systemPipeR: NGS workflow and report generation environment

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1 Introduction

systemPipeR provides utilities for building *end-to-end* analysis workflows with automated report generation for next generation sequence (NGS) applications such as RNA-Seq, ChIP-Seq, BS-Seq, VAR-Seq and many others (Girke, 2014). An important feature is support for running command-line software, such as NGS aligners, on both single machines or compute clusters. This includes both interactive job submissions or batch submissions to queuing systems of clusters (tested only with Torque). For instance, *systemPipeR* can be used with most command-line aligners such as `BWA` (Li, 2013; Li and Durbin, 2009), `TopHat 2` (Kim et al., 2013) and `Bowtie 2` (Langmead and Salzberg, 2012), as well as the R-based NGS aligner *Rsubread* (Liao et al., 2013). Efficient handling of complex sample sets and experimental designs is facilitated by a well-defined sample annotation infrastructure which improves reproducibility and user-friendliness of many typical analysis workflows in the NGS area (Lawrence et al., 2013).

Templates for setting up custom project reports are provided as `*.Rnw` files in the `vignettes` subdirectory of this package. The corresponding PDFs of these report templates are linked here: systemPipeRNAseq, systemPipeChIPseq and systemPipeVARseq.

Contents

2 Getting Started

2.1 Installation

The R software can be downloaded from CRAN (http://cran.at.r-project.org/) and the *systemPipeR* package from GitHub (https://github.com/tgirke/systemPipeR). The *systemPipeR* package can be installed from R using the `install.packages` command after downloading and uncompressing the package directory.

```
> system("R CMD build systemPipeR") # Builds package
> install.packages("systemPipeR.X.X.X.tar.gz", repos=NULL, type="source") # Installs the package
```

2.2 Loading the Package and Documentation

```
> library("systemPipeR") # Loads the package
> library(help="systemPipeR") # Lists all functions and classes
> vignette("systemPipeR") # Opens this PDF manual from R
```

2.3 Sample FASTQ Files

The mini sample FASTQ files used by this overview vignette as well as the associated workflow reporting vignettes can be downloaded from here. The chosen data set SRP010938 contains 18 paired-end (PE) read sets from *Arabidposis thaliana* (Howard et al., 2013). To minimize processing time during testing, each FASTQ file has been subsetted to 90,000-100,000 random sampled PE reads that map to the first 100,000 nucleotides of each chromosome of the *A. thalina* genome. The corresponding reference genome sequence (FASTA) and its GFF annotion files (provided in the same download) have been truncated accordingly. This way the entire test sample data set is less than 200MB in storage space. A PE read set has been chosen for this test data set for flexibility, because it can be used for testing both types of analysis routines requiring either SE (single end) reads or PE reads.

3 Structure of `targets` file

The `targets` file defines all FASTQ files and sample comparisons of an analysis workflow. The following shows the format of a sample `targets` file provided by this package.

```
> library(systemPipeR)
> targetspath <- paste0(system.file("extdata", package="systemPipeR"), "/targets.txt")
> read.delim(targetspath, comment.char = "#")
```

```
                  FileName SampleName Factor SampleLong Experiment        Date
1  ./data/SRR446027_1.fastq        M1A     M1  Mock.1h.A          1 23-Mar-2012
2  ./data/SRR446028_1.fastq        M1B     M1  Mock.1h.B          1 23-Mar-2012
3  ./data/SRR446029_1.fastq        A1A     A1   Avr.1h.A          1 23-Mar-2012
4  ./data/SRR446030_1.fastq        A1B     A1   Avr.1h.B          1 23-Mar-2012
5  ./data/SRR446031_1.fastq        V1A     V1   Vir.1h.A          1 23-Mar-2012
6  ./data/SRR446032_1.fastq        V1B     V1   Vir.1h.B          1 23-Mar-2012
7  ./data/SRR446033_1.fastq        M6A     M6  Mock.6h.A          1 23-Mar-2012
8  ./data/SRR446034_1.fastq        M6B     M6  Mock.6h.B          1 23-Mar-2012
9  ./data/SRR446035_1.fastq        A6A     A6   Avr.6h.A          1 23-Mar-2012
10 ./data/SRR446036_1.fastq        A6B     A6   Avr.6h.B          1 23-Mar-2012
11 ./data/SRR446037_1.fastq        V6A     V6   Vir.6h.A          1 23-Mar-2012
12 ./data/SRR446038_1.fastq        V6B     V6   Vir.6h.B          1 23-Mar-2012
13 ./data/SRR446039_1.fastq       M12A    M12 Mock.12h.A          1 23-Mar-2012
14 ./data/SRR446040_1.fastq       M12B    M12 Mock.12h.B          1 23-Mar-2012
15 ./data/SRR446041_1.fastq       A12A    A12  Avr.12h.A          1 23-Mar-2012
16 ./data/SRR446042_1.fastq       A12B    A12  Avr.12h.B          1 23-Mar-2012
17 ./data/SRR446043_1.fastq       V12A    V12  Vir.12h.A          1 23-Mar-2012
18 ./data/SRR446044_1.fastq       V12B    V12  Vir.12h.B          1 23-Mar-2012
```

