

Class 14 DESeq2 Mini Project

Nicole Alfonso, (PID: A16429176)

About our Input Data

The data for for hands-on session comes from GEO entry: [GSE37704](#), which is associated with the following publication:

- Trapnell C, Hendrickson DG, Sauvageau M, Goff L et al. “*Differential analysis of gene regulation at transcript resolution with RNA-seq*”. Nat Biotechnol 2013 Jan;31(1):46-53. [PMID: 23222703](#)

Section 1. Differential Expression Analysis

```
library(DESeq2)
```

```
Loading required package: S4Vectors
```

```
Loading required package: stats4
```

```
Loading required package: BiocGenerics
```

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

```
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
```

Attaching package: 'S4Vectors'

The following object is masked from 'package:utils':

```
findMatches
```

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

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

Loading required package: IRanges

Loading required package: GenomicRanges

Loading required package: GenomeInfoDb

Loading required package: SummarizedExperiment

Loading required package: MatrixGenerics

Loading required package: matrixStats

Attaching package: 'MatrixGenerics'

The following objects are masked from 'package:matrixStats':

```
colAlls, colAnyNAs, colAnys, colAvgsPerRowSet, colCollapse,
colCounts, colCummaxs, colCummins, colCumprods, colCumsums,
colDiffs, colIQRDiffs, colIQRs, colLogSumExps, colMadDiffs,
colMads, colMaxs, colMeans2, colMedians, colMins, colOrderStats,
colProds, colQuantiles, colRanges, colRanks, colSdDiffs, colSds,
colSums2, colTabulates, colVarDiffs, colVars, colWeightedMads,
colWeightedMeans, colWeightedMedians, colWeightedSds,
colWeightedVars, rowAlls, rowAnyNAs, rowAnys, rowAvgsPerColSet,
rowCollapse, rowCounts, rowCummaxs, rowCummins, rowCumprods,
rowCumsums, rowDiffs, rowIQRDiffs, rowIQRs, rowLogSumExps,
rowMadDiffs, rowMads, rowMaxs, rowMeans2, rowMedians, rowMins,
rowOrderStats, rowProds, rowQuantiles, rowRanges, rowRanks,
rowSdDiffs, rowSds, rowSums2, rowTabulates, rowVarDiffs, rowVars,
rowWeightedMads, rowWeightedMeans, rowWeightedMedians,
rowWeightedSds, rowWeightedVars
```

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")'.
```

Attaching package: 'Biobase'

The following object is masked from 'package:MatrixGenerics':

```
rowMedians
```

The following objects are masked from 'package:matrixStats':

```
anyMissing, rowMedians
```

```
metaFile <- "GSE37704_metadata.csv"
countFile <- "GSE37704_featurecounts.csv"
```

```
# Import metadata and take a peak
colData = read.csv(metaFile, row.names=1)
head(colData)
```

```
          condition
SRR493366 control_sirna
SRR493367 control_sirna
SRR493368 control_sirna
SRR493369      hoxa1_kd
SRR493370      hoxa1_kd
SRR493371      hoxa1_kd
```

```
# Import countdata
countData = read.csv(countFile, row.names=1)
head(countData)
```

```
          length SRR493366 SRR493367 SRR493368 SRR493369 SRR493370
ENSG00000186092    918         0         0         0         0         0
ENSG00000279928    718         0         0         0         0         0
ENSG00000279457   1982        23        28        29        29        28
ENSG00000278566    939         0         0         0         0         0
ENSG00000273547    939         0         0         0         0         0
ENSG00000187634   3214       124       123       205       207       212
          SRR493371
ENSG00000186092         0
ENSG00000279928         0
ENSG00000279457        46
ENSG00000278566         0
ENSG00000273547         0
ENSG00000187634       258
```

Q. Complete the code below to remove the troublesome first column from countData

```
# Note we need to remove the odd first $length col
countData <- as.matrix(countData[,-1])
head(countData)
```

```
          SRR493366 SRR493367 SRR493368 SRR493369 SRR493370 SRR493371
ENSG00000186092         0         0         0         0         0         0
```

ENSG00000279928	0	0	0	0	0	0
ENSG00000279457	23	28	29	29	28	46
ENSG00000278566	0	0	0	0	0	0
ENSG00000273547	0	0	0	0	0	0
ENSG00000187634	124	123	205	207	212	258

This looks better but there are lots of zero entries in there so let's get rid of them as we have no data for these.

Q. Complete the code below to filter `countData` to exclude genes (i.e. rows) where we have 0 read count across all samples (i.e. columns).

Tip: What will `rowSums()` of `countData` return and how could you use it in this context?

```
# Filter count data where you have 0 read count across all samples.
countData <- countData[rowSums(countData) > 0, ]
head(countData)
```

	SRR493366	SRR493367	SRR493368	SRR493369	SRR493370	SRR493371
ENSG00000279457	23	28	29	29	28	46
ENSG00000187634	124	123	205	207	212	258
ENSG00000188976	1637	1831	2383	1226	1326	1504
ENSG00000187961	120	153	180	236	255	357
ENSG00000187583	24	48	65	44	48	64
ENSG00000187642	4	9	16	14	16	16

Running DESeq2

Nice now lets setup the `DESeqDataSet` object required for the `DESeq()` function and then run the DESeq pipeline.

```
dds = DESeqDataSetFromMatrix(countData=countData,
                              colData=colData,
                              design=~condition)
```

Warning in `DESeqDataSet(se, design = design, ignoreRank)`: some variables in design formula are characters, converting to factors

```
dds = DESeq(dds)
```

estimating size factors

estimating dispersions

gene-wise dispersion estimates

mean-dispersion relationship

final dispersion estimates

fitting model and testing

```
dds
```

```
class: DESeqDataSet
dim: 15975 6
metadata(1): version
assays(4): counts mu H cooks
rownames(15975): ENSG00000279457 ENSG00000187634 ... ENSG00000276345
               ENSG00000271254
rowData names(22): baseMean baseVar ... deviance maxCooks
colnames(6): SRR493366 SRR493367 ... SRR493370 SRR493371
colData names(2): condition sizeFactor
```

Next, get results for the HoxA1 knockdown versus control siRNA (remember that these were labeled as “**hoxa1_kd**” and “**control_sirna**” in our original `colData` metaFile input to DESeq, you can check this above and by running `resultsNames(dds)` command).

```
res = results(dds, contrast=c("condition", "hoxa1_kd", "control_sirna"))
```

Q. Call the `summary()` function on your results to get a sense of how many genes are up or down-regulated at the default 0.1 p-value cutoff.

