

```
title: "Affymetrix Microarray Minimal pipeline"
author: "Simon Tomlinson 10/02/2021"
output: html_document
```

Affymetrix Microarray Analysis Basic (Skeleton) Workflow

```
##Load the required libraries & load the files for the workflow
```

```
library(limma)
library(affy)
```

```
## Loading required package: BiocGenerics
```

```
##
```

```
## Attaching package: 'BiocGenerics'
```

```
## The following object is masked from 'package:limma':
```

```
##
```

```
##      plotMA
```

```
## The following objects are masked from 'package:stats':
```

```
##
```

```
##      IQR, mad, sd, var, xtabs
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##      anyDuplicated, aperm, append, as.data.frame, basename, cbind,
##      colnames, dirname, do.call, duplicated, eval, evalq, Filter, Find,
##      get, grep, grepl, intersect, is.unsorted, lapply, Map, mapply,
##      match, mget, order, paste, pmax, pmax.int, pmin, pmin.int,
##      Position, rank, rbind, Reduce, rownames, sapply, setdiff, sort,
##      table, tapply, union, unique, unsplit, which.max, which.min
```

```
## Loading required package: Biobase
```

```
## Welcome to Bioconductor
```

```
##
```

```
##      Vignettes contain introductory material; view with
```

```
##      'browseVignettes()'. To cite Bioconductor, see
```

```
##      'citation("Biobase)"', and for packages 'citation("pkgname)"'.
```

```
library(annotate)
```

```
## Loading required package: AnnotationDbi
```

```
## Loading required package: stats4
```

```
## Loading required package: IRanges
```

```
## Loading required package: S4Vectors
```

```
##
```

```
## Attaching package: 'S4Vectors'
```

```
## The following objects are masked from 'package:base':
```

```
##
```

```
##      expand.grid, I, unname
```

```
## Loading required package: XML
```

```
library(mouse4302.db) # load chip-specific annotation

## Loading required package: org.Mm.eg.db
##
##
#install.packages("scatterplot3d",repo="http://cran.ma.imperia#l.ac.uk")
#Then load the library
library(scatterplot3d)
```

Load the main data- commented code is just for information

```
system("tar -xvf /shared_files/FGT_T3_GSE10806_RAW.tar")
system("cp /shared_files/FGT_T3_targets.txt .")
# Load the target file into an AnnotatedDataFrame object
adf<-read.AnnotatedDataFrame("FGT_T3_targets.txt",header=TRUE,row.names=1,as.is=TRUE)
# Load the expression values of all the CEL files in the targets file
#mydata <- ReadAffy(filenamees=pData(adf)$FileName,phenoData=adf)

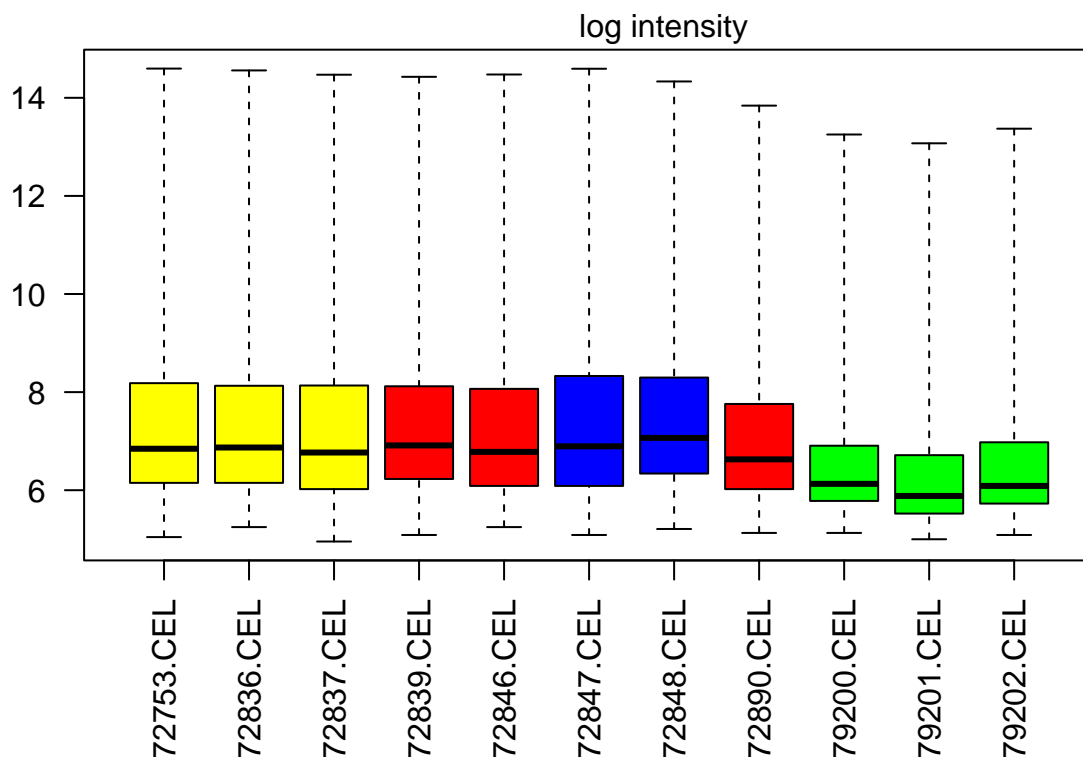
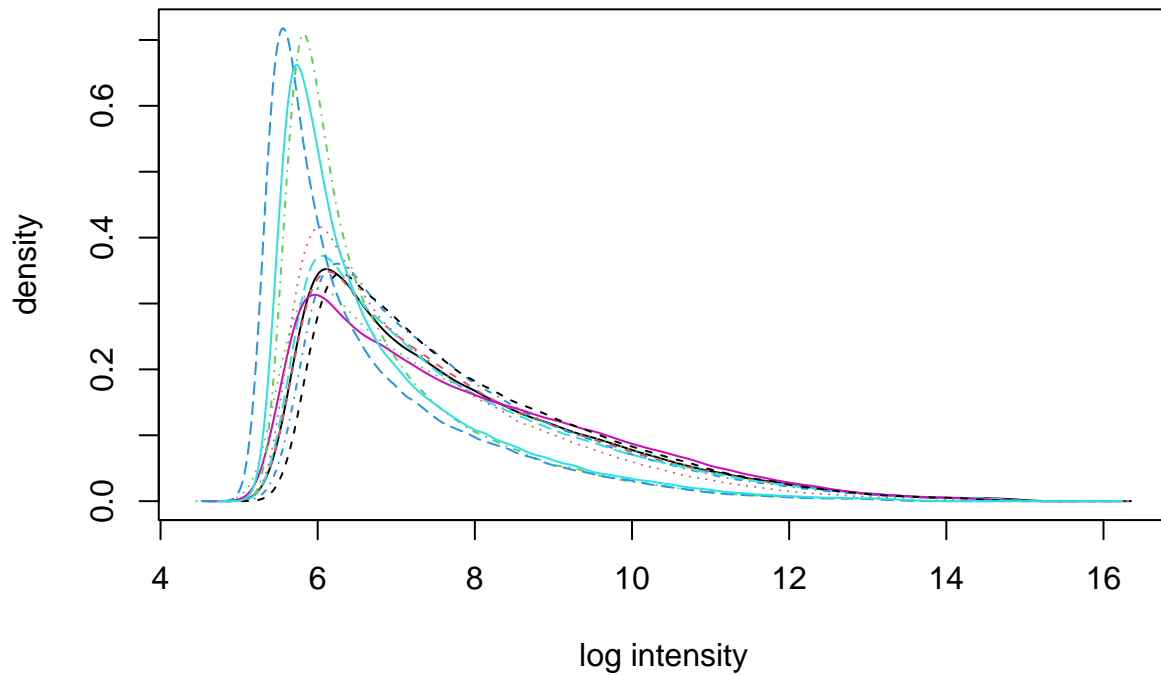
# Or just to quickly load all CEL files in the R working directory
mydata <- ReadAffy()
# View a summary of the example data
mydata

## Warning: replacing previous import 'AnnotationDbi::tail' by 'utils::tail' when
## loading 'mouse4302cdf'

## Warning: replacing previous import 'AnnotationDbi::head' by 'utils::head' when
## loading 'mouse4302cdf'

##
## AffyBatch object
## size of arrays=1002x1002 features (22 kb)
## cdf=Mouse430_2 (45101 affyids)
## number of samples=11
## number of genes=45101
## annotation=mouse4302
## notes=
```