Structure of `targets` file for paired end (PE) samples.

```
> library(systemPipeR)
> targetspath <- paste0(system.file("extdata", package="systemPipeR"), "/targetsPE.txt")
> read.delim(targetspath, comment.char = "#")[1:2,1:6]
```

```
                FileName1                FileName2 SampleName Factor SampleLong Experiment
1 ./data/SRR446027_1.fastq ./data/SRR446027_2.fastq        M1A     M1  Mock.1h.A          1
2 ./data/SRR446028_1.fastq ./data/SRR446028_2.fastq        M1B     M1  Mock.1h.B          1
```

Comparisons are defined in the header lines of the `targets` starting with '# <CMP>'. The function `readComp` imports the comparison and stores them in a `list`.

```
> readComp(file=targetspath, format="vector", delim="-")
```

```
$CMPset1
[1] "M1-A1"   "M1-V1"   "A1-V1"   "M6-A6"   "M6-V6"   "A6-V6"   "M12-A12" "M12-V12" "A12-V12"

$CMPset2
 [1] "M1-A1"   "M1-V1"   "M1-M6"   "M1-A6"   "M1-V6"   "M1-M12"  "M1-A12"  "M1-V12"  "A1-V1"
[10] "A1-M6"   "A1-A6"   "A1-V6"   "A1-M12"  "A1-A12"  "A1-V12"  "V1-M6"   "V1-A6"   "V1-V6"
[19] "V1-M12"  "V1-A12"  "V1-V12"  "M6-A6"   "M6-V6"   "M6-M12"  "M6-A12"  "M6-V12"  "A6-V6"
[28] "A6-M12"  "A6-A12"  "A6-V12"  "V6-M12"  "V6-A12"  "V6-V12"  "M12-A12" "M12-V12" "A12-V12"
```

4 Structure of param file and SYSargs container

The param file defines the parameters of the command-line software. The following shows the format of a sample param file provided by this package.

```
> parampath <- paste0(system.file("extdata", package="systemPipeR"), "/tophat.param")
> read.delim(parampath, comment.char = "#")
```

```
     PairSet         Name                                Value
1    modules         <NA>                 bowtie2/2.1.0
2    modules         <NA>                 tophat/2.0.8b
3   software         <NA>                        tophat
```

```
4      cores           -p                                    4
5      other         <NA> -g 1 --segment-length 25 -i 30 -I 3000
6   outfile1           -o                                <FileName1>
7   outfile1         path                                 ./results/
8   outfile1       remove                                       <NA>
9   outfile1       append                                    .tophat
10  outfile1 outextension                .tophat/accepted_hits.bam
11 reference         <NA>                      ./data/tair10.fasta
12  infile1          <NA>                                <FileName1>
13  infile1          path                                       <NA>
14  infile2          <NA>                                <FileName2>
15  infile2          path                                       <NA>
```

The systemArgs function imports the definitions of both the param file and the targets file, and stores all relevant information as SYSargs object.

```
> args <- systemArgs(sysma=parampath, mytargets=targetspath)
> args
```

```
An instance of 'SYSargs' for running 'tophat' on 18 samples
```

Several accessor functions are available that are named after the slot names of the SYSargs object class.

```
> names(args)
```

```
 [1] "modules"   "software"  "cores"     "other"     "reference" "results"   "infile1"
 [8] "infile2"   "outfile1"  "sysargs"   "outpaths"
```

```
> modules(args)
```

```
[1] "bowtie2/2.1.0" "tophat/2.0.8b"
```

```
> cores(args)
```

```
[1] 4
```

```
> outpaths(args)[1]
```

```
                                                                                                                M1A
"/rhome/tgirke/Projects/github/systemPipeR/vignettes/results/SRR446027_1.fastq.tophat/accepted_hits.bam"
```

```
> sysargs(args)[1]
```

```
"tophat -p 4 -g 1 --segment-length 25 -i 30 -I 3000 -o /rhome/tgirke/Projects/github/systemPipeR/vignettes/
```

The content of the param file can be returned as JSON object as follows (requires *rjson* package).

```
> systemArgs(sysma=parampath, mytargets=targetspath, type="json")
```

```
[1] "{\"modules\":{\"n1\":\"\",\"v2\":\"bowtie2/2.1.0\",\"n1\":\"\",\"v2\":\"tophat/2.0.8b\"},\"software\"
```