```
summary(res)
```

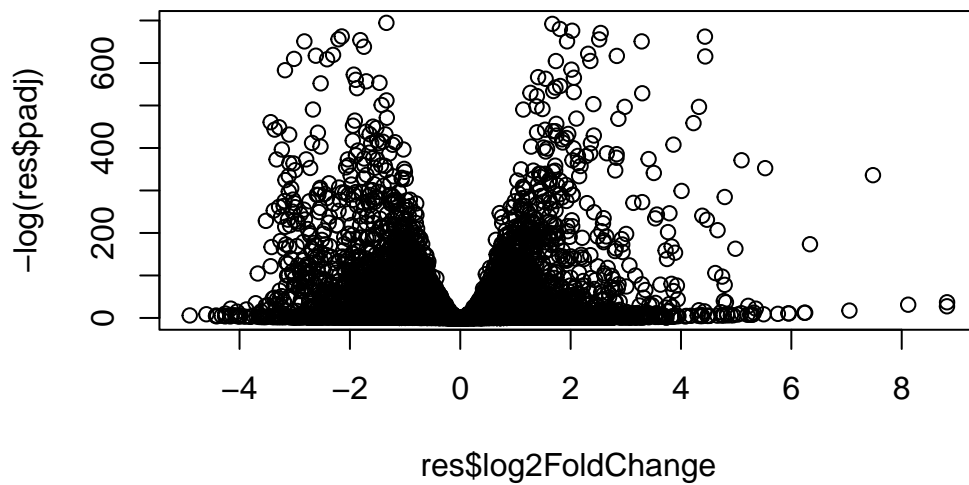
```

out of 15975 with nonzero total read count
adjusted p-value < 0.1
LFC > 0 (up)      : 4349, 27%
LFC < 0 (down)    : 4396, 28%
outliers [1]      : 0, 0%
low counts [2]    : 1237, 7.7%
(mean count < 0)
[1] see 'cooksCutoff' argument of ?results
[2] see 'independentFiltering' argument of ?results

```

Volcano Plot

```
plot( res$log2FoldChange, -log(res$padj) )
```



Q. Improve this plot by completing the below code, which adds color and axis labels

```

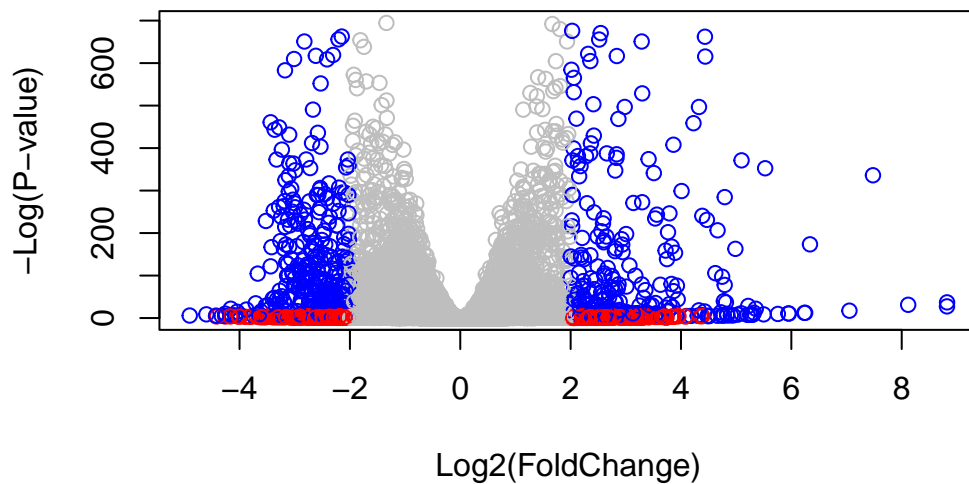
# Make a color vector for all genes
mycols <- rep("gray", nrow(res) )

```

```
# Color red the genes with absolute fold change above 2
mycols[ abs(res$log2FoldChange) > 2 ] <- "red"

# Color blue those with adjusted p-value less than 0.01
# and absolute fold change more than 2
inds <- (res$padj < 0.01) & (abs(res$log2FoldChange) > 2 )
mycols[ inds ] <- "blue"

plot( res$log2FoldChange, -log(res$padj), col=mycols, xlab="Log2(FoldChange)", ylab="-Log(
```



Adding gene annotation

Q. Use the `mapIDs()` function multiple times to add SYMBOL, ENTREZID and GENENAME annotation to our results by completing the code below.

```
library("AnnotationDbi")
library("org.Hs.eg.db")
```



```
columns(org.Hs.eg.db)
```

[1]	"ACCNUM"	"ALIAS"	"ENSEMBL"	"ENSEMBLPROT"	"ENSEMBLTRANS"
[6]	"ENTREZID"	"ENZYME"	"EVIDENCE"	"EVIDENCEALL"	"GENENAME"
[11]	"GENETYPE"	"GO"	"GOALL"	"IPI"	"MAP"
[16]	"OMIM"	"ONTOLOGY"	"ONTOLOGYALL"	"PATH"	"PFAM"
[21]	"PMID"	"PROSITE"	"REFSEQ"	"SYMBOL"	"UCSCKG"
[26]	"UNIPROT"				

```
res$symbol = mapIds(org.Hs.eg.db,  
  keys=row.names(res),  
  keytype="ENSEMBL",  
  column="SYMBOL",  
  multiVals="first")
```

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

```
res$entrez = mapIds(org.Hs.eg.db,  
  keys=row.names(res),  
  keytype="ENSEMBL",  
  column="ENTREZID",  
  multiVals="first")
```

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

```
res$name = mapIds(org.Hs.eg.db,  
  keys=row.names(res),  
  keytype="ENSEMBL",  
  column="GENENAME",  
  multiVals="first")
```

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

```
head(res, 10)
```

log2 fold change (MLE): condition hoxa1_kd vs control_sirna

Wald test p-value: condition hoxa1 kd vs control sirna

DataFrame with 10 rows and 9 columns

	baseMean	log2FoldChange	lfcSE	stat	pvalue
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
ENSG00000279457	29.913579	0.1792571	0.3248216	0.551863	5.81042e-01
ENSG00000187634	183.229650	0.4264571	0.1402658	3.040350	2.36304e-03
ENSG00000188976	1651.188076	-0.6927205	0.0548465	-12.630158	1.43989e-36
ENSG00000187961	209.637938	0.7297556	0.1318599	5.534326	3.12428e-08
ENSG00000187583	47.255123	0.0405765	0.2718928	0.149237	8.81366e-01
ENSG00000187642	11.979750	0.5428105	0.5215599	1.040744	2.97994e-01
ENSG00000188290	108.922128	2.0570638	0.1969053	10.446970	1.51282e-25
ENSG00000187608	350.716868	0.2573837	0.1027266	2.505522	1.22271e-02
ENSG00000188157	9128.439422	0.3899088	0.0467163	8.346304	7.04321e-17
ENSG00000237330	0.158192	0.7859552	4.0804729	0.192614	8.47261e-01
	padj	symbol	entrez	name	
	<numeric>	<character>	<character>	<character>	
ENSG00000279457	6.86555e-01	NA	NA	NA	
ENSG00000187634	5.15718e-03	SAMD11	148398	sterile alpha motif ..	
ENSG00000188976	1.76549e-35	NOC2L	26155	NOC2 like nucleolar ..	
ENSG00000187961	1.13413e-07	KLHL17	339451	kelch like family me..	
ENSG00000187583	9.19031e-01	PLEKHN1	84069	pleckstrin homology ..	
ENSG00000187642	4.03379e-01	PERM1	84808	PPARGC1 and ESRR ind..	
ENSG00000188290	1.30538e-24	HES4	57801	hes family bHLH tran..	
ENSG00000187608	2.37452e-02	ISG15	9636	ISG15 ubiquitin like..	
ENSG00000188157	4.21963e-16	AGRN	375790	agrin	
ENSG00000237330	NA	RNF223	401934	ring finger protein ..	

Q. Finally for this section let's reorder these results by adjusted p-value and save them to a CSV file in your current project directory.