Build Quality Control Plots



malise the data using RMA

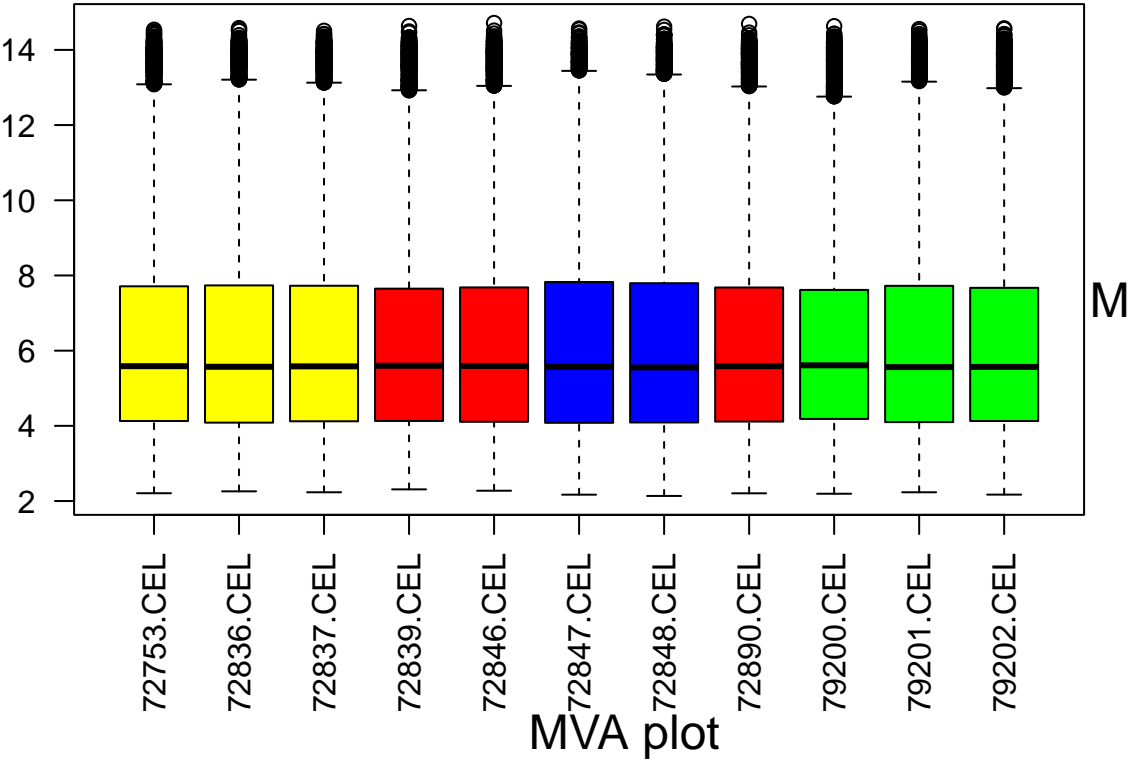
```
## Background correcting
## Normalizing
## Calculating Expression

## ExpressionSet (storageMode: lockedEnvironment)
## assayData: 45101 features, 11 samples
##   element names: exprs
## protocolData
```

Nor-

```
## sampleNames: GSM272753.CEL GSM272836.CEL ... GSM279202.CEL (11 total)
## varLabels: ScanDate
## varMetadata: labelDescription
## phenoData
## sampleNames: GSM272753.CEL GSM272836.CEL ... GSM279202.CEL (11 total)
## varLabels: sample
## varMetadata: labelDescription
## featureData: none
## experimentData: use 'experimentData(object)'
## Annotation: mouse4302
```

