

# Package ‘hpgltools’

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**Type** Package

**Title** A pile of (hopefully) useful R functions

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**Description** This is a set of functions I have been using in my various analyses in the El-Sayed laboratory. The set of tasks included herein run a spectrum from preprocessing count-tables from RNAseq-like data, through differential expression analyses, to post-processing tasks like gene ontology enrichment. Along the way, these function seek to make plotting analyses consistent, provide multiple entry-points to the various tools, and handle corner cases which are not flexibly handled by the packages this is based upon.

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**Suggests** acepack, ade4, affy, AnnotationDbi, AnnotationForge, AnnotationHub, base64enc, Biobase, BiocGenerics, BiocInstaller, Biostrings, biomaRt, bumphunter, Category, caTools, clusterProfiler, corpcor, corrplot, DBI, DESeq2, DESeq, devtools, directlabels, dplyr, doParallel, DOSE, EDASeq, edgeR, ffpe, fission, Formula, gdata, genbankr, genefilter, genomeIntervals, GenomeInfoDb, GenomicFeatures, genoPlotR, GenomicRanges, ggdendro, ggrepel, GO.db, googleVis, goseq, GOSTats, gplots, graph, gProfileR, GSEABase, gtools, gridExtra, hash, Heatplus, Hmisc, htmlTable, igraph, inflection, IRanges, iterators, jsonlite, KEGGgraph, KEGGREST, knitcitations, knitr, lattice, limma, matrixStats, motifRG, multtest, mygene, openxlsx, OrganismDbi, pander, parallel, pasilla, pathview, plyr, preprocessCore, qvalue, RamiGO, RColorBrewer, ReactomePA, readr, rentrez, reshape2, RCurl, rGADEM, Rgraphviz, rmarkdown, RMySQL, robustbase, RefManageR, reshape, rjson, robust, Rsamtools, rtracklayer, RUVSeq, S4Vectors, scales, seqinr, seqLogo, statmod, stringi, stringr, survival, sva, taxize, testthat, topGO, variancePartition, xtable, XVector, survJamda

**Imports** Biobase, data.table, knitr, ggplot2, magrittr, methods, foreach

**VignetteBuilder** knitr

**RoxygenNote** 6.0.1

**R topics documented:**

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all\_ontology\_searches *Perform ontology searches given the results of a differential expression analysis.*

---

**Description**

This takes a set of differential expression results, extracts a subset of up/down expressed genes; passes them to goseq, clusterProfiler, topGO, GOstats, and gProfiler; collects the outputs; and returns them in a (hopefully) consistent fashion. It attempts to handle the differing required annotation/GOid inputs required for each tool and/or provide supported species in ways which the various tools expect.

**Usage**

```
all_ontology_searches(de_out, gene_lengths = NULL, goids = NULL, n = NULL,
  z = NULL, fc = NULL, p = NULL, overwrite = FALSE,
  species = "unsupported", orgdb = "org.Dm.eg.db",
  goid_map = "reference/go/id2go.map", gff_file = NULL, gff_type = "gene",
  do_goseq = TRUE, do_cluster = TRUE, do_topgo = TRUE,
  do_gostats = TRUE, do_gprofiler = TRUE, do_trees = FALSE, ...)
```

**Arguments**

de_out	List of topTables comprising limma/deseq/edger outputs.
gene_lengths	Data frame of gene lengths for goseq.
goids	Data frame of goids and genes.
n	Number of genes at the top/bottom of the fold-changes to define 'significant.'
z	Number of standard deviations from the mean fold-change used to define 'significant.'
fc	Log fold-change used to define 'significant'.
p	Maximum pvalue to define 'significant.'
overwrite	Overwrite existing excel results file?
species	Supported organism used by the tools.
orgdb	Provide an organismDbi/Orgdb to hold the various annotation data, in response to the shift of clusterprofiler and friends towards using them.
goid_map	Mapping file used by topGO, if it does not exist then goids_df creates it.
gff_file	gff file containing the annotations used by gff2genetable from clusterprofiler.
gff_type	Column to use from the gff file for the universe of genes.
do_goseq	Perform simple_goseq()?
do_cluster	Perform simple_clusterprofiler()?
do_topgo	Perform simple_topgo()?
do_gostats	Perform simple_gostats()?
do_gprofiler	Perform simple_gprofiler()?
do_trees	make topGO trees from the data?
...	Arguments to pass through in arglist.

**Value**

a list of up/down ontology results from goseq/clusterprofiler/topgo/gostats, and associated trees.

**See Also**

**goseq clusterProfiler topGO goStats gProfiler GO.db**



## Examples

```
## Not run:
many_comparisons = limma_pairwise(expt=an_expt)
tables = many_comparisons$limma
this_takes_forever = limma_ontology(tables, gene_lengths=lengthdb,
                                   goids=goids_df, z=1.5, gff_file='length_db.gff')

## End(Not run)
```

all\_pairwise

*Perform limma, DESeq2, EdgeR pairwise analyses.*

## Description

This takes an expt object, collects the set of all possible pairwise comparisons, sets up experimental models appropriate for the differential expression analyses, and performs them.