```
res = res[order(res$pvalue),]  
write.csv(res, file = "deseq_results.csv", row.names = FALSE)
```

Section 2. Pathway Analysis

KEGG pathways

```
library(pathview)
```

```
#####
Pathview is an open source software package distributed under GNU General
Public License version 3 (GPLv3). Details of GPLv3 is available at
http://www.gnu.org/licenses/gpl-3.0.html. Particullary, users are required to
formally cite the original Pathview paper (not just mention it) in publications
or products. For details, do citation("pathview") within R.
```

The pathview downloads and uses KEGG data. Non-academic uses may require a KEGG license agreement (details at <http://www.kegg.jp/kegg/legal.html>).

```
#####
```

```
library(gage)
```

```
library(gageData)
```

```
data(kegg.sets.hs)
data(sigmet.idx.hs)
```

```
# Focus on signaling and metabolic pathways only
kegg.sets.hs = kegg.sets.hs[sigmet.idx.hs]
```

```
# Examine the first 3 pathways
head(kegg.sets.hs, 3)
```

```
$`hsa00232 Caffeine metabolism`
```

```
[1] "10" "1544" "1548" "1549" "1553" "7498" "9"
```

```
$`hsa00983 Drug metabolism - other enzymes`
```

```
[1] "10" "1066" "10720" "10941" "151531" "1548" "1549" "1551"
[9] "1553" "1576" "1577" "1806" "1807" "1890" "221223" "2990"
[17] "3251" "3614" "3615" "3704" "51733" "54490" "54575" "54576"
[25] "54577" "54578" "54579" "54600" "54657" "54658" "54659" "54963"
[33] "574537" "64816" "7083" "7084" "7172" "7363" "7364" "7365"
[41] "7366" "7367" "7371" "7372" "7378" "7498" "79799" "83549"
[49] "8824" "8833" "9" "978"
```

```
$`hsa00230 Purine metabolism`
```

```
[1] "100" "10201" "10606" "10621" "10622" "10623" "107" "10714"
```

```

[9] "108"      "10846"    "109"      "111"      "11128"    "11164"    "112"      "113"
[17] "114"      "115"      "122481"   "122622"   "124583"   "132"      "158"      "159"
[25] "1633"     "171568"   "1716"     "196883"   "203"      "204"      "205"      "221823"
[33] "2272"     "22978"    "23649"    "246721"   "25885"    "2618"     "26289"    "270"
[41] "271"      "27115"    "272"      "2766"     "2977"     "2982"     "2983"     "2984"
[49] "2986"     "2987"     "29922"    "3000"     "30833"    "30834"    "318"      "3251"
[57] "353"      "3614"     "3615"     "3704"     "377841"   "471"      "4830"     "4831"
[65] "4832"     "4833"     "4860"     "4881"     "4882"     "4907"     "50484"    "50940"
[73] "51082"    "51251"    "51292"    "5136"     "5137"     "5138"     "5139"     "5140"
[81] "5141"     "5142"     "5143"     "5144"     "5145"     "5146"     "5147"     "5148"
[89] "5149"     "5150"     "5151"     "5152"     "5153"     "5158"     "5167"     "5169"
[97] "51728"    "5198"     "5236"     "5313"     "5315"     "53343"    "54107"    "5422"
[105] "5424"     "5425"     "5426"     "5427"     "5430"     "5431"     "5432"     "5433"
[113] "5434"     "5435"     "5436"     "5437"     "5438"     "5439"     "5440"     "5441"
[121] "5471"     "548644"   "55276"    "5557"     "5558"     "55703"    "55811"    "55821"
[129] "5631"     "5634"     "56655"    "56953"    "56985"    "57804"    "58497"    "6240"
[137] "6241"     "64425"    "646625"   "654364"   "661"      "7498"     "8382"     "84172"
[145] "84265"    "84284"    "84618"    "8622"     "8654"     "87178"    "8833"     "9060"
[153] "9061"     "93034"    "953"      "9533"     "954"      "955"      "956"      "957"
[161] "9583"     "9615"

```

```

foldchanges = res$log2FoldChange
names(foldchanges) = res$entrez
head(foldchanges)

```

```

      1266      54855      1465      51232      2034      2317
-2.422719  3.201955 -2.313738 -2.059631 -1.888019 -1.649792

```