Plot Normalised Data

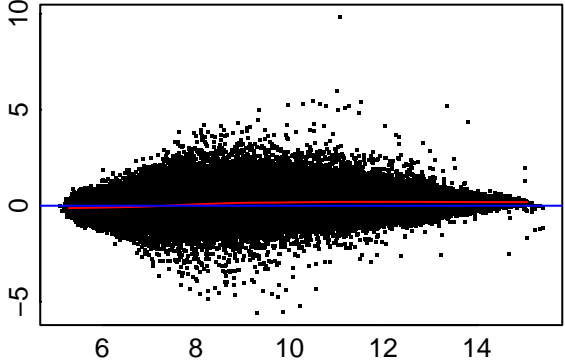


GSM2727

Median: —
IQR: 0

M

GSM272753.CEL



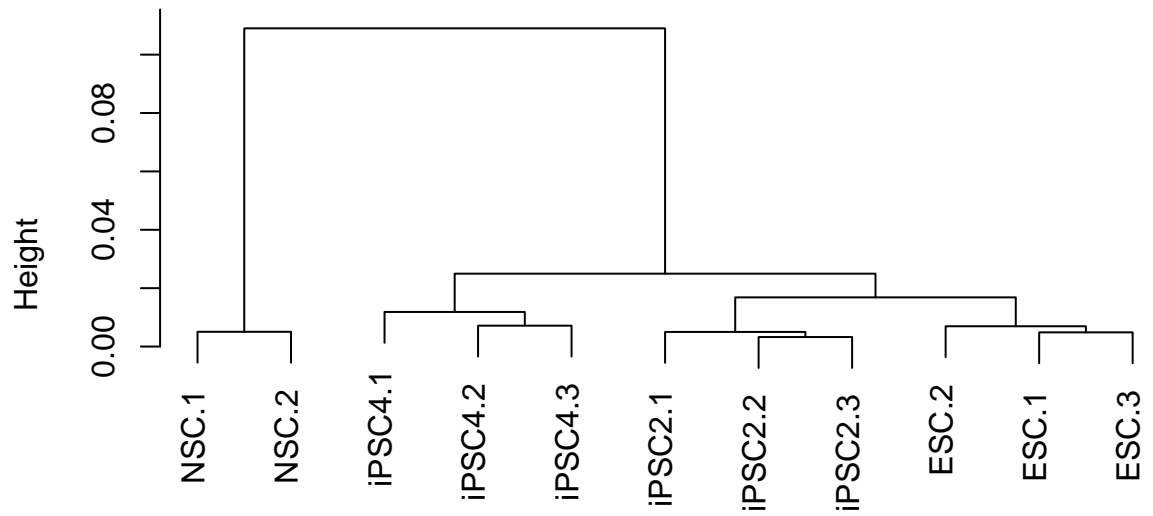
Median: 0
IQR: 0.486

GSM272839.CEL

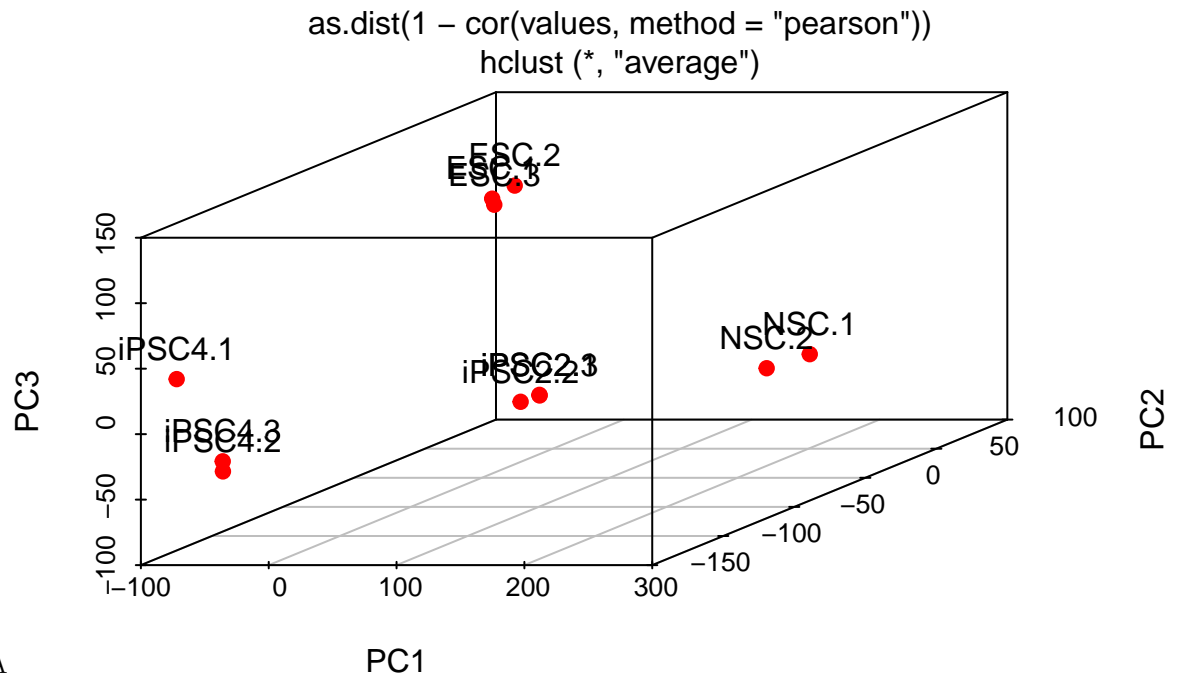
A

##

Cluster Dendrogram



Plot Heatmap



Perform PCA

Perform fold filtering

```
#obtaining a matrix of expression values
exprsvals <- exprs(eset)
#RMA outputs log2 data while MAS5 outputs linear data
#To convert from log...
exprsvals10 <- 2^exprsvals
#check conversion
exprsvals[1:10,]
```

##	GSM272753.CEL	GSM272836.CEL	GSM272837.CEL	GSM272839.CEL
## 1415670_at	9.669418	9.468712	9.840497	9.542554
## 1415671_at	10.804052	10.560056	11.161637	10.006636
## 1415672_at	11.137131	11.004639	11.177958	11.265057
## 1415673_at	9.065874	9.002128	8.882502	9.359967
## 1415674_a_at	10.075517	9.794644	9.838132	9.877397
## 1415675_at	8.808742	8.668103	8.629835	9.120798
## 1415676_a_at	11.802675	11.477381	11.960382	11.134994
## 1415677_at	8.093115	7.773758	8.056709	7.423166
## 1415678_at	10.273131	10.384452	10.557665	10.513949
## 1415679_at	10.886946	10.582367	10.711379	10.492362
##	GSM272846.CEL	GSM272847.CEL	GSM272848.CEL	GSM272890.CEL
## 1415670_at	9.566148	9.556946	9.555320	9.570322
## 1415671_at	10.203007	9.731251	9.542029	10.510781
## 1415672_at	11.253738	11.133394	11.147553	11.388213
## 1415673_at	9.397668	9.355186	9.524904	9.200095
## 1415674_a_at	9.924118	9.680461	9.816652	9.673921
## 1415675_at	9.068031	8.790371	8.846509	8.956731
## 1415676_a_at	11.281870	11.358769	11.387082	11.107652
## 1415677_at	7.416413	8.870749	8.918135	7.399723
## 1415678_at	10.664771	10.095007	9.642961	10.883287
## 1415679_at	10.549639	10.961153	11.149409	10.404885
##	GSM279200.CEL	GSM279201.CEL	GSM279202.CEL	
## 1415670_at	9.997091	10.291382	10.041643	
## 1415671_at	10.753063	10.494127	10.333424	
## 1415672_at	10.746576	10.887394	10.960298	
## 1415673_at	8.500078	8.831864	8.938540	
## 1415674_a_at	9.135410	9.433351	9.794644	
## 1415675_at	8.847440	9.019164	9.162779	
## 1415676_a_at	11.219547	11.548926	11.431180	
## 1415677_at	7.072158	7.420528	7.466735	
## 1415678_at	10.668909	10.876593	10.378917	
## 1415679_at	10.625891	10.558164	10.572555	

```
#converted
exprsvals10[1:10,]
```