5 Workflow

5.1 Define environment settings and samples

Load package:

```
> library(systemPipeR)
```

Construct SYSargs object from param and targets files.

```
> args <- systemArgs(sysma="tophat.param", mytargets="targetsPE.txt")
```

5.2 FASTQ quality report

The following seeFastq and seeFastqPlot functions generate and plot a series of useful quality statistics for a set of FASTQ files including per cycle quality box plots, base proportions, base-level quality trends, relative k-mer diversity, length and occurrence distribution of reads, number of reads above quality cutoffs and mean quality distribution.

```
> fqlist <- seeFastq(fastq=infile1(args), batchsize=10000, klength=8)
> pdf("./results/fastqReport.pdf", height=18, width=4*length(fqlist))
> seeFastqPlot(fqlist)
> dev.off()
```

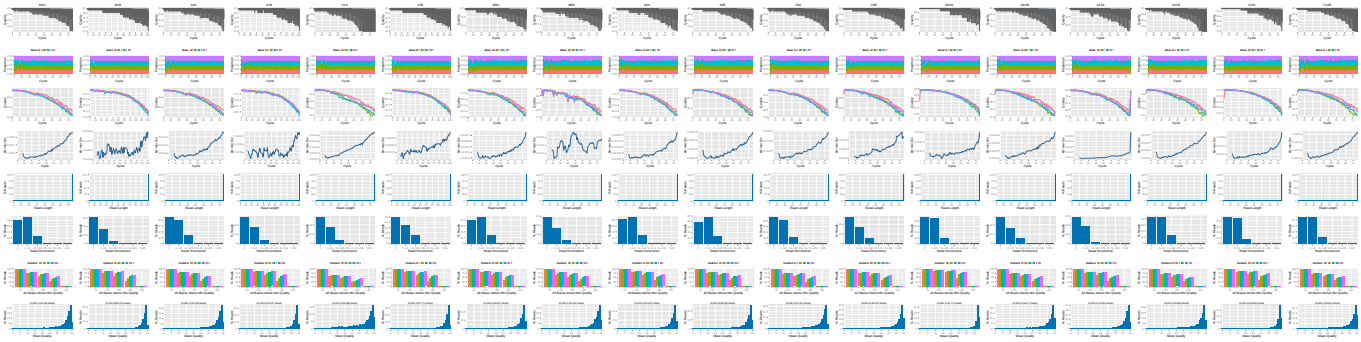

Figure 1: QC report for 18 FASTQ files.

5.3 Alignment with Tophat 2

Build Bowtie 2 index.

```
> moduleload(modules(args)) # Skip if module system is not available
> system("bowtie2-build ./data/tair10.fasta ./data/tair10.fasta")
```

Execute SYSargs on a single machine without submitting to a queuing system of a compute cluster. This way the input FASTQ files will be processed sequentially. If available, multiple CPU cores can be used for processing each file. The number of CPU cores (here 4) to use for each process is defined in the *.param file. With cores(args) one can return this value from the SYSargs object.

```
> bampaths <- runCommandline(args=args)
```

Alternatively, the computation can be greatly acclerated by processing many files in parallel using several compute nodes of a cluster, where a scheduling/queuing system is used for load balancing. To avoid oversubscription of CPU cores on each compute node, the value from cores(args) is passed on to the submission command, here cores under getQsubargs. The number or independent parallel qsub processes is defined under in the Nqsubs argument. The following example will run 18 processes in parallel using for each 4 CPU cores. If the resources available on a cluster allow to run all 18 processes at the same time then the shown sample submission will utilize in total 72 CPU cores.

```
> qsubargs <- getQsubargs(queue="batch", cores=cores(args), memory="mem=10gb", time="walltime=20:00:00")
> (joblist <- qsubRun(args=args, qsubargs=qsubargs, Nqsubs=18, package="systemPipeR"))
```

Alignment Stats

```
> read_statsDF <- alignStats(args, fqgz=TRUE)
> write.table(read_statsDF, "results/alignStats.xls", row.names=FALSE, quote=FALSE, sep="\t")
```

5.4 Create symbolic links for viewing BAM files in IGV

```
> symLink2bam(sysargs=args, htmldir=c("~/.html/", "somedir/"),
+             urlbase="http://myserver.edu/~username/",
+             urlfile="IGVurl.txt")
```

5.5 Alignment with Bowtie 2 (here for miRNA profiling experiment)

Run as single process without submitting to cluster, e.g. via qsub -I.

```
> args <- systemArgs(sysma="bowtieSE.param", mytargets="targets.txt")
> bampaths <- runCommandline(args=args)
```