```

# Get the results
keggres = gage(foldchanges, gsets=kegg.sets.hs)

```

```

attributes(keggres)

```

```

$names
[1] "greater" "less"    "stats"

```

```

# Look at the first few down (less) pathways
head(keggres$less)

```

	p.geomean	stat.mean	p.val
hsa04110 Cell cycle	8.995727e-06	-4.378644	8.995727e-06
hsa03030 DNA replication	9.424076e-05	-3.951803	9.424076e-05
hsa03013 RNA transport	1.375901e-03	-3.028500	1.375901e-03
hsa03440 Homologous recombination	3.066756e-03	-2.852899	3.066756e-03
hsa04114 Oocyte meiosis	3.784520e-03	-2.698128	3.784520e-03
hsa00010 Glycolysis / Gluconeogenesis	8.961413e-03	-2.405398	8.961413e-03

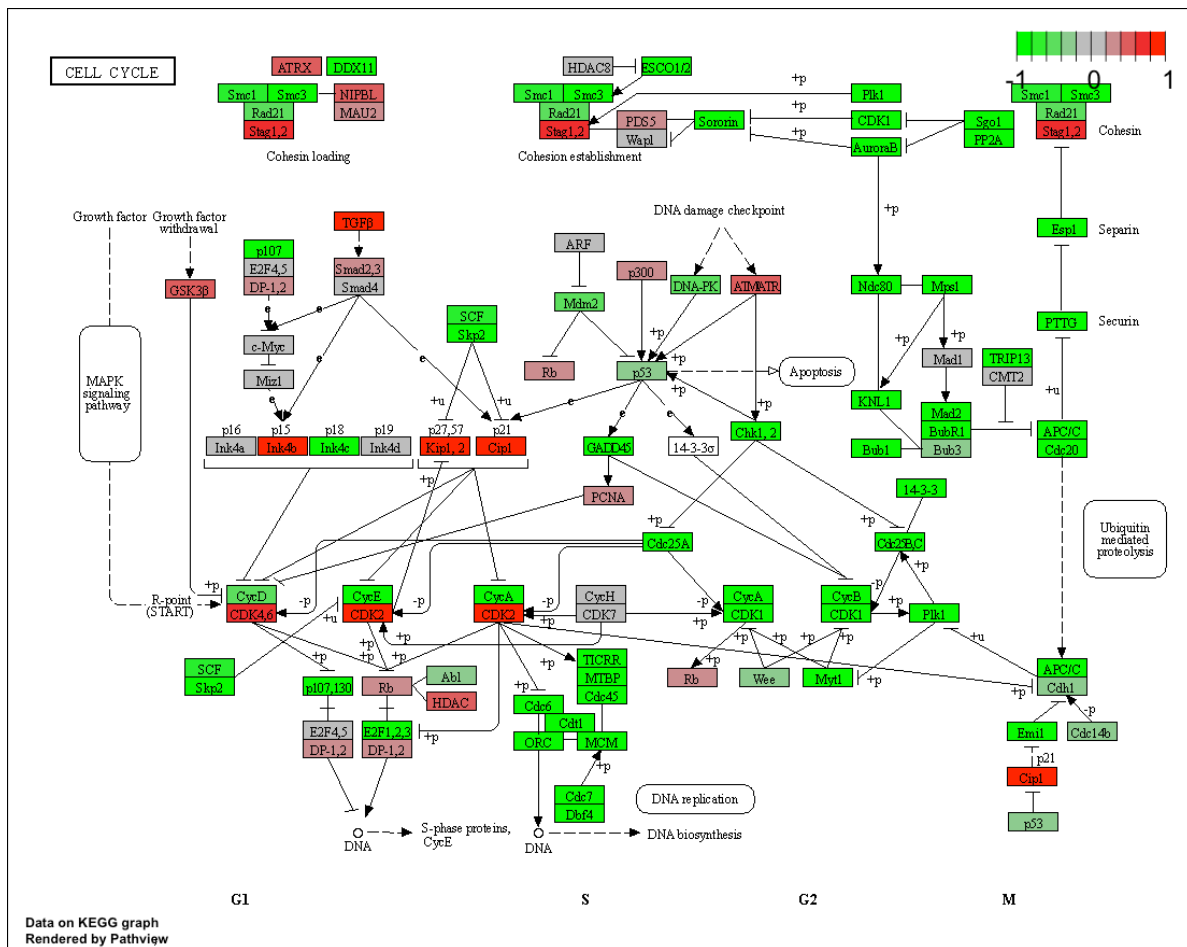
	q.val	set.size	exp1
hsa04110 Cell cycle	0.001448312	121	8.995727e-06
hsa03030 DNA replication	0.007586381	36	9.424076e-05
hsa03013 RNA transport	0.073840037	144	1.375901e-03
hsa03440 Homologous recombination	0.121861535	28	3.066756e-03
hsa04114 Oocyte meiosis	0.121861535	102	3.784520e-03
hsa00010 Glycolysis / Gluconeogenesis	0.212222694	53	8.961413e-03

```
pathview(gene.data=foldchanges, pathway.id="hsa04110")
```

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

Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa04110.pathview.png



Focus on top 5 upregulated pathways here for demo purposes only

```
keggrespathways <- rownames(keggres$greater)[1:5]
```

Extract the 8 character long IDs part of each string