##	GSM272753.CEL	GSM272836.CEL	GSM272837.CEL	GSM272839.CEL
## 1415670_at	814.3011	708.5432	916.8216	745.7532
## 1415671_at	1787.9027	1509.7102	2290.8016	1028.7211
## 1415672_at	2252.2186	2054.5958	2316.8651	2461.0480
## 1415673_at	535.9201	512.7556	471.9539	657.0988
## 1415674_a_at	1079.0283	888.1406	915.3197	940.5738
## 1415675_at	448.4310	406.7795	396.1313	556.7162
## 1415676_a_at	3572.3920	2851.2542	3985.0485	2248.8846
## 1415677_at	273.0677	218.8438	266.2632	171.6309
## 1415678_at	1237.4294	1336.6927	1507.2107	1462.2242
## 1415679_at	1893.6399	1533.2386	1676.6650	1440.5079
##	GSM272846.CEL	GSM272847.CEL	GSM272848.CEL	GSM272890.CEL
## 1415670_at	758.0494	753.2296	752.3812	760.2456
## 1415671_at	1178.7210	849.9598	745.4817	1459.0169
## 1415672_at	2441.8139	2246.3920	2268.5474	2680.3630
## 1415673_at	674.4967	654.9251	736.6850	588.1723
## 1415674_a_at	971.5322	820.5579	901.7928	816.8465
## 1415675_at	536.7219	442.7568	460.3251	496.8721

```
## 1415676_a_at      2489.8964      2626.2153      2678.2635      2206.6647
## 1415677_at        170.8295       468.1245       483.7556       168.8645
## 1415678_at        1623.3647      1093.7045       799.5036      1888.8425
## 1415679_at        1498.8490      1993.5893      2271.4681      1355.7585
##                GSM279200.CEL GSM279201.CEL GSM279202.CEL
## 1415670_at        1021.9374      1253.1837      1053.9879
## 1415671_at        1725.8164      1442.2710      1290.2406
## 1415672_at        1718.0732      1894.2279      1992.4085
## 1415673_at         362.0583       455.6758       490.6463
## 1415674_a_at        562.3835       691.3876       888.1406
## 1415675_at         460.6221       518.8465       573.1540
## 1415676_a_at       2384.6249      2996.2171      2761.3917
## 1415677_at         134.5649       171.3174       176.8933
## 1415678_at        1628.0272      1880.0990      1331.5738
## 1415679_at        1580.1998      1507.7313      1522.8465
```

```
#More fold filtering
#check order of sample names
mysamples <- sampleNames(eset)
#display the list
mysamples
```

```
## [1] "GSM272753.CEL" "GSM272836.CEL" "GSM272837.CEL" "GSM272839.CEL"
## [5] "GSM272846.CEL" "GSM272847.CEL" "GSM272848.CEL" "GSM272890.CEL"
## [9] "GSM279200.CEL" "GSM279201.CEL" "GSM279202.CEL"
```

```
#it is useful to obtain a vector of ProbeIDs here
probesets <- probeNames(mydata)
#display the first 10 ProbeSets
probesets[1:10]
```

```
## [1] "1415670_at" "1415670_at" "1415670_at" "1415670_at" "1415670_at"
## [6] "1415670_at" "1415670_at" "1415670_at" "1415670_at" "1415670_at"
```

```
#Build final fold table
#Calculate the means
#Note mean of the log is not the same as the log of the mean!!
ES.mean <- apply(exprsvals10[,c("GSM272753.CEL", "GSM272836.CEL", "GSM272837.CEL")], 1, mean)
iPS_OK.mean <- apply(exprsvals10[,c("GSM272839.CEL", "GSM272846.CEL", "GSM272890.CEL")], 1, mean)
iPS_4F.mean <- apply(exprsvals10[,c("GSM279200.CEL", "GSM279201.CEL", "GSM279202.CEL")], 1, mean)
NSC.mean <- apply(exprsvals10[,c("GSM272847.CEL", "GSM272848.CEL")], 1, mean)
#calculate some fold changes
ES_iPS_OK <- ES.mean / iPS_OK.mean
ES_iPS_4F <- ES.mean / iPS_4F.mean
ES_NSC <- ES.mean / NSC.mean
#build a summary table to hold all the data
all.data = cbind(ES.mean, iPS_OK.mean, iPS_4F.mean, NSC.mean, ES_iPS_OK,
ES_iPS_4F, ES_NSC)
#check the column names
colnames(all.data)
```

```
## [1] "ES.mean"      "iPS_OK.mean" "iPS_4F.mean" "NSC.mean"    "ES_iPS_OK"
## [6] "ES_iPS_4F"   "ES_NSC"
```

```
#write the table of means as an output
write.table(all.data, file="group_means.txt", quote=F,
sep="\t", col.names=NA)
```


Beginning statistical analysis

```
#Check original sample order
sampleNames(eset)
```

```
## [1] "GSM272753.CEL" "GSM272836.CEL" "GSM272837.CEL" "GSM272839.CEL"
## [5] "GSM272846.CEL" "GSM272847.CEL" "GSM272848.CEL" "GSM272890.CEL"
## [9] "GSM279200.CEL" "GSM279201.CEL" "GSM279202.CEL"
```

```
#Rename the samples
sampleNames(eset) <-
c("ESC.1", "ESC.2", "ESC.3", "iPS2.2", "iPS2.3", "NSC.1", "NSC.2", "iPS2.1", "iPS4.1", "iPS4.2", "iPS.3")
#Check the samples have renamed
sampleNames(eset)
```

```
## [1] "ESC.1" "ESC.2" "ESC.3" "iPS2.2" "iPS2.3" "NSC.1" "NSC.2" "iPS2.1"
## [9] "iPS4.1" "iPS4.2" "iPS.3"
```

```
##Building annotation for differential gene identification
#establish annotation for MOE430v2
#which annotation do we need
#modified from #http://gettinggeneticsdone.blogspot.co.uk/2012/01/annotating-limma-#results-with-gene.h

eset@annotation
```

```
## [1] "mouse4302"
```

```
#packages in the annotation package
ls("package:mouse4302.db")
```

```
## [1] "mouse4302"           "mouse4302_dbconn"      "mouse4302_dbfile"
## [4] "mouse4302_dbInfo"    "mouse4302_dbschema"    "mouse4302.db"
## [7] "mouse4302ACCNUM"     "mouse4302ALIAS2PROBE"  "mouse4302CHR"
## [10] "mouse4302CHRLNGTHS"  "mouse4302CHRLLOC"      "mouse4302CHRLCEND"
## [13] "mouse4302ENSEMBL"    "mouse4302ENSEMBL2PROBE" "mouse4302ENTREZID"
## [16] "mouse4302ENZYME"     "mouse4302ENZYME2PROBE" "mouse4302GENENAME"
## [19] "mouse4302GO"         "mouse4302GO2ALLPROBES" "mouse4302GO2PROBE"
## [22] "mouse4302MAPCOUNTS" "mouse4302MGI"          "mouse4302MGI2PROBE"
## [25] "mouse4302ORGANISM"   "mouse4302ORGPKG"       "mouse4302PATH"
## [28] "mouse4302PATH2PROBE" "mouse4302PFAM"         "mouse4302PMID"
## [31] "mouse4302PMID2PROBE" "mouse4302PROSITE"      "mouse4302REFSEQ"
## [34] "mouse4302SYMBOL"     "mouse4302UNIPROT"
```

```
#build an annotation table
ID <- featureNames(eset)
Symbol <- getSYMBOL(ID, "mouse4302.db")
Name <- as.character(lookUp(ID, "mouse4302.db", "GENENAME"))
tmp <- data.frame(ID=ID, Symbol=Symbol, Name=Name, stringsAsFactors=F)
tmp[tmp=="NA"] <- NA #fix padding with NA characters
#assign as feature data of the current Eset
fData(eset) <- tmp
```