Submit to compute nodes

```
> qsubargs <- getQsubargs(queue="batch", cores=cores(args), memory="mem=10gb", time="walltime=20:00:00")
> (joblist <- qsubRun(args=args, qsubargs=qsubargs, Nqsubs=18, package="systemPipeR"))
```

5.6 Read counting for mRNA profiling experiments

Create txdb (do only once)

```
> library(GenomicFeatures)
> txdb <- makeTranscriptDbFromGFF(file="data/tair10.gff", format="gff", dataSource="TAIR", species="A. thal
> saveDb(txdb, file="./data/tair10.sqlite")
```

Read counting with summarizeOverlaps in parallel mode with multiple cores

```
> library(BiocParallel)
> txdb <- loadDb("./data/tair10.sqlite")
> eByg <- exonsBy(txdb, by="gene")
> bfl <- BamFileList(outpaths(args), yieldSize=50000, index=character())
> multicoreParam <- MulticoreParam(workers=4); register(multicoreParam); registered()
> counteByg <- bplapply(bfl, function(x) summarizeOverlaps(eByg, x, mode="Union", ignore.strand=TRUE, inter
> countDFeByg <- sapply(seq(along=counteByg), function(x) assays(counteByg[[x]])$counts)
> rownames(countDFeByg) <- names(rowData(counteByg[[1]])); colnames(countDFeByg) <- names(bfl)
> rpkmDFeByg <- apply(countDFeByg, 2, function(x) returnRPKM(counts=x, ranges=eByg))
> write.table(countDFeByg, "results/countDFeByg.xls", col.names=NA, quote=FALSE, sep="\t")
> write.table(rpkmDFeByg, "results/rpkmDFeByg.xls", col.names=NA, quote=FALSE, sep="\t")
```

5.7 Read counting for miRNA profiling experiments

Download miRNA genes from miRBase

```
> system("wget ftp://mirbase.org/pub/mirbase/19/genomes/My_species.gff3 -P ./data/")
> gff <- import.gff("./data/My_species.gff3", asRangedData=FALSE)
> gff <- split(gff, elementMetadata(gff)$ID)
> bams <- names(bampaths); names(bams) <- targets$SampleName
> bfl <- BamFileList(bams, yieldSize=50000, index=character())
> countDFmiR <- summarizeOverlaps(gff, bfl, mode="Union", ignore.strand=FALSE, inter.feature=FALSE) # Note
> rpkmDFmiR <- apply(countDFmiR, 2, function(x) returnRPKM(counts=x, gffsub=gff))
> write.table(assays(countDFmiR)$counts, "results/countDFmiR.xls", col.names=NA, quote=FALSE, sep="\t")
> write.table(rpkmDFmiR, "results/rpkmDFmiR.xls", col.names=NA, quote=FALSE, sep="\t")
```

5.8 Correlation analysis of samples

The following computes the sample-wise Spearman correlation coefficients from the RPKM normalized expresssion values. After transformation to a distance matrix, hierarchical clustring is performed with the `hclust` function and the result is plotted as a dendrogram (sample_tree.pdf).

```
> library(ape)
> rpkmDFeByg <- read.table("./results/rpkmDFeByg.xls", check.names=FALSE)
> rpkmDFeByg <- rpkmDFeByg[rowMeans(rpkmDFeByg) > 50,]
> d <- cor(rpkmDFeByg, method="spearman")
> hc <- hclust(as.dist(1-d))
> plot.phylo(as.phylo(hc), type="p", edge.col="blue", edge.width=2, show.node.label=TRUE, no.margin=TRUE)
```

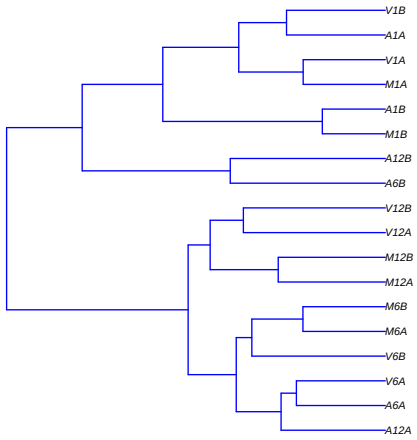

Figure 2: Correlation dendrogram of samples.