```
keggresids = substr(keggrespathways, start=1, stop=8)
```

```
keggresids
```

```
[1] "hsa04640" "hsa04630" "hsa00140" "hsa04142" "hsa04330"
```

```
pathview(gene.data=foldchanges, pathway.id=keggresids, species="hsa")
```

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

Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa04640.pathview.png

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

Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa04630.pathview.png

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

Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa00140.pathview.png

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

Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

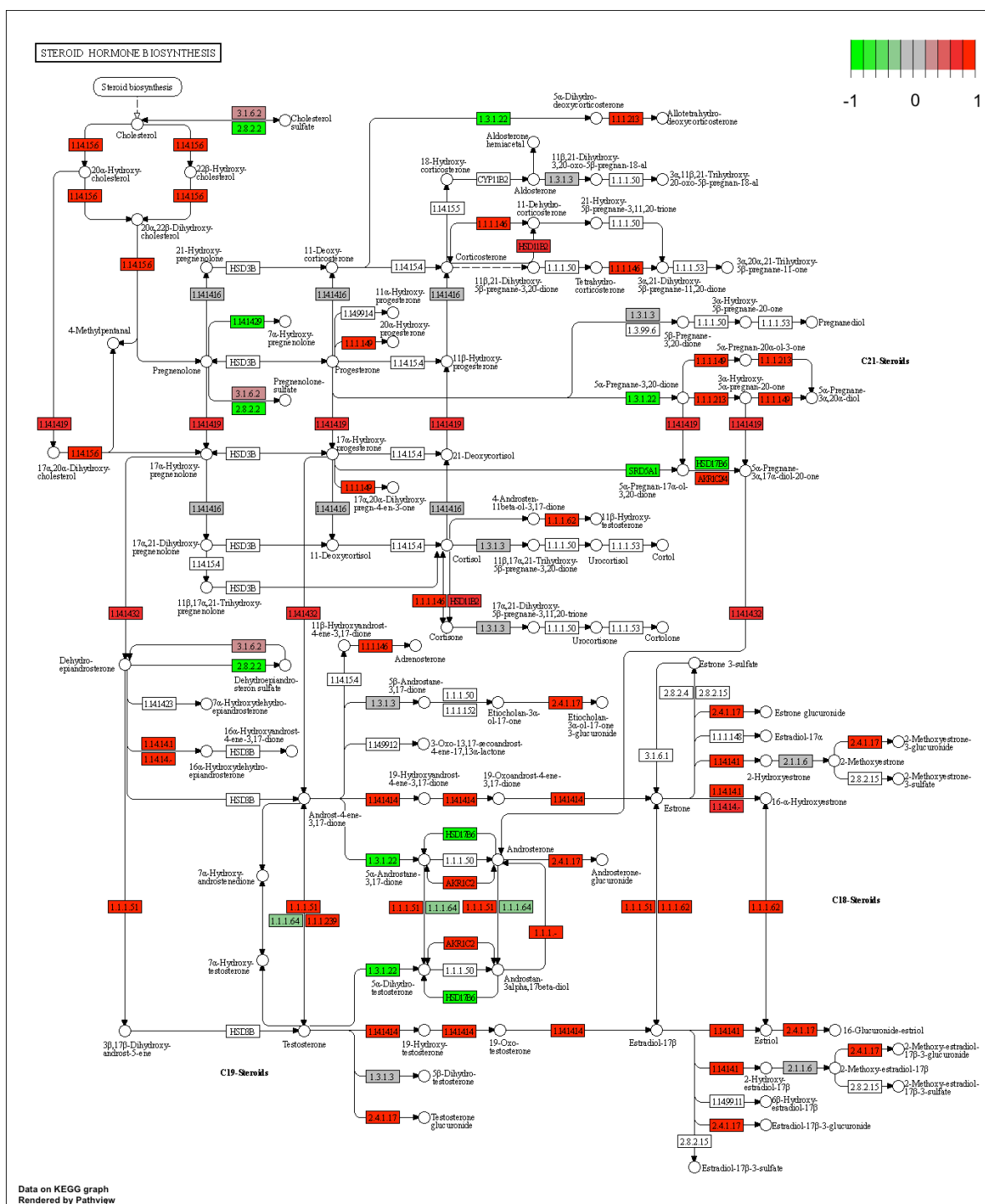
Info: Writing image file hsa04142.pathview.png

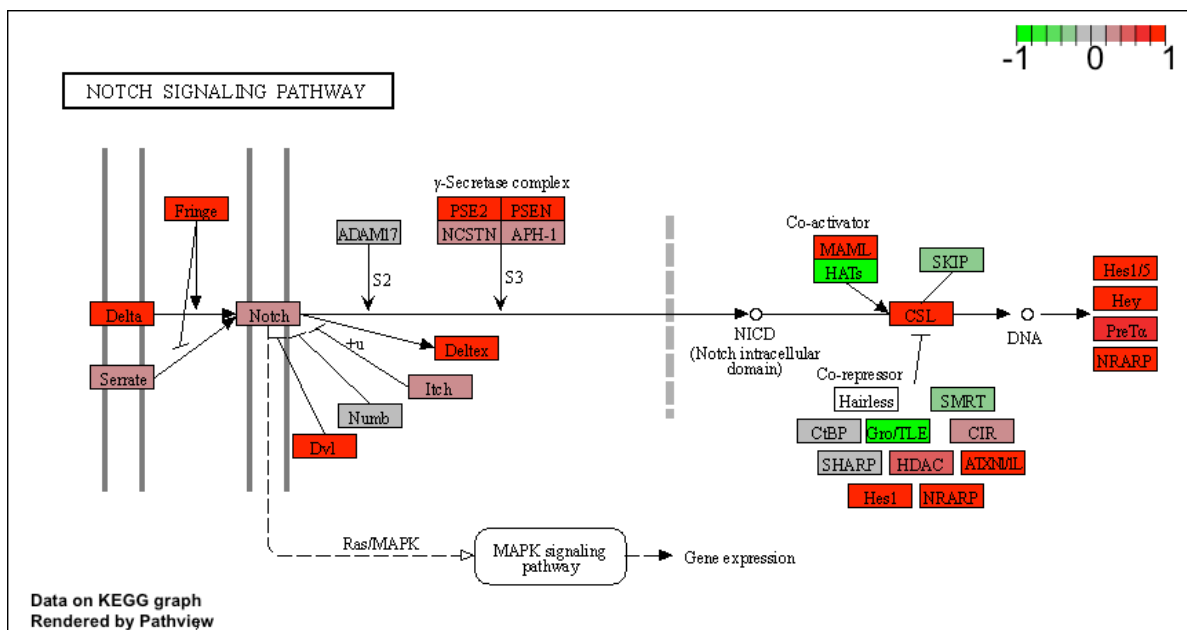
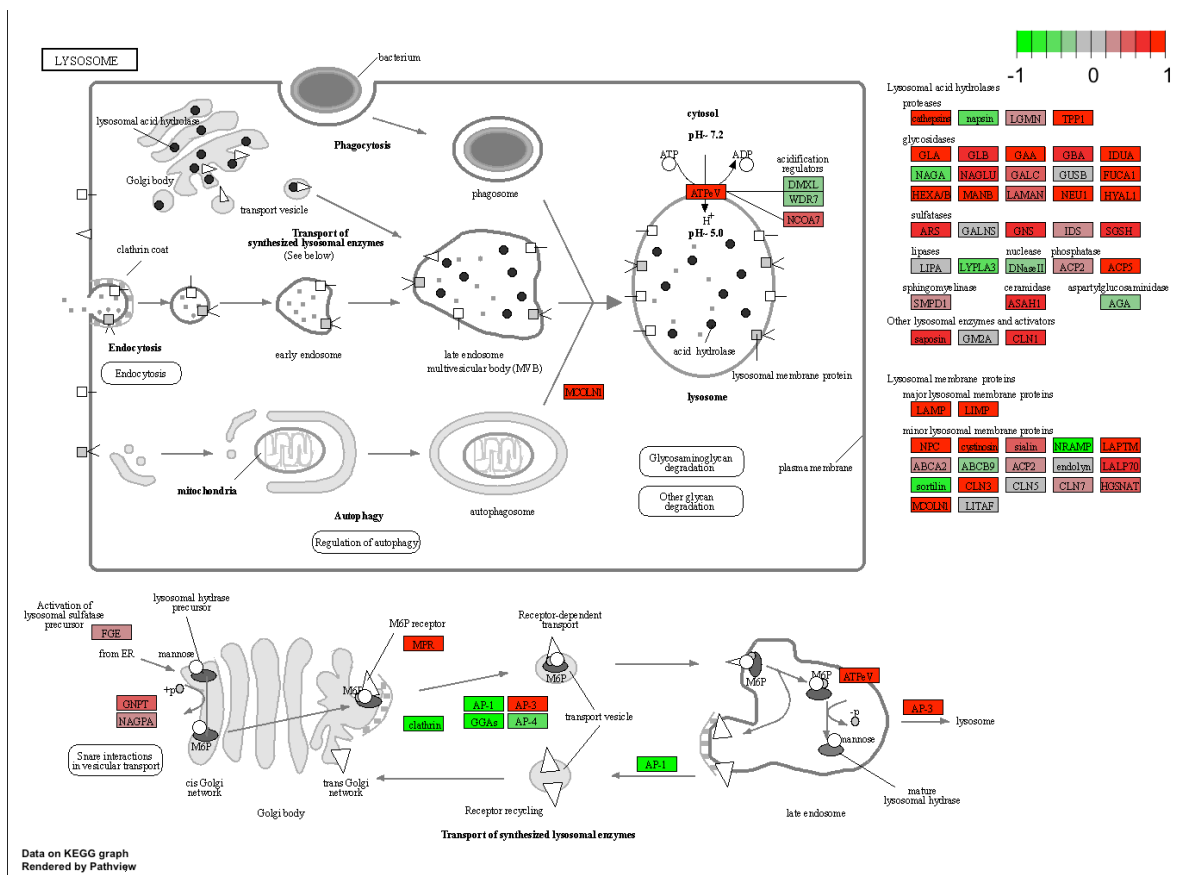
Info: some node width is different from others, and hence adjusted!

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

Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa04330.pathview.png





Q. Can you do the same procedure as above to plot the pathview figures for the top 5 down-regulated pathways?