## Usage

```
all_pairwise(input = NULL, conditions = NULL, batches = NULL,
             model_cond = TRUE, modify_p = FALSE, model_batch = TRUE,
             model_intercept = TRUE, extra_contrasts = NULL, alt_model = NULL,
             libsize = NULL, test_pca = TRUE, annot_df = NULL, parallel = TRUE,
             ...)
```

## Arguments

input	Dataframe/vector or expt class containing count tables, normalization state, etc.
conditions	Factor of conditions in the experiment.
batches	Factor of batches in the experiment.
model_cond	Include condition in the model? This is likely always true.
modify_p	Depending on how it is used, sva may require a modification of the p-values.
model_batch	Include batch in the model? This may be true/false/"sva" or other methods supported by get_model_adjust().
model_intercept	Use an intercept model instead of cell means?
extra_contrasts	Optional extra contrasts beyond the pairwise comparisons. This can be pretty neat, let's say one has conditions A,B,C,D,E and wants to do (C/B)/A and (E/D)/A or (E/D)/(C/B) then use this with a string like: "c_vs_b_ctrla = (C-B)-A, e_vs_d_ctrla = (E-D)-A, de_vs_cb = (E-D)-(C-B)".
alt_model	Alternate model to use rather than just condition/batch.
libsize	Library size of the original data to help voom().
annot_df	Annotations to add to the result tables.
parallel	Use dopar to run limma, deseq, edgeR, and basic simultaneously.
...	Picks up extra arguments into arglist, currently only passed to write_limma().

**Details**

Tested in test\_29de\_shared.R This runs limma\_pairwise(), deseq\_pairwise(), edger\_pairwise(), basic\_pairwise() each in turn. It collects the results and does some simple comparisons among them.

**Value**

A list of limma, deseq, edger results.

**See Also**

**limma DESeq2 edgeR** [link{limma\\_pairwise}](#) [deseq\\_pairwise](#) [edger\\_pairwise](#) [basic\\_pairwise](#)

**Examples**

```
## Not run:
finished_comparison = eBayes(limma_output)
data_list = all_pairwise(expt)

## End(Not run)
```

---

 backup\_file

---

*Make a backup of an existing file with n revisions, like VMS!*


---

**Description**

Sometimes I just want to kick myself for overwriting important files and then I remember using VMS and wish modern computers were a little more like it.

**Usage**

```
backup_file(backup_file, backups = 4)
```

**Arguments**

backup_file	Filename to backup.
backups	How many revisions?

---

basic\_pairwise*The simplest possible differential expression method.*

---

## Description

Perform a pairwise comparison among conditions which takes nothing into account. It `_only_` takes the conditions, a mean value/variance among them, divides by condition, and returns the result. No fancy normalizations, no statistical models, no nothing. It should be the very worst method possible. But, it should also provide a baseline to compare the other tools against, they should all do better than this, always.

## Usage

```
basic_pairwise(input = NULL, design = NULL, force = FALSE, ...)
```

## Arguments

<code>input</code>	Count table by sample.
<code>design</code>	Data frame of samples and conditions.
<code>force</code>	Force as input non-normalized data?
<code>...</code>	Extra options passed to arglist.

## Details

Tested in `test_27de_basic.R` This function was written after the corresponding functions in `de_deseq.R`, `de_edger.R`, and `de_limma.R`. Like those, it performs the full set of pairwise comparisons and returns a list of the results. As mentioned above, unlike those, it is purposefully stupid.

## Value

Df of pseudo-logFC, p-values, numerators, and denominators.

## See Also

**limma DESeq2 edgeR**

## Examples

```
## Not run:
stupid_de <- basic_pairwise(expt)

## End(Not run)
```

---

batch_counts	<i>Perform different batch corrections using limma, sva, ruvq, and cbcbs-SEQ.</i>
--------------	---

---

## Description

I found this note which is the clearest explanation of what happens with batch effect data: <https://support.bioconductor.org/p/7>  
 Just to be clear, there's an important difference between removing a batch effect and modelling a batch effect. Including the batch in your design formula will model the batch effect in the regression step, which means that the raw data are not modified (so the batch effect is not removed), but instead the regression will estimate the size of the batch effect and subtract it out when performing all other tests. In addition, the model's residual degrees of freedom will be reduced appropriately to reflect the fact that some degrees of freedom were "spent" modelling the batch effects. This is the preferred approach for any method that is capable of using it (this includes DESeq2). You would only remove the batch effect (e.g. using limma's removeBatchEffect function) if you were going to do some kind of downstream analysis that can't model the batch effects, such as training a classifier. I don't have experience with ComBat, but I would expect that you run it on log-transformed CPM values, while DESeq2 expects raw counts as input. I couldn't tell you how to properly use the two methods together.