5.9 DEG analysis with edgeR

```
> library(edgeR)
> targets <- read.delim(targetspath, comment="#")
> cmp <- readComp(file=targetspath, format="matrix", delim="-")
> cmp[[1]]
```

```
      [,1]  [,2]
 [1,] "M1"  "A1"
 [2,] "M1"  "V1"
 [3,] "A1"  "V1"
 [4,] "M6"  "A6"
 [5,] "M6"  "V6"
 [6,] "A6"  "V6"
 [7,] "M12" "A12"
 [8,] "M12" "V12"
 [9,] "A12" "V12"
```

Run *edgeR*

```
> countDFeByg <- read.delim("./results/countDFeByg.xls", row.names=1)
> edgeDF <- run_edgeR(countDF=countDFeByg, targets=targets, cmp=cmp[[1]], independent=FALSE, mdsplot="")
```

Filter and plot DEG results for up and down regulated genes. Because of the toy sample set used in this vignette, the FDR value has been set to a relatively high threshold (here 10%). More commonly used FDR cutoffs are 1% or 5%.

```
> DEG_list <- filterDEGs(degDF=edgeDF, filter=c(Fold=2, FDR=10))
```

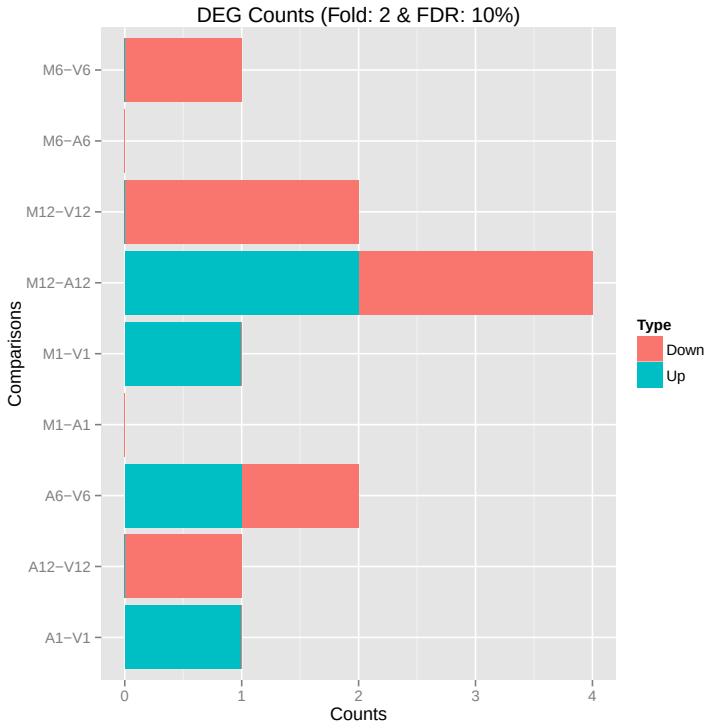

Figure 3: Up and down regulated DEGs.

```
> names(DEG_list)
> DEG_list$Summary
```

5.10 GO term enrichment analysis of DEGs

5.10.1 Obtain gene-to-GO mappings

The following shows how to obtain gene-to-GO mappings from *biomaRt* (here for *A. thaliana*) and how to organize them for the downstream GO term enrichment analysis. Alternatively, the gene-to-GO mappings can be obtained for many organisms from Bioconductor's `*.db` genome annotation packages or GO annotation files provided by various genome databases. For each annotation this relatively slow preprocessing step needs to be performed only once. Subsequently, the preprocessed data can be loaded with the `loadData` function as shown in the next subsection.

```
> library("biomaRt")
> listMarts() # To choose BioMart database
> m <- useMart("ENSEMBL_MART_PLANT"); listDatasets(m)
> m <- useMart("ENSEMBL_MART_PLANT", dataset="athaliana_eg_gene")
> listAttributes(m) # Choose data types you want to download
> go <- getBM(attributes=c("go_accession", "tair_locus", "go_namespace_1003"), mart=m)
> go <- go[go[,3]!="",]; go[,3] <- as.character(go[,3])
> go[go[,3]=="molecular_function", 3] <- "F"; go[go[,3]=="biological_process", 3] <- "P"; go[go[,3]=="cellu
> go[1:4,]
> dir.create("./data/GO")
> write.table(go, "data/GO/GOannotationsBiomart_mod.txt", quote=FALSE, row.names=FALSE, col.names=FALSE, se
```

```
> readGOorg(myfile = "data/GO/GOannotationsBiomart_mod.txt", outdir="data/GO", org="", colno = c(1,2,3))
> gene2GOlist(outdir="data/GO", rootUK=FALSE)
```

