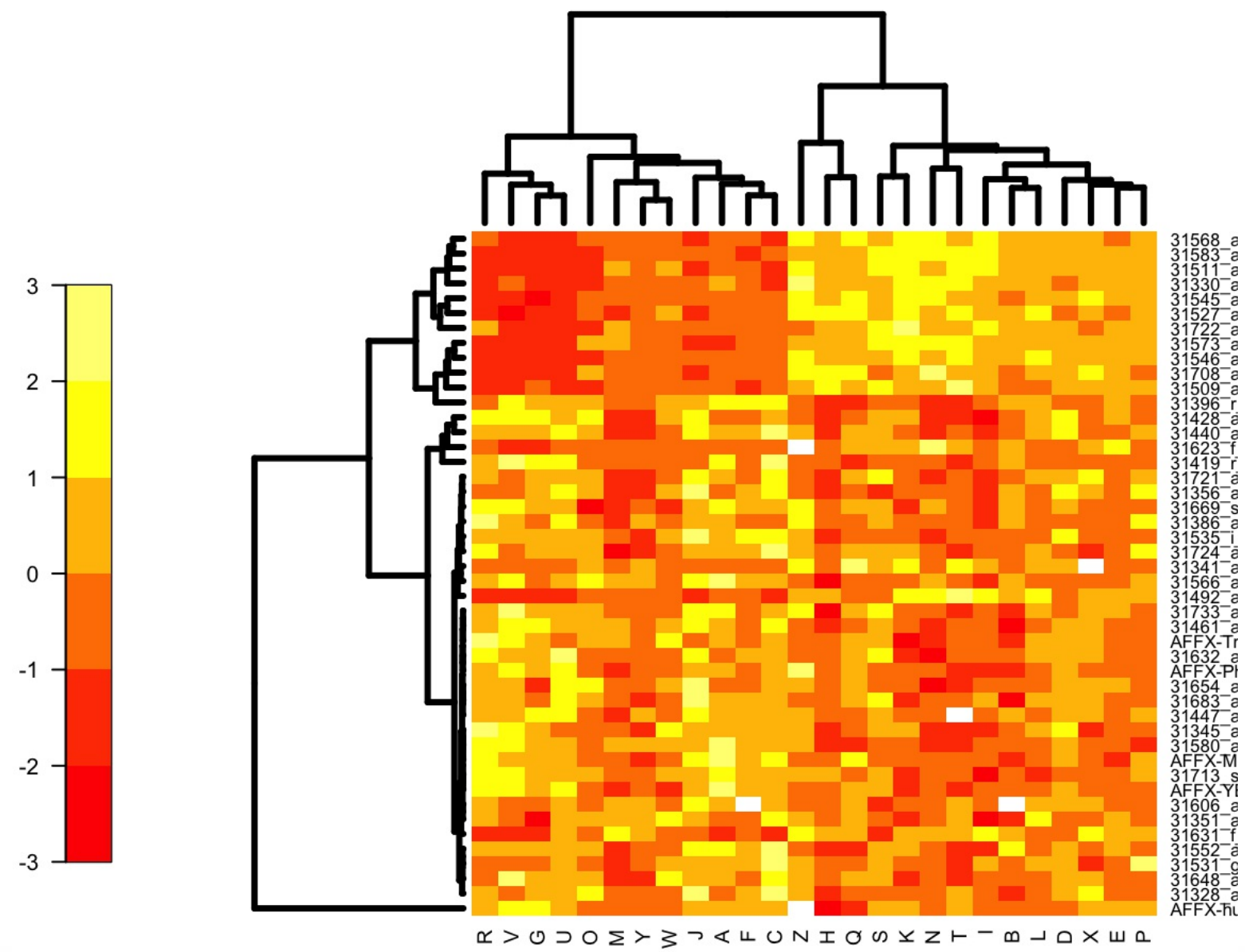
```
library(Biobase)
data(sample.ExpressionSet)
exdat <- sample.ExpressionSet
library(limma)
design1 <- model.matrix(~type, data=pData(exdat))
lm1 <- lmFit(exprs(exdat), design1)
lm1 <- eBayes(lm1) # compute linear model for each probeset
geneID <- rownames(topTable(lm1, coef=2, num=100, adjust='none',p.value=0.05))
exdat2 <- exdat[geneID,] # Keep features with p-values < 0.05
exdat2
```

```
# ExpressionSet (storageMode: lockedEnvironment)
# assayData: 46 features, 26 samples
#   element names: exprs, se.exprs
# protocolData: none
# phenoData
#   