```
keggrespathways <- rownames(keggres$less)[1:5]
```

```
# Extract the 8 character long IDs part of each string
keggresids = substr(keggrespathways, start=1, stop=8)
keggresids
```

```
[1] "hsa04110" "hsa03030" "hsa03013" "hsa03440" "hsa04114"
```

```
pathview(gene.data=foldchanges, pathway.id=keggresids, species="hsa")
```

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

Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa04110.pathview.png

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

Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa03030.pathview.png

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

Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa03013.pathview.png

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

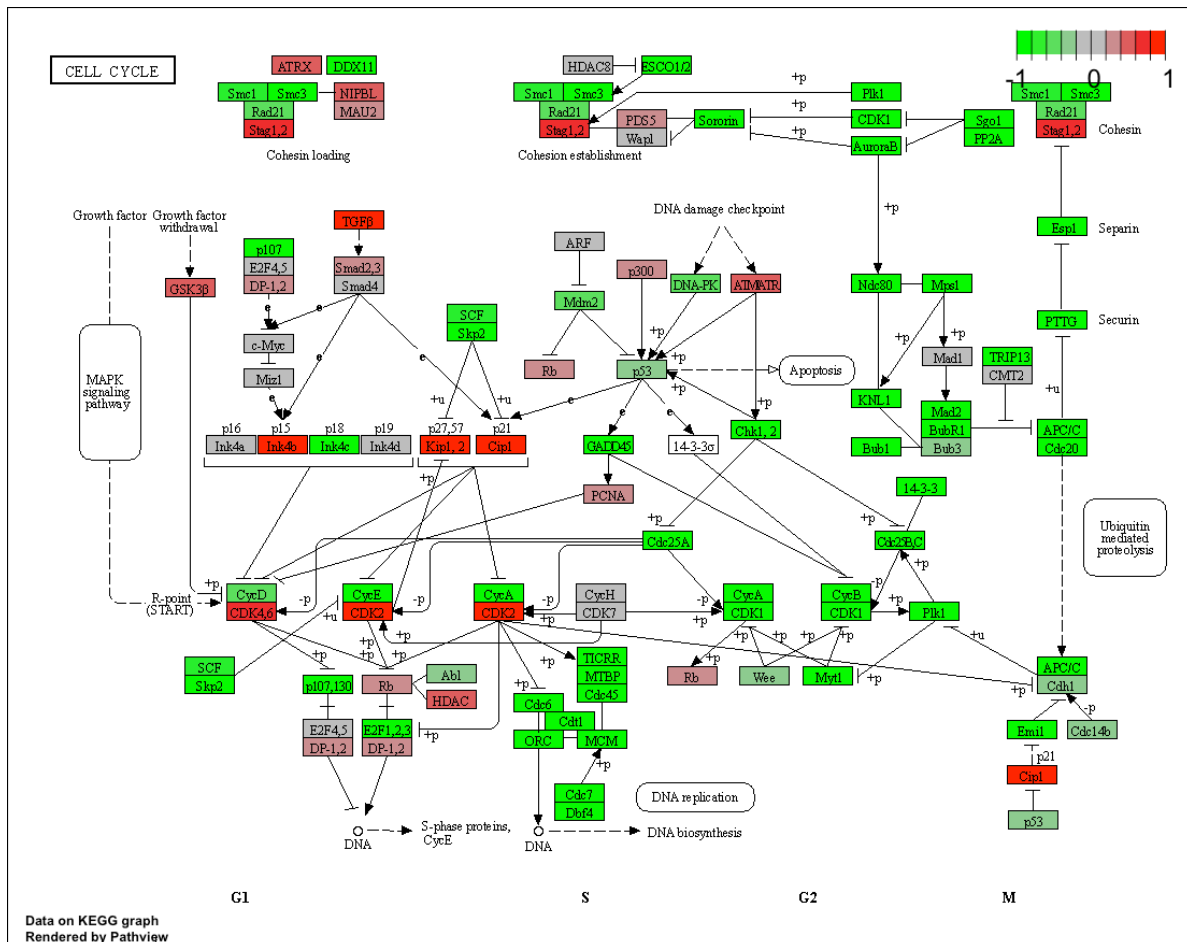
Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa03440.pathview.png

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

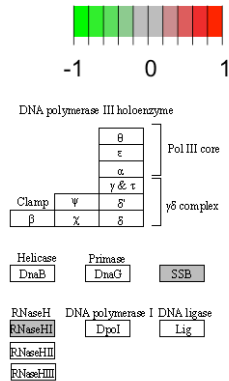
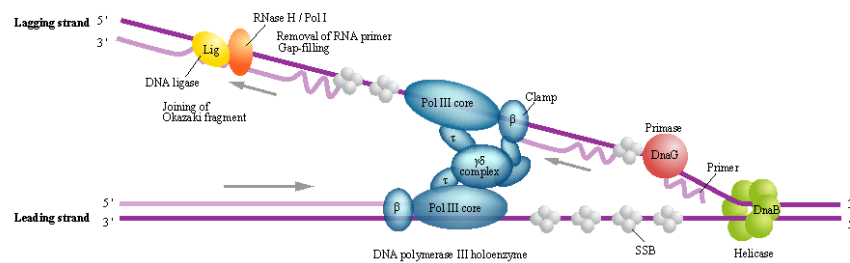
Info: Working in directory /Users/francesnicolealfonso/BIMM143/class14

Info: Writing image file hsa04114.pathview.png

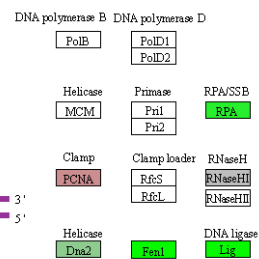
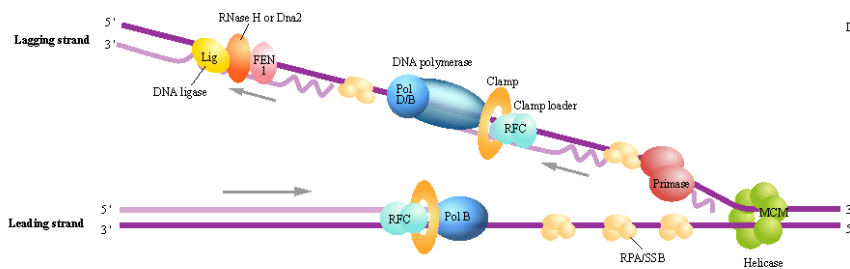


DNA REPLICATION

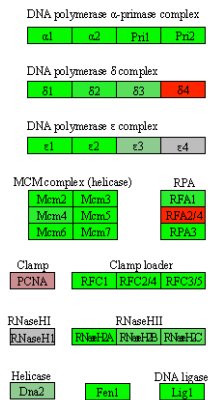
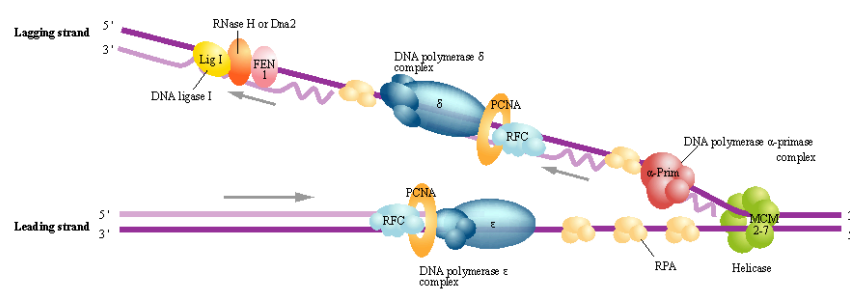
Replication complex (Bacteria)



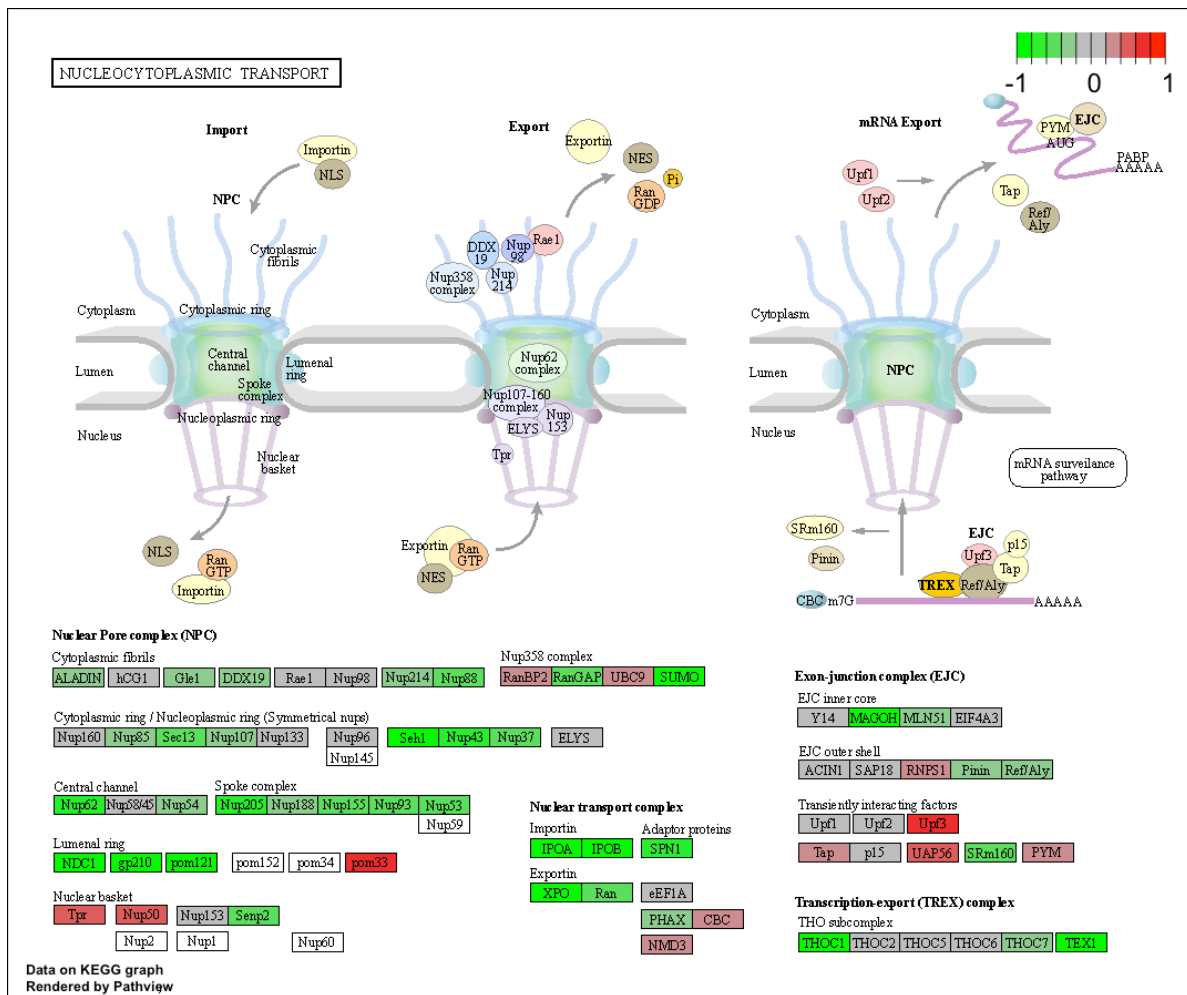
Replication complex (Archaea)



Replication complex (Eukaryotes)



Data on KEGG graph
Rendered by Pathview



G0:0002009	morphogenesis of an epithelium	1.396681e-04	3.653886	1.396681e-04
G0:0048729	tissue morphogenesis	1.432451e-04	3.643242	1.432451e-04
G0:0007610	behavior	1.925222e-04	3.565432	1.925222e-04