5.10.2 Batch GO term enrichment analysis

Apply the enrichment analysis to the DEG sets obtained the above differential expression analysis. Note in the following example the FDR filter is set here to an unreasonably high value, simply because of the small size of the toy data set used in this vignette. Batch enrichment analysis of many gene sets is performed with the GOCluster_Report function. When method="all", it returns all GO terms passing the p-value cutoff specified under the cutoff arguments. When method="slim", it returns only the GO terms specified under the myslimv argument. The given example shows how a GO slim vector for a specific organism can be obtained from BioMart.

```
> loadData("data/GO")
> DEG_list <- filterDEGs(degDF=edgeDF, filter=c(Fold=2, FDR=50), plot=FALSE)
> up_down <- DEG_list$UporDown; names(up_down) <- paste(names(up_down), "_up_down", sep="")
> up <- DEG_list$Up; names(up) <- paste(names(up), "_up", sep="")
> down <- DEG_list$Down; names(down) <- paste(names(down), "_down", sep="")
> DEGlist <- c(up_down, up, down)
> DEGlist <- DEGlist[sapply(DEGlist, length) > 0]
> BatchResult <- GOCluster_Report(setlist=DEGlist, method="all", id_type="gene", CLSZ=2, cutoff=0.9, gocats
> library("biomaRt"); m <- useMart("ENSEMBL_MART_PLANT", dataset="athaliana_eg_gene")
> goslimvec <- as.character(getBM(attributes=c("goslim_goa_accession"), mart=m)[,1])
> BatchResultslim <- GOCluster_Report(setlist=DEGlist, method="slim", id_type="gene", myslimv=goslimvec, C
```

5.10.3 Plot batch GO term results

The data.frame generated by GOCluster_Report can be plotted with the goBarplot function. Because of the variable size of the sample sets, it may not always be desirable to show the results from different DEG sets in the same bar plot. Plotting single sample sets is achieved by subsetting the input data frame as shown in the first line of the following example.

```
> gos <- BatchResultslim[grep("M6-V6_up_down", BatchResultslim$CLID), ]
> gos <- BatchResultslim
> pdf("GOslimbarplotMF.pdf", height=8, width=10); goBarplot(gos, gocat="MF"); dev.off()
> goBarplot(gos, gocat="BP")
> goBarplot(gos, gocat="CC")
```