Statistical analysis using Limma

```
#Build the design matrix
design <- model.matrix(~-1+factor(c(1,1,1,2,2,3,3,2,4,4,4)))
colnames(design) <- c("ESC", "iPS2", "NSC", "iPS4")
```

```

#Check it makes sense
sampleNames(eset)

## [1] "ESC.1" "ESC.2" "ESC.3" "iPS2.2" "iPS2.3" "NSC.1" "NSC.2" "iPS2.1"
## [9] "iPS4.1" "iPS4.2" "iPS.3"

#output the design matrix
design

##      ESC iPS2 NSC iPS4
## 1      1    0  0    0
## 2      1    0  0    0
## 3      1    0  0    0
## 4      0    1  0    0
## 5      0    1  0    0
## 6      0    0  1    0
## 7      0    0  1    0
## 8      0    1  0    0
## 9      0    0  0    1
## 10     0    0  0    1
## 11     0    0  0    1
## attr("assign")
## [1] 1 1 1 1
## attr("contrasts")
## attr("contrasts")$`factor(c(1, 1, 1, 2, 2, 3, 3, 2, 4, 4, 4))`
## [1] "contr.treatment"

#This instructs Limma which comparisons to make
contrastmatrix <- makeContrasts(ESC-iPS2,ESC-NSC,ESC-iPS4,
levels=design)
contrastmatrix

##      Contrasts
## Levels ESC - iPS2 ESC - NSC ESC - iPS4
##   ESC      1      1      1
##  iPS2     -1      0      0
##   NSC      0     -1      0
##  iPS4      0      0     -1

#issue these commands to fit the model
#and make the contrasts
fit <- lmFit(eset, design)

fit2 <- contrasts.fit(fit, contrastmatrix)

#this last part essentially moderates the t-statistic using
#the borrowed variance approach described in class
fit2 <- eBayes(fit2)

#get the results
topTable(fit2,coef=1,adjust="fdr")

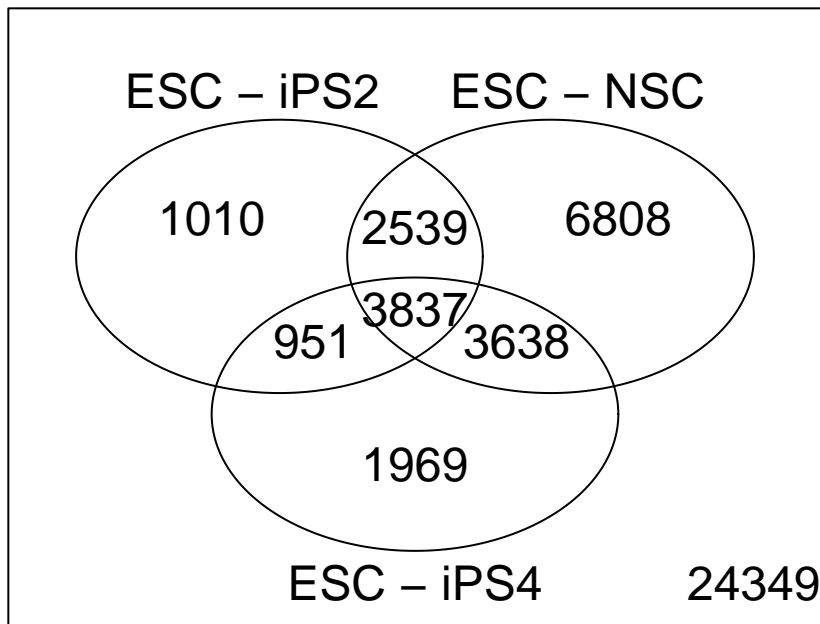
##      ID      Symbol
## 1421144_at 1421144_at Rpgrip1
## 1437967_at 1437967_at Ccdc141
## 1425137_a_at 1425137_a_at H2-Q10

```

```
## 1425427_at      1425427_at  Gm20767
## 1425220_x_at    1425220_x_at  AF067061
## 1445226_at      1445226_at  AI506816
## 1418704_at      1418704_at  S100a13
## 1430979_a_at    1430979_a_at  Prdx2
## 1420773_at      1420773_at  Usp17la
## 1454971_x_at    1454971_x_at  Tsc22d1
##
##                                     Name
## 1421144_at      retinitis pigmentosa GTPase regulator interacting protein 1
## 1437967_at      coiled-coil domain containing 141
## 1425137_a_at    histocompatibility 2, Q region locus 10
## 1425427_at      predicted gene, 20767
## 1425220_x_at    cDNA sequence AF067061
## 1445226_at      expressed sequence AI506816
## 1418704_at      S100 calcium binding protein A13
## 1430979_a_at    peroxiredoxin 2
## 1420773_at      ubiquitin specific peptidase 17-like A
## 1454971_x_at    TSC22 domain family, member 1
##
##          logFC  AveExpr      t      P.Value  adj.P.Val      B
## 1421144_at    5.177794 10.718373 39.80404 2.024468e-14 9.130555e-10 21.15821
## 1437967_at    3.890379  5.694028 28.66822 1.120095e-12 1.526453e-08 18.52879
## 1425137_a_at -3.651515  5.599389 -28.25430 1.337197e-12 1.526453e-08 18.39780
## 1425427_at   -3.426349  4.074569 -27.77323 1.648182e-12 1.526453e-08 18.24169
## 1425220_x_at -3.548330  6.182014 -27.71308 1.692261e-12 1.526453e-08 18.22187
## 1445226_at   -4.509854  7.539736 -27.12318 2.198722e-12 1.539552e-08 18.02388
## 1418704_at    3.648166  7.897353 26.78701 2.558847e-12 1.539552e-08 17.90804
## 1430979_a_at -3.163601  7.443417 -26.64406 2.730852e-12 1.539552e-08 17.85810
## 1420773_at   -4.061445  5.430320 -26.19480 3.357846e-12 1.682691e-08 17.69845
## 1454971_x_at  2.297421 11.820596 25.59797 4.442621e-12 1.946981e-08 17.47982
```

```
myresults <-topTable(fit2,coef=1, adjust="fdr", number=nrow(eset))
write.table(myresults,"myresults.txt")
```

```
#make a venn diagram
clas <- classifyTestsF(fit2)
vennDiagram(clas)
```