G0:0060562	epithelial tube morphogenesis	5.932837e-04	3.261376	5.932837e-04
G0:0035295	tube development	5.953254e-04	3.253665	5.953254e-04

		q.val	set.size	exp1
G0:0007156	homophilic cell adhesion	0.1952430	113	8.519724e-05
G0:0002009	morphogenesis of an epithelium	0.1952430	339	1.396681e-04
G0:0048729	tissue morphogenesis	0.1952430	424	1.432451e-04
G0:0007610	behavior	0.1968058	426	1.925222e-04
G0:0060562	epithelial tube morphogenesis	0.3566193	257	5.932837e-04
G0:0035295	tube development	0.3566193	391	5.953254e-04

\$less

		p.geomean	stat.mean	p.val
G0:0048285	organelle fission	1.536227e-15	-8.063910	1.536227e-15
G0:0000280	nuclear division	4.286961e-15	-7.939217	4.286961e-15
G0:0007067	mitosis	4.286961e-15	-7.939217	4.286961e-15
G0:0000087	M phase of mitotic cell cycle	1.169934e-14	-7.797496	1.169934e-14
G0:0007059	chromosome segregation	2.028624e-11	-6.878340	2.028624e-11
G0:0000236	mitotic prometaphase	1.729553e-10	-6.695966	1.729553e-10

		q.val	set.size	exp1
G0:0048285	organelle fission	5.843127e-12	376	1.536227e-15
G0:0000280	nuclear division	5.843127e-12	352	4.286961e-15
G0:0007067	mitosis	5.843127e-12	352	4.286961e-15
G0:0000087	M phase of mitotic cell cycle	1.195965e-11	362	1.169934e-14
G0:0007059	chromosome segregation	1.659009e-08	142	2.028624e-11
G0:0000236	mitotic prometaphase	1.178690e-07	84	1.729553e-10

\$stats

		stat.mean	exp1
G0:0007156	homophilic cell adhesion	3.824205	3.824205
G0:0002009	morphogenesis of an epithelium	3.653886	3.653886
G0:0048729	tissue morphogenesis	3.643242	3.643242
G0:0007610	behavior	3.565432	3.565432
G0:0060562	epithelial tube morphogenesis	3.261376	3.261376
G0:0035295	tube development	3.253665	3.253665

Section 4. Reactome Analysis