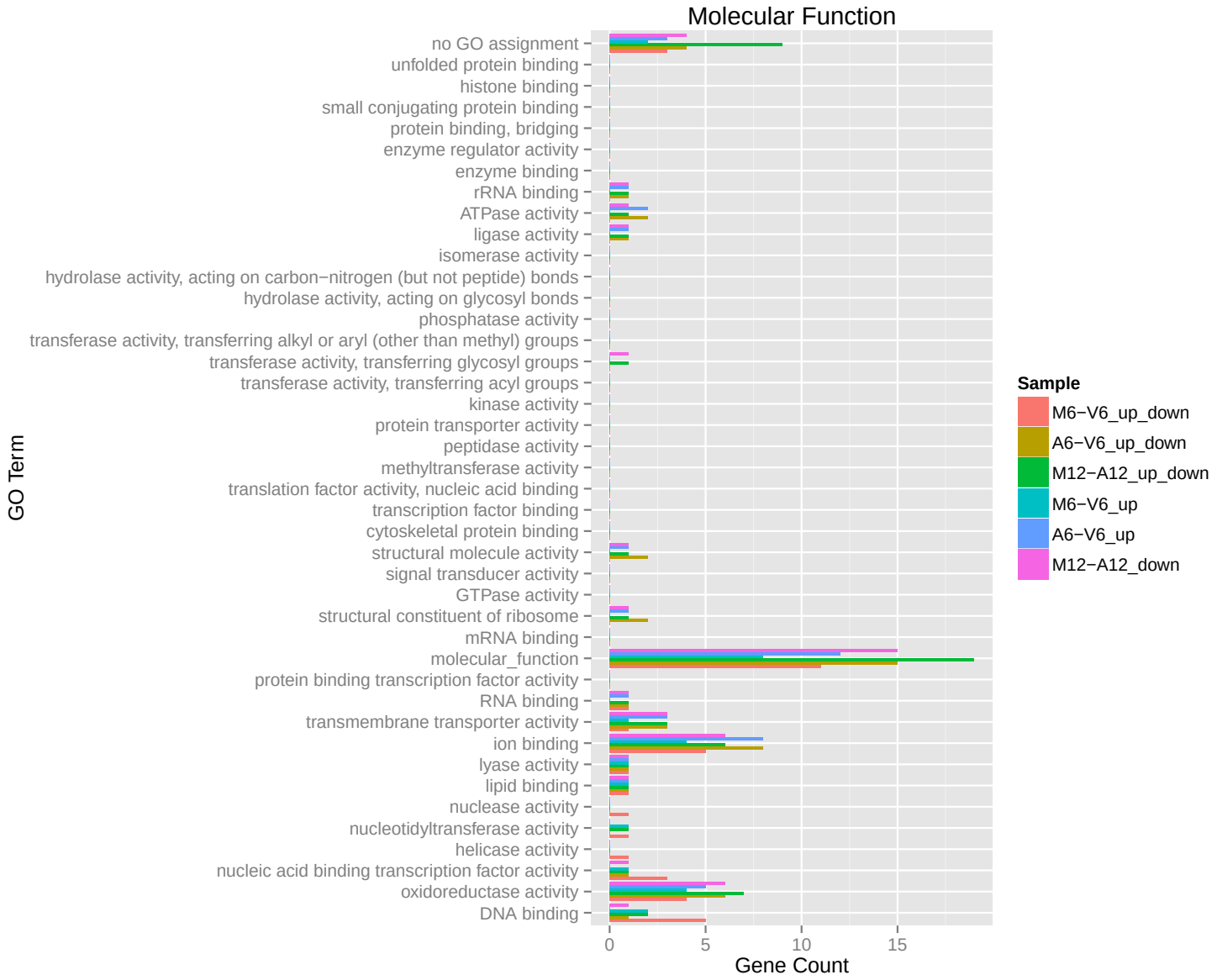

Figure 4: GO Slim Barplot for MF Ontology.

5.11 Clustering and heat maps

The following example performs hierarchical clustering on the RPKM normalized expression matrix subsetted by the DEGs identified in the above differential expression analysis. It uses a Pearson correlation-based distance measure and complete linkage for cluster joining.

```
> library(pheatmap)
> geneids <- as.character(unlist(DEGlist))
> y <- rpkmDFeByg[geneids, ]
> pdf("heatmap1.pdf")
> pheatmap(y, scale="row", clustering_distance_rows="correlation", clustering_distance_cols="correlation")
> dev.off()
```

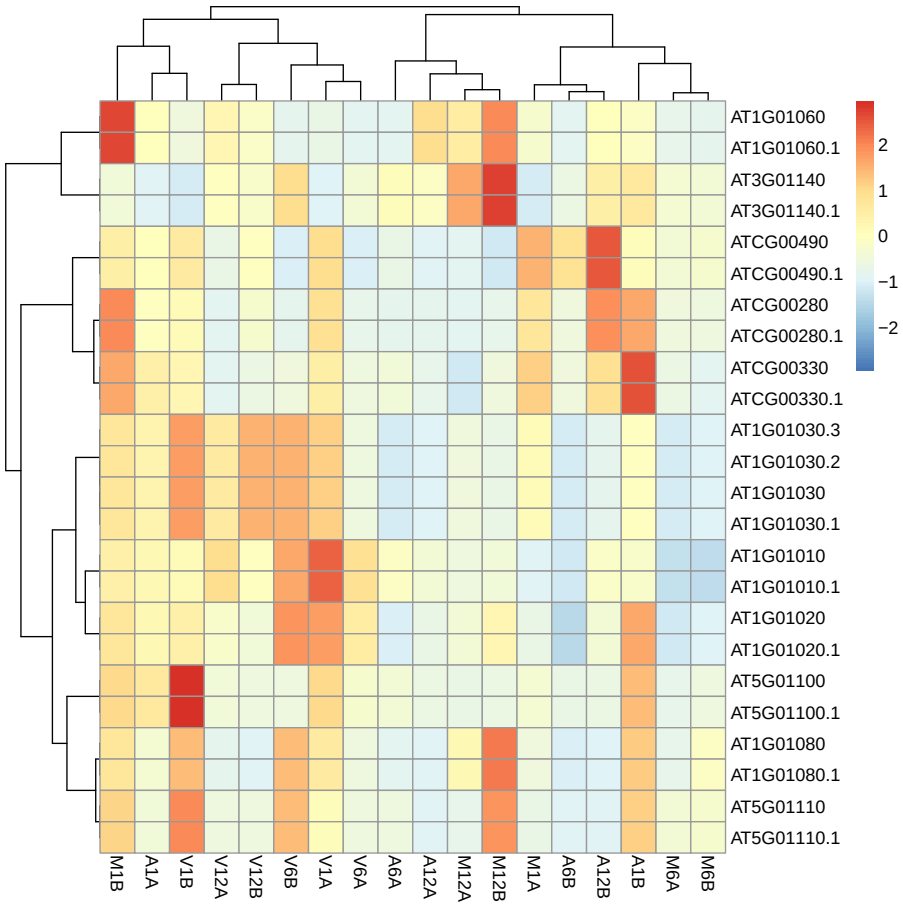

Figure 5: Heat map with hierarchical clustering dendrograms of DEGs.