Carry out Functional Enrichment analysis

```
Mm.H <- readRDS("/shared_files/MSigDB/Mm.h.all.v7.1.entrez.rds")
```

```
#Check that you have the required objects
```

```
ls()
```

```
## [1] "adf"           "all.data"      "clas"          "colours"
## [5] "contrastmatrix" "design"         "ES_iPS_4F"     "ES_iPS_OK"
## [9] "ES_NSC"        "ES.mean"       "eset"          "exprsvals"
## [13] "exprsvals10"   "fit"           "fit2"          "hc"
## [17] "ID"            "iPS_4F.mean"   "iPS_OK.mean"   "Mm.H"
## [21] "mydata"        "myresults"     "mysamples"     "Name"
## [25] "NSC.mean"      "pca"           "probesets"     "s3d"
## [29] "s3d.coords"    "Symbol"        "tmp"           "values"
```

```
#Show the full contents of the annotation package
```

```
ls("package:mouse4302.db")
```

```
## [1] "mouse4302"           "mouse4302_dbconn"      "mouse4302_dbfile"
## [4] "mouse4302_dbInfo"    "mouse4302_dbschema"    "mouse4302.db"
## [7] "mouse4302ACCNUM"     "mouse4302ALIAS2PROBE"  "mouse4302CHR"
## [10] "mouse4302CHRLNGTHS"  "mouse4302CHRLoc"       "mouse4302CHRLOCEND"
## [13] "mouse4302ENSEMBL"    "mouse4302ENSEMBL2PROBE" "mouse4302ENTREZID"
## [16] "mouse4302ENZYME"     "mouse4302ENZYME2PROBE" "mouse4302GENENAME"
## [19] "mouse4302GO"         "mouse4302GO2ALLPROBES" "mouse4302GO2PROBE"
## [22] "mouse4302MAPCOUNTS" "mouse4302MGI"          "mouse4302MGI2PROBE"
## [25] "mouse4302ORGANISM"   "mouse4302ORGPKG"       "mouse4302PATH"
## [28] "mouse4302PATH2PROBE" "mouse4302PFAM"         "mouse4302PMID"
## [31] "mouse4302PMID2PROBE" "mouse4302PROSITE"      "mouse4302REFSEQ"
## [34] "mouse4302SYMBOL"     "mouse4302UNIPROT"
```

```
#Show the annotation keys in this database
```

```
keytypes(mouse4302.db)
```

```
## [1] "ACCNUM"      "ALIAS"      "ENSEMBL"    "ENSEMBLPROT" "ENSEMBLTRANS"
## [6] "ENTREZID"    "ENZYME"    "EVIDENCE"   "EVIDENCEALL" "GENENAME"
## [11] "GENETYPE"    "GO"        "GOALL"     "IPI"        "MGI"
## [16] "ONTOLOGY"    "ONTOLOGYALL" "PATH"      "PFAM"       "PMID"
## [21] "PROBEID"    "PROSITE"   "REFSEQ"    "SYMBOL"     "UNIPROT"
```

```
sampleNames(eset)
```

```
## [1] "ESC.1" "ESC.2" "ESC.3" "iPS2.2" "iPS2.3" "NSC.1" "NSC.2" "iPS2.1"
## [9] "iPS4.1" "iPS4.2" "iPS.3"
```

Process annotation for functional enrichment

#Here we select from the annotation a number of keys with the primary key being PROBEID

```
res <- select(mouse4302.db, keys = rownames(eset), columns = c("ENTREZID", "ENSEMBL", "SYMBOL"), keytype = "PROBEID")
```

```
## 'select()' returned 1:many mapping between keys and columns
```

#View the top of the table

```
head(res)
```

```
##      PROBEID ENTREZID      ENSEMBL  SYMBOL
## 1  1415670_at   54161 ENSMUSG00000030058  Copg1
## 2  1415671_at   11972 ENSMUSG00000013160 Atp6v0d1
## 3  1415672_at   57437 ENSMUSG00000015341  Golga7
## 4  1415673_at  100678 ENSMUSG00000029446   Psph
## 5  1415674_a_at  60409 ENSMUSG00000032112 Trappc4
## 6  1415675_at  13481 ENSMUSG00000026810   Dpm2
```

#find the index of each row of the expression set in the #annotation object res

```
idx <- match(rownames(eset), res$PROBEID)
```

#Use the index to set the phenotypic data in the ExpressionSet

```
fData(eset) <- res[idx, ]
```

```
head(fData(eset), 10)
```

```
##      PROBEID ENTREZID      ENSEMBL  SYMBOL
## 1  1415670_at   54161 ENSMUSG00000030058  Copg1
## 2  1415671_at   11972 ENSMUSG00000013160 Atp6v0d1
## 3  1415672_at   57437 ENSMUSG00000015341  Golga7
## 4  1415673_at  100678 ENSMUSG00000029446   Psph
## 5  1415674_a_at  60409 ENSMUSG00000032112 Trappc4
## 6  1415675_at  13481 ENSMUSG00000026810   Dpm2
## 7  1415676_a_at  19173 ENSMUSG00000022193  Psmb5
## 8  1415677_at   52585 ENSMUSG00000002332  Dhrrs1
## 9  1415678_at   19042 ENSMUSG000000021096  Ppm1a
## 10 1415679_at   66340 ENSMUSG00000036835  Psenen
```

#Find all rows that don't have an EntreZID and remove them

```
eset_t<-eset[is.na(fData(eset)$ENTREZID)==0,]
```

Functional Enrichment Analysis

#convert to indexes

```
H.indices <- ids2indices(Mm.H, fData(eset_t)$ENTREZID)
```

#Pick the most suitable enrichment analysis tool to find #enrichment signatures in the data and run this

```
#I just run mroast here as an example- justify the selection of this method!
```

```
#if you want to run mroast
```

```
results <-mroast(eset_t,index=H.indices,design=design,contrast=contrastmatrix[,1],adjust.method = "BH")
```

```
#if you want to run camera
```

```
#results <-camera(eset_t,index=H.indices,design=design,contrast=contrastmatrix[,1],adjust.method = "BH")
```

```
#if you want to run romer
```

```
#results <-romer(eset_t,index=H.indices,design=design,contrast=contrastmatrix[,1],adjust.method = "BH")
```

```
#View the results
```

```
results
```

##	NGenes	PropDown	PropUp
## HALLMARK_MYC_TARGETS_V1	609	0.4548440	0.05582923
## HALLMARK_UNFOLDED_PROTEIN_RESPONSE	348	0.3477011	0.13793103
## HALLMARK_SPERMATOGENESIS	450	0.2422222	0.17333333
## HALLMARK_PROTEIN_SECRETION	327	0.1712538	0.32415902
## HALLMARK_APICAL_SURFACE	149	0.1073826	0.26174497
## HALLMARK_MYC_TARGETS_V2	128	0.5390625	0.07812500
## HALLMARK_ANGIOGENESIS	157	0.3375796	0.15286624
## HALLMARK_EPITHELIAL_MESENCHYMAL_TRANSITION	638	0.3652038	0.13949843
## HALLMARK_HEME_METABOLISM	628	0.1608280	0.27866242
## HALLMARK_PANCREAS_BETA_CELLS	131	0.2137405	0.12213740
## HALLMARK_ALLOGRAFT_REJECTION	553	0.2332731	0.13562387
## HALLMARK_G2M_CHECKPOINT	708	0.3206215	0.15677966
## HALLMARK_TNFA_SIGNALING_VIA_NFKB	529	0.2079395	0.29300567
## HALLMARK_E2F_TARGETS	596	0.3456376	0.13590604
## HALLMARK_INTERFERON_ALPHA_RESPONSE	256	0.2343750	0.14062500
## HALLMARK_P53_PATHWAY	612	0.1911765	0.26797386
## HALLMARK_COMPLEMENT	648	0.2330247	0.16512346
## HALLMARK_CHOLESTEROL_HOMEOSTASIS	200	0.2200000	0.29000000
## HALLMARK_APOPTOSIS	476	0.2689076	0.22478992
## HALLMARK_DNA_REPAIR	376	0.3164894	0.13829787
## HALLMARK_HEDGEHOG_SIGNALING	135	0.1851852	0.29629630
## HALLMARK_MITOTIC_SPINDLE	805	0.1913043	0.23105590
## HALLMARK_ESTROGEN_RESPONSE_LATE	561	0.1853832	0.27807487
## HALLMARK_MTORC1_SIGNALING	633	0.2654028	0.21484992
## HALLMARK_COAGULATION	364	0.2252747	0.16208791
## HALLMARK_UV_RESPONSE_UP	610	0.2442623	0.19672131
## HALLMARK_INTERFERON_GAMMA_RESPONSE	519	0.2177264	0.14643545
## HALLMARK_PI3K_AKT_MTOR_SIGNALING	391	0.2404092	0.18158568
## HALLMARK_APICAL_JUNCTION	729	0.2304527	0.17009602
## HALLMARK_ESTROGEN_RESPONSE_EARLY	654	0.2125382	0.27675841
## HALLMARK_INFLAMMATORY_RESPONSE	551	0.2050817	0.16333938
## HALLMARK_IL6_JAK_STAT3_SIGNALING	209	0.2248804	0.13397129
## HALLMARK_OXIDATIVE_PHOSPHORYLATION	455	0.2065934	0.25934066
## HALLMARK_REACTIVE_OXYGEN_SPECIES_PATHWAY	162	0.1666667	0.23456790
## HALLMARK_HYPOXIA	648	0.2114198	0.28086420
## HALLMARK_XENOBIOTIC_METABOLISM	563	0.2202487	0.23090586
## HALLMARK_GLYCOLYSIS	628	0.2531847	0.20382166
## HALLMARK_IL2_STAT5_SIGNALING	625	0.1984000	0.25600000
## HALLMARK_NOTCH_SIGNALING	115	0.2000000	0.21739130
## HALLMARK_TGF_BETA_SIGNALING	234	0.1965812	0.25641026
## HALLMARK_MYOGENESIS	692	0.2052023	0.23121387
## HALLMARK_ADIPOGENESIS	638	0.2288401	0.23197492