```
sig_genes <- res[res$padj <= 0.05 & !is.na(res$padj), "symbol"]
print(paste("Total number of significant genes:", length(sig_genes)))
```

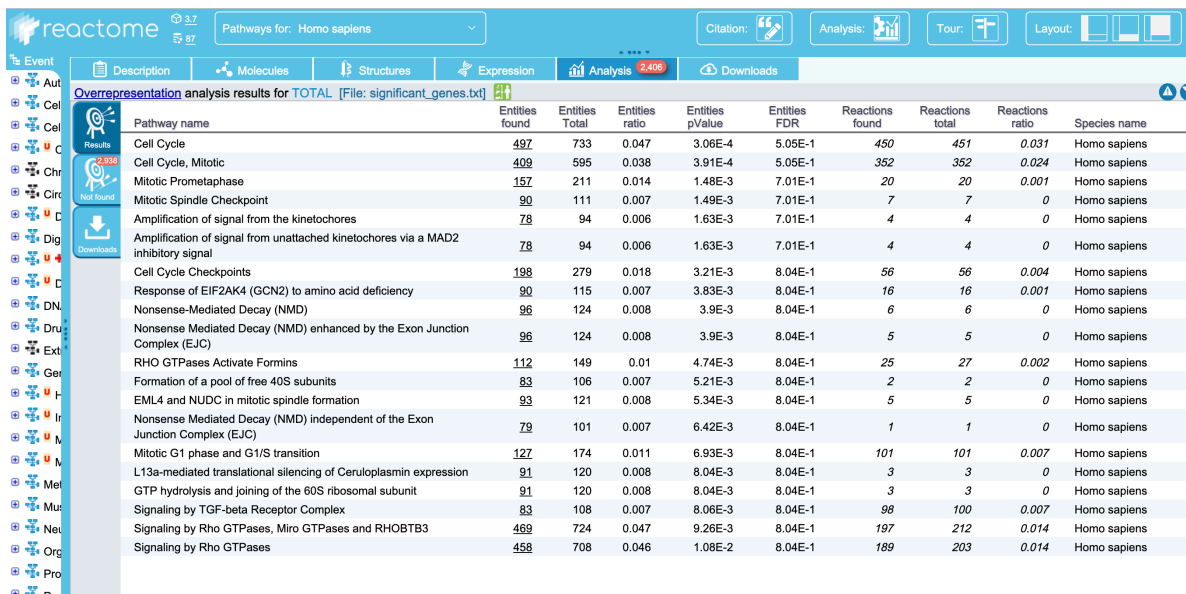
```
[1] "Total number of significant genes: 8147"
```

```
write.table(sig_genes, file="significant_genes.txt", row.names=FALSE, col.names=FALSE, quo
```

Then, to perform pathway analysis online go to the Reactome website (<https://reactome.org/PathwayBrowser/#TOOL=AT>). Select “choose file” to upload your significant gene list. Then, select the parameters “Project to Humans”, then click “Analyze”.

Q. What pathway has the most significant “Entities p-value”? Do the most significant pathways listed match your previous KEGG results? What factors could cause differences between the two methods?

The most significant pathway is “Cell Cycle”. The most significant pathways do relatively match our previous KESS results as it only matches the top result \$less, but not \$greater.



The screenshot shows the Reactome Pathway Browser interface. The top navigation bar includes the Reactome logo, version 3.7, and a dropdown menu for 'Pathways for: Homo sapiens'. There are buttons for 'Citation', 'Analysis' (with a red badge showing '2,406'), 'Tour', and 'Layout'. Below the navigation bar, the main content area displays 'Overrepresentation analysis results for TOTAL [File: significant_genes.txt]'. A table lists various pathways with columns for Pathway name, Entities found, Entities Total, Entities ratio, Entities pValue, Entities FDR, Reactions found, Reactions total, Reactions ratio, and Species name. The pathways are sorted by p-value, with 'Cell Cycle' being the most significant.

Pathway name	Entities found	Entities Total	Entities ratio	Entities pValue	Entities FDR	Reactions found	Reactions total	Reactions ratio	Species name
Cell Cycle	497	733	0.047	3.06E-4	5.05E-1	450	451	0.031	Homo sapiens
Cell Cycle, Mitotic	409	595	0.038	3.91E-4	5.05E-1	352	352	0.024	Homo sapiens
Mitotic Prometaphase	157	211	0.014	1.48E-3	7.01E-1	20	20	0.001	Homo sapiens
Mitotic Spindle Checkpoint	90	111	0.007	1.49E-3	7.01E-1	7	7	0	Homo sapiens
Amplification of signal from the kinetochores	78	94	0.006	1.63E-3	7.01E-1	4	4	0	Homo sapiens
Amplification of signal from unattached kinetochores via a MAD2 inhibitory signal	78	94	0.006	1.63E-3	7.01E-1	4	4	0	Homo sapiens
Cell Cycle Checkpoints	198	279	0.018	3.21E-3	8.04E-1	56	56	0.004	Homo sapiens
Response of EIF2AK4 (GCN2) to amino acid deficiency	90	115	0.007	3.83E-3	8.04E-1	16	16	0.001	Homo sapiens
Nonsense-Mediated Decay (NMD)	96	124	0.008	3.9E-3	8.04E-1	6	6	0	Homo sapiens
Nonsense Mediated Decay (NMD) enhanced by the Exon Junction Complex (EJC)	96	124	0.008	3.9E-3	8.04E-1	5	5	0	Homo sapiens
RHO GTPases Activate Formins	112	149	0.01	4.74E-3	8.04E-1	25	27	0.002	Homo sapiens
Formation of a pool of free 40S subunits	83	106	0.007	5.21E-3	8.04E-1	2	2	0	Homo sapiens
EML4 and NUDC in mitotic spindle formation	93	121	0.008	5.34E-3	8.04E-1	5	5	0	Homo sapiens
Nonsense Mediated Decay (NMD) independent of the Exon Junction Complex (EJC)	79	101	0.007	6.42E-3	8.04E-1	1	1	0	Homo sapiens
Mitotic G1 phase and G1/S transition	127	174	0.011	6.93E-3	8.04E-1	101	101	0.007	Homo sapiens
L13a-mediated translational silencing of Ceruloplasmin expression	91	120	0.008	8.04E-3	8.04E-1	3	3	0	Homo sapiens
GTP hydrolysis and joining of the 60S ribosomal subunit	91	120	0.008	8.04E-3	8.04E-1	3	3	0	Homo sapiens
Signaling by TGF-beta Receptor Complex	83	108	0.007	8.06E-3	8.04E-1	98	100	0.007	Homo sapiens
Signaling by Rho GTPases, Miro GTPases and RHOBTB3	469	724	0.047	9.26E-3	8.04E-1	197	212	0.014	Homo sapiens
Signaling by Rho GTPases	458	708	0.046	1.08E-2	8.04E-1	189	203	0.014	Homo sapiens