6 Version Information

```
> toLatex(sessionInfo())
```

- R version 3.1.0 (2014-04-10), `x86_64-unknown-linux-gnu`
- Locale: `C`
- Base packages: base, datasets, grDevices, graphics, methods, parallel, stats, utils
- Other packages: AnnotationDbi 1.26.0, BSgenome 1.32.0, Biobase 2.24.0, BiocGenerics 0.10.0, BiocParallel 0.6.1, Biostrings 2.32.0, DBI 0.2-7, GenomeInfoDb 1.0.2, GenomicAlignments 1.0.1, GenomicRanges 1.16.3, IRanges 1.22.9, RSQLite 0.11.4, Rsamtools 1.16.1, ShortRead 1.22.0, XVector 0.4.0, edgeR 3.6.2, limma 3.20.6, systemPipeR 1.0.12
- Loaded via a namespace (and not attached): AnnotationForge 1.6.1, BBmisc 1.7, BatchJobs 1.2, BiocStyle 1.2.0, Category 2.30.0, GO.db 2.14.0, GOstats 2.30.0, GSEABase 1.26.0, MASS 7.3-33, Matrix 1.1-4, RBGL 1.40.0, RColorBrewer 1.0-5, Rcpp 0.11.2, XML 3.98-1.1, annotate 1.42.0, bitops 1.0-6, brew 1.0-6, checkmate 1.0, codetools 0.2-8, colorspace 1.2-4, digest 0.6.4, fail 1.2, foreach 1.4.2, genefilter 1.46.1, ggplot2 1.0.0, graph 1.42.0, grid 3.1.0, gtable 0.1.2, hwriter 1.3, iterators 1.0.7, lattice 0.20-29, latticeExtra 0.6-26, munsell 0.4.2, pheatmap 0.7.7, plyr 1.8.1, proto 0.3-10, reshape2 1.4, rjson 0.2.14, scales 0.2.4, sendmailR 1.1-2, splines 3.1.0, stats4 3.1.0, stringr 0.6.2, survival 2.37-7, tools 3.1.0, xtable 1.7-3, zlibbioc 1.10.0

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8 References

Thomas Girke. systemPipeR: NGS workflow and report generation environment, 28 June 2014. URL https://github.com/tgirke/systemPipeR.

Brian E Howard, Qiwen Hu, Ahmet Can Babaoglu, Manan Chandra, Monica Borghi, Xiaoping Tan, Luyan He, Heike Winter-Sederoff, Walter Gassmann, Paola Veronese, and Steffen Heber. High-throughput RNA sequencing of pseudomonas-infected arabidopsis reveals hidden transcriptome complexity and novel splice variants. *PLoS One*, 8 (10):e74183, 1 October 2013. ISSN 1932-6203. doi: 10.1371/journal.pone.0074183. URL http://dx.doi.org/10.1371/journal.pone.0074183.

Daehwan Kim, Geo Pertea, Cole Trapnell, Harold Pimentel, Ryan Kelley, and Steven L Salzberg. TopHat2: accurate alignment of transcriptomes in the presence of insertions, deletions and gene fusions. *Genome Biol.*, 14(4):R36, 25 April 2013. ISSN 1465-6906. doi: 10.1186/gb-2013-14-4-r36. URL http://dx.doi.org/10.1186/gb-2013-14-4-r36.

Ben Langmead and Steven L Salzberg. Fast gapped-read alignment with bowtie 2. *Nat. Methods*, 9(4):357–359, April 2012. ISSN 1548-7091. doi: 10.1038/nmeth.1923. URL http://dx.doi.org/10.1038/nmeth.1923.

Michael Lawrence, Wolfgang Huber, Hervé Pagès, Patrick Aboyoun, Marc Carlson, Robert Gentleman, Martin T Morgan, and Vincent J Carey. Software for computing and annotating genomic ranges. *PLoS Comput. Biol.*, 9(8):e1003118, 8 August 2013. ISSN 1553-734X. doi: 10.1371/journal.pcbi.1003118. URL http://dx.doi.org/10.1371/journal.pcbi.1003118.

H Li and R Durbin. Fast and accurate short read alignment with Burrows-Wheeler transform. *Bioinformatics*, 25(14): 1754–1760, July 2009. ISSN 1367-4803. doi: 10.1093/bioinformatics/btp324. URL http://dx.doi.org/10.1093/bioinformatics/btp324.

Heng Li. Aligning sequence reads, clone sequences and assembly contigs with BWA-MEM. 03 2013. URL http://arxiv.org/abs/1303.3997.

Yang Liao, Gordon K Smyth, and Wei Shi. The subread aligner: fast, accurate and scalable read mapping by seed-and-vote. *Nucleic Acids Res.*, 41(10):e108, 4 April 2013. ISSN 0305-1048. doi: 10.1093/nar/gkt214. URL http://dx.doi.org/10.1093/nar/gkt214.