## HALLMARK_ANDROGEN_RESPONSE	396	0.2424242	0.22727273
## HALLMARK_PEROXISOME	336	0.2410714	0.21130952
## HALLMARK_BILE_ACID_METABOLISM	267	0.1985019	0.19101124
## HALLMARK_KRAS_SIGNALING_DN	712	0.1516854	0.14185393
## HALLMARK_KRAS_SIGNALING_UP	629	0.2289348	0.21144674
## HALLMARK_UV_RESPONSE_DN	751	0.2330226	0.21704394
## HALLMARK_FATTY_ACID_METABOLISM	438	0.2260274	0.20547945
## HALLMARK_WNT_BETA_CATENIN_SIGNALING	151	0.1788079	0.18543046
##	Direction	PValue	FDR
## HALLMARK_MYC_TARGETS_V1	Down	0.0010	0.01250000
## HALLMARK_UNFOLDED_PROTEIN_RESPONSE	Down	0.0010	0.01250000
## HALLMARK_SPERMATOGENESIS	Down	0.0010	0.01250000
## HALLMARK_PROTEIN_SECRETION	Up	0.0015	0.01562500
## HALLMARK_APICAL_SURFACE	Up	0.0020	0.01607143
## HALLMARK_MYC_TARGETS_V2	Down	0.0025	0.01607143
## HALLMARK_ANGIOGENESIS	Down	0.0025	0.01607143
## HALLMARK_EPITHELIAL_MESENCHYMAL_TRANSITION	Down	0.0035	0.01805556
## HALLMARK_HEME_METABOLISM	Up	0.0035	0.01805556
## HALLMARK_PANCREAS_BETA_CELLS	Down	0.0040	0.01875000
## HALLMARK_ALLOGRAFT_REJECTION	Down	0.0045	0.01931818
## HALLMARK_G2M_CHECKPOINT	Down	0.0070	0.02788462
## HALLMARK_TNFA_SIGNALING_VIA_NFKB	Up	0.0075	0.02788462
## HALLMARK_E2F_TARGETS	Down	0.0140	0.04910714
## HALLMARK_INTERFERON_ALPHA_RESPONSE	Down	0.0215	0.07083333
## HALLMARK_P53_PATHWAY	Up	0.0380	0.11796875
## HALLMARK_COMPLEMENT	Down	0.0500	0.14632353
## HALLMARK_CHOLESTEROL_HOMEOSTASIS	Up	0.0635	0.17569444
## HALLMARK_APOPTOSIS	Down	0.0700	0.18355263
## HALLMARK_DNA_REPAIR	Down	0.0830	0.20416667
## HALLMARK_HEDGEHOG_SIGNALING	Up	0.0860	0.20416667
## HALLMARK_MITOTIC_SPINDLE	Up	0.1235	0.28011364
## HALLMARK_ESTROGEN_RESPONSE_LATE	Up	0.1405	0.29218750
## HALLMARK_MTORC1_SIGNALING	Down	0.1405	0.29218750
## HALLMARK_COAGULATION	Down	0.1560	0.31150000
## HALLMARK_UV_RESPONSE_UP	Down	0.1675	0.32163462
## HALLMARK_INTERFERON_GAMMA_RESPONSE	Down	0.1835	0.33750000
## HALLMARK_PI3K_AKT_MTOR_SIGNALING	Down	0.1930	0.33750000
## HALLMARK_APICAL_JUNCTION	Down	0.2055	0.33750000
## HALLMARK_ESTROGEN_RESPONSE_EARLY	Up	0.2080	0.33750000
## HALLMARK_INFLAMMATORY_RESPONSE	Down	0.2095	0.33750000
## HALLMARK_IL6_JAK_STAT3_SIGNALING	Down	0.2260	0.35273437
## HALLMARK_OXIDATIVE_PHOSPHORYLATION	Up	0.2360	0.35719697
## HALLMARK_REACTIVE_OXYGEN_SPECIES_PATHWAY	Up	0.2485	0.36507353
## HALLMARK_HYPOXIA	Up	0.2940	0.41964286
## HALLMARK_XENOBIOTIC_METABOLISM	Up	0.3130	0.43437500
## HALLMARK_GLYCOLYSIS	Down	0.3335	0.45033784
## HALLMARK_IL2_STAT5_SIGNALING	Up	0.3495	0.45953947
## HALLMARK_NOTCH_SIGNALING	Down	0.5020	0.62708333
## HALLMARK_TGF_BETA_SIGNALING	Up	0.5145	0.62708333
## HALLMARK_MYOGENESIS	Up	0.5160	0.62708333
## HALLMARK_ADIPOGENESIS	Up	0.5270	0.62708333
## HALLMARK_ANDROGEN_RESPONSE	Up	0.5625	0.65377907
## HALLMARK_PEROXISOME	Down	0.5920	0.67244318
## HALLMARK_BILE_ACID_METABOLISM	Up	0.6820	0.75750000