sampleNames: A B ... Z (26 total)
#   varLabels: sex type score
#   varMetadata: labelDescription
```

# Heatmaps using Heatplus

```
source('http://bioconductor.org/biocLite.R')  
biocLite('Heatplus')
```

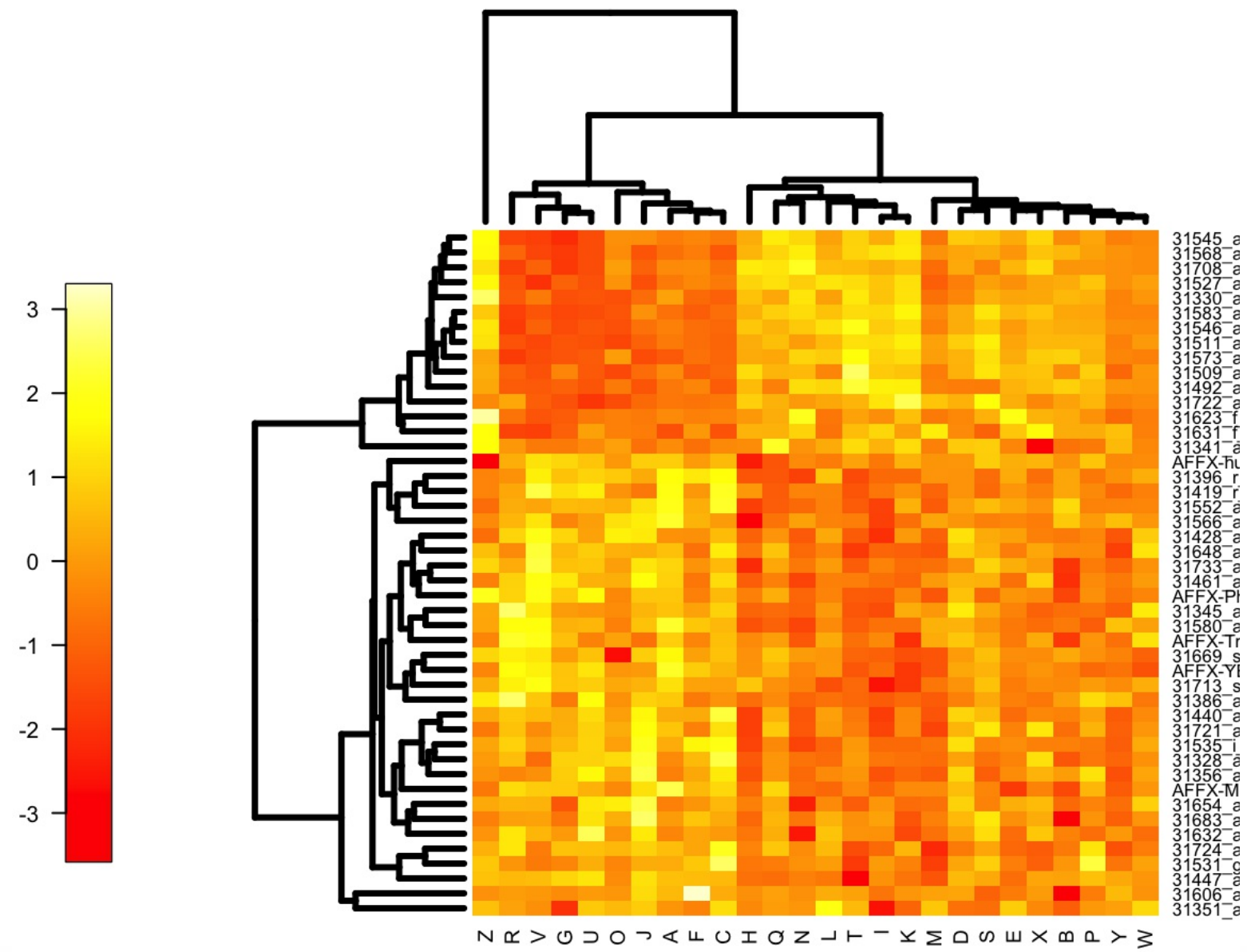
```
library(Heatplus)
reg1 <- regHeatmap(exprs(exdat2), legend=2, col=heat.colors,
                   breaks=-3:3)
plot(reg1)
```



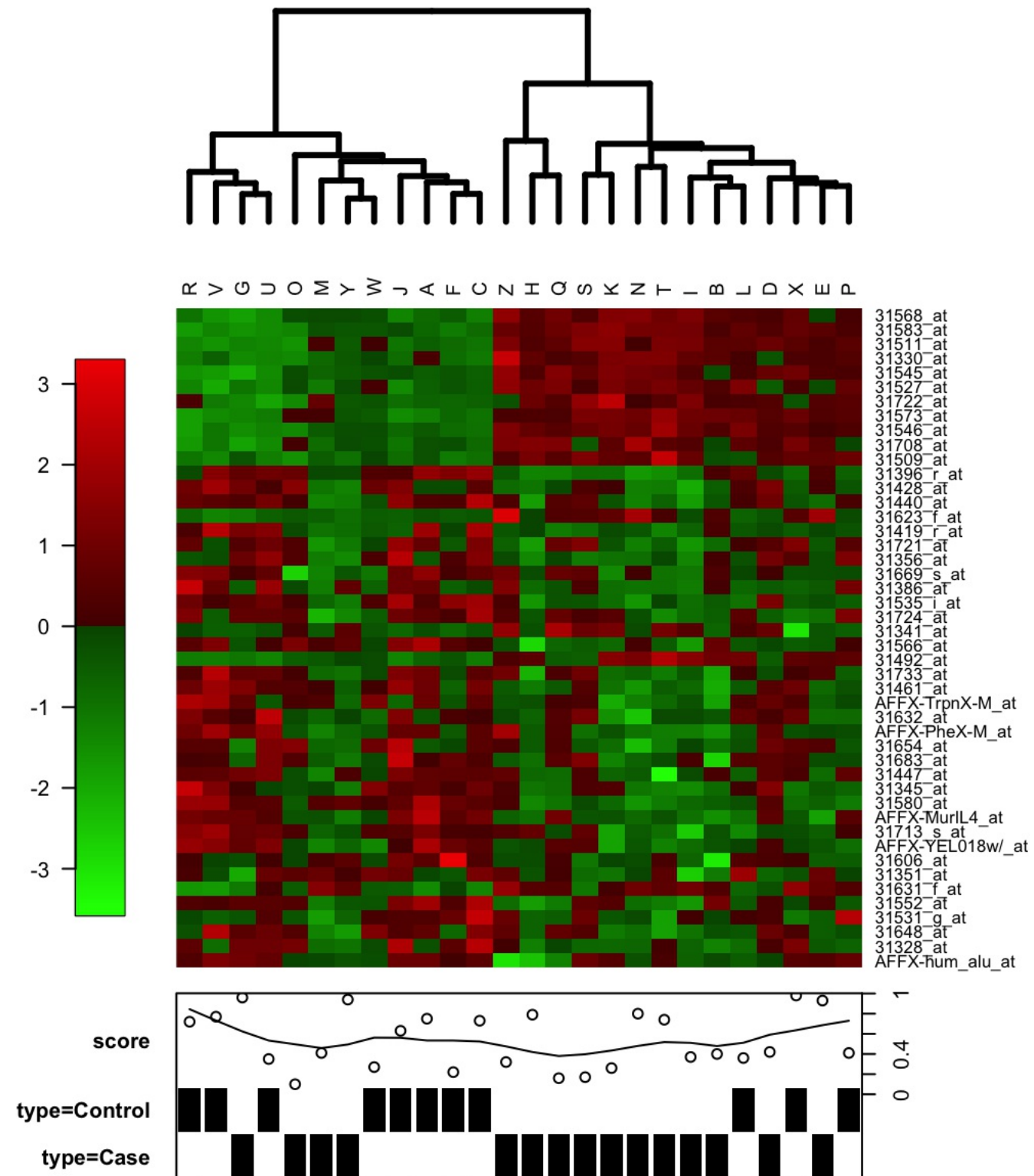


```
library(Heatplus)
reg1 <- regHeatmap(exprs(exdat2), legend=2, col=heat.colors,
                   breaks=-3:3)
plot(reg1)
```

```
corrdist <- function(x) as.dist(1-cor(x))
hclust.avl <- function(x) hclust(x, method='average')
reg2 <- regHeatmap(exprs(exdat2), legend=2, col=heat.colors,
                   breaks=-3:3,
                   dendrogram = list(clustfun=hclust.avl, distfun=corrdist))
plot(reg2)
```



```
ann1 <- annHeatmap(exprs(exdat2), ann=pData(exdat2))  
plot(ann1)
```



```
ann1 <- annHeatmap(exprs(exdat2), ann=pData(exdat2))  
plot(ann1)
```

```
ann2 <- annHeatmap(exprs(exdat2), ann=pData(exdat2),  
                   cluster = list(cuth=7500,  
                                  label=c('Control-like', 'Case-like'))))  
plot(ann3)
```