## HALLMARK_KRAS_SIGNALING_DN	Down	0.6990	0.75951087
## HALLMARK_KRAS_SIGNALING_UP	Down	0.7675	0.81096939
## HALLMARK_UV_RESPONSE_DN	Down	0.7855	0.81096939
## HALLMARK_FATTY_ACID_METABOLISM	Down	0.7950	0.81096939
## HALLMARK_WNT_BETA_CATENIN_SIGNALING	Down	0.8265	0.82650000
##	PValue.Mixed	FDR.Mixed	
## HALLMARK_MYC_TARGETS_V1	5e-04	5e-04	
## HALLMARK_UNFOLDED_PROTEIN_RESPONSE	5e-04	5e-04	
## HALLMARK_SPERMATOGENESIS	5e-04	5e-04	
## HALLMARK_PROTEIN_SECRETION	5e-04	5e-04	
## HALLMARK_APICAL_SURFACE	5e-04	5e-04	
## HALLMARK_MYC_TARGETS_V2	1e-03	1e-03	
## HALLMARK_ANGIOGENESIS	5e-04	5e-04	
## HALLMARK_EPITHELIAL_MESENCHYMAL_TRANSITION	5e-04	5e-04	
## HALLMARK_HEME_METABOLISM	5e-04	5e-04	
## HALLMARK_PANCREAS_BETA_CELLS	5e-04	5e-04	
## HALLMARK_ALLOGRAFT_REJECTION	5e-04	5e-04	
## HALLMARK_G2M_CHECKPOINT	1e-03	1e-03	
## HALLMARK_TNFA_SIGNALING_VIA_NFKB	5e-04	5e-04	
## HALLMARK_E2F_TARGETS	5e-04	5e-04	
## HALLMARK_INTERFERON_ALPHA_RESPONSE	5e-04	5e-04	
## HALLMARK_P53_PATHWAY	5e-04	5e-04	
## HALLMARK_COMPLEMENT	5e-04	5e-04	
## HALLMARK_CHOLESTEROL_HOMEOSTASIS	5e-04	5e-04	
## HALLMARK_APOPTOSIS	5e-04	5e-04	
## HALLMARK_DNA_REPAIR	1e-03	1e-03	
## HALLMARK_HEDGEHOG_SIGNALING	5e-04	5e-04	
## HALLMARK_MITOTIC_SPINDLE	5e-04	5e-04	
## HALLMARK_ESTROGEN_RESPONSE_LATE	5e-04	5e-04	
## HALLMARK_MTORC1_SIGNALING	5e-04	5e-04	
## HALLMARK_COAGULATION	5e-04	5e-04	
## HALLMARK_UV_RESPONSE_UP	5e-04	5e-04	
## HALLMARK_INTERFERON_GAMMA_RESPONSE	5e-04	5e-04	
## HALLMARK_PI3K_AKT_MTOR_SIGNALING	5e-04	5e-04	
## HALLMARK_APICAL_JUNCTION	5e-04	5e-04	
## HALLMARK_ESTROGEN_RESPONSE_EARLY	5e-04	5e-04	
## HALLMARK_INFLAMMATORY_RESPONSE	5e-04	5e-04	
## HALLMARK_IL6_JAK_STAT3_SIGNALING	5e-04	5e-04	
## HALLMARK_OXIDATIVE_PHOSPHORYLATION	5e-04	5e-04	
## HALLMARK_REACTIVE_OXYGEN_SPECIES_PATHWAY	5e-04	5e-04	
## HALLMARK_HYPOXIA	5e-04	5e-04	
## HALLMARK_XENOBIOTIC_METABOLISM	5e-04	5e-04	
## HALLMARK_GLYCOLYSIS	5e-04	5e-04	
## HALLMARK_IL2_STAT5_SIGNALING	5e-04	5e-04	
## HALLMARK_NOTCH_SIGNALING	5e-04	5e-04	
## HALLMARK_TGF_BETA_SIGNALING	5e-04	5e-04	
## HALLMARK_MYOGENESIS	5e-04	5e-04	
## HALLMARK_ADIPOGENESIS	5e-04	5e-04	
## HALLMARK_ANDROGEN_RESPONSE	5e-04	5e-04	
## HALLMARK_PEROXISOME	5e-04	5e-04	
## HALLMARK_BILE_ACID_METABOLISM	5e-04	5e-04	
## HALLMARK_KRAS_SIGNALING_DN	5e-04	5e-04	
## HALLMARK_KRAS_SIGNALING_UP	5e-04	5e-04	
## HALLMARK_UV_RESPONSE_DN	5e-04	5e-04	


```
## HALLMARK_FATTY_ACID_METABOLISM          5e-04      5e-04
## HALLMARK_WNT_BETA_CATENIN_SIGNALING      1e-03      1e-03

#Use help for other parameters. Note we might decide to use #exactly the same model as our differential
#sv <- squeezeVar(fit$sigma^2,df=fit$df.residual)

write.table(results,"enrichment.txt",sep="\t")
#You can then examine the results in "enrichment.txt". It is a text file. It can be downloaded to view
```

Session Information

```
sessionInfo()

## R version 4.2.2 (2022-10-31)
## Platform: x86_64-pc-linux-gnu (64-bit)
## Running under: Ubuntu 22.04.4 LTS
##
## Matrix products: default
## BLAS:   /usr/lib/x86_64-linux-gnu/blas/libblas.so.3.10.0
## LAPACK: /usr/lib/x86_64-linux-gnu/lapack/liblapack.so.3.10.0
##
## locale:
##  [1] LC_CTYPE=en_US.UTF-8      LC_NUMERIC=C
##  [3] LC_TIME=en_US.UTF-8      LC_COLLATE=en_US.UTF-8
##  [5] LC_MONETARY=en_US.UTF-8  LC_MESSAGES=en_US.UTF-8
##  [7] LC_PAPER=en_US.UTF-8     LC_NAME=C
##  [9] LC_ADDRESS=C             LC_TELEPHONE=C
## [11] LC_MEASUREMENT=en_US.UTF-8 LC_IDENTIFICATION=C
##
## attached base packages:
## [1] stats4      stats      graphics  grDevices  utils      datasets  methods
## [8] base
##
## other attached packages:
##  [1] mouse4302cdf_2.18.0  scatterplot3d_0.3-43 mouse4302.db_3.13.0
##  [4] org.Mm.eg.db_3.16.0  annotate_1.76.0      XML_3.99-0.14
##  [7] AnnotationDbi_1.60.2 IRanges_2.32.0      S4Vectors_0.36.2
## [10] affy_1.76.0          Biobase_2.58.0      BiocGenerics_0.44.0
## [13] limma_3.54.2
##
## loaded via a namespace (and not attached):
##  [1] Rcpp_1.0.10          highr_0.10          compiler_4.2.2
##  [4] BiocManager_1.30.20  GenomeInfoDb_1.34.9 XVector_0.38.0
##  [7] bitops_1.0-7         tools_4.2.2         zlibbioc_1.44.0
## [10] digest_0.6.31        bit_4.0.5           RSQLite_2.3.0
## [13] evaluate_0.20        memoise_2.0.1       preprocessCore_1.60.2
## [16] pkgconfig_2.0.3      png_0.1-8           rlang_1.1.2
## [19] DBI_1.1.3            cli_3.6.1           rstudioapi_0.15.0
## [22] yaml_2.3.7           xfun_0.41           fastmap_1.1.1
## [25] GenomeInfoDbData_1.2.9 httr_1.4.5          knitr_1.42
## [28] Biostrings_2.66.0    vctrs_0.6.5         bit64_4.0.5
## [31] R6_2.5.1             rmarkdown_2.20      blob_1.2.4
## [34] htmltools_0.5.5      KEGGREST_1.38.0     xtable_1.8-4
## [37] RCurl_1.98-1.10     cachem_1.0.7        crayon_1.5.2
```

```
## [40] affyio_1.68.0
```