## Usage

```
batch_counts(count_table, design, batch = TRUE, batch1 = "batch",
             expt_state = NULL, batch2 = NULL, noscale = TRUE, ...)
```

## Arguments

count_table	Matrix of (pseudo)counts.
design	Model matrix defining the experimental conditions/batches/etc.
batch	String describing the method to try to remove the batch effect (or FALSE to leave it alone, TRUE uses limma).
batch1	Column in the design table describing the presumed covariant to remove.
expt_state	Current state of the expt in an attempt to avoid double-normalization.
batch2	Column in the design table describing the second covariant to remove (only used by limma at the moment).
noscale	Used for combatmod, when true it removes the scaling parameter from the invocation of the modified combat.
...	More options for you!

## Value

The 'batch corrected' count table and new library size. Please remember that the library size which comes out of this may not be what you want for voom/limma and would therefore lead to spurious differential expression values.

**See Also****limma edgeR RUVSeq sva cbcSEQ****Examples**

```
## Not run:
limma_batch <- batch_counts(table, design, batch1='batch', batch2='strain')
sva_batch <- batch_counts(table, design, batch='sva')

## End(Not run)
```

bioc\_all

*Grab a copy of all bioconductor packages and install them by type***Description**

This uses jsonlite to get a copy of all bioconductor packages by name and then iterates through them with BiocInstaller to install all of them. It performs a sleep between each installation in an attempt to avoid being obnoxious. As a result, it will of a necessity take forever.

**Usage**

```
bioc_all(release = "3.4", mirror = "bioconductor.statistik.tu-dortmund.de",
  base = "packages", type = "software", suppress_updates = TRUE,
  suppress_auto = TRUE, force = FALSE)
```

**Arguments**

release	Bioconductor release to use, should probably be adjusted to automatically find it.
mirror	Bioconductor mirror to use.
base	Base directory on the mirror to download from.
type	Type in the tree to use (software or annotation)
suppress_updates	For BiocLite(), don't update?
suppress_auto	For BiocLite(), don't update?
force	Install if already installed?

**Value**

a number of packages installed

**See Also****BiocInstaller**

**Examples**

```
## Not run:
go_get_some_coffee_this_will_take_a_while <- bioc_all()

## End(Not run)
```

---

biomart_orthologs	<i>Use biomaRt to get orthologs between supported species.</i>
-------------------	--

---

**Description**

BiomaRt's function `getLDS` is incredibly powerful, but it makes me think very polite people are going to start knocking on my door, and it fails weirdly pretty much always. This function attempts to alleviate some of that frustration.

**Usage**

```
biomart_orthologs(gene_ids, first_species = "hsapiens",
  second_species = "mmusculus", host = "dec2015.archive.ensembl.org",
  trymart = "ENSEMBL_MART_ENSEMBL", first_attributes = "ensembl_gene_id",
  second_attributes = c("ensembl_gene_id", "hgnc_symbol"))
```

**Arguments**

<code>gene_ids</code>	List of gene IDs to translate.
<code>first_species</code>	Linnean species name for one species.
<code>second_species</code>	Linnean species name for the second species.
<code>host</code>	Ensembl server to query.
<code>trymart</code>	Assumed mart name to use.
<code>first_attributes</code>	Key(s) of the first database to use.
<code>second_attributes</code>	Key(s) of the second database to use.

**Details**

Tested in `test_40ann_biomaRt.R`. As with my other biomaRt functions, this one grew out of frustrations when attempting to work with the incredibly unforgiving biomaRt service. It does not attempt to guarantee a useful biomaRt connection, but will hopefully point out potentially correct marts and attributes to use for a successful query. I can say with confidence that it works well between mice and humans.

**Value**

Df of orthologs.

**See Also****biomaRt** [getLDS](#) [useMart](#)**Examples**

```
## Not run:
mouse_genes <- biomaRt_orthologs(some_ids)
## Hopefully the defaults are sufficient to translate from human to mouse.
yeast_genes <- biomaRt_orthologs(some_ids, first_species='mmusculus', second_species='scerevisiae')

## End(Not run)
```

---

cbcb_batch_effect	<i>A function suggested by Hector Corrada Bravo and Kwame Okrah for batch removal</i>
-------------------	---

---

**Description**

During a lab meeting, the following function was suggested as a quick and dirty batch removal tool

**Usage**

```
cbcb_batch_effect(normalized_counts, model)
```

**Arguments**

normalized_counts	Data frame of log2cpm counts.
model	Balanced experimental model containing condition and batch factors.

**Value**

Dataframe of residuals after subtracting batch from the model.

**See Also****limma** [voom](#) [lmFit](#)**Examples**

```
## Not run:
newdata <- cbcb_batch_effect(counts, expt_model)

## End(Not run)
```

---

cbcb_filter_counts	<i>Filter low-count genes from a data set using cpm data and a threshold.</i>
--------------------	---

---

### Description

This was a function written by Kwame Okrah and perhaps also Laura Dillon to remove low-count genes. It drops genes based on a cpm threshold and number of samples.

### Usage

```
cbcb_filter_counts(count_table, threshold = 2, min_samples = 2)
```

### Arguments

count_table	Data frame of (pseudo)counts by sample.
threshold	Lower threshold of counts for each gene.
min_samples	Minimum number of samples.

### Value

Dataframe of counts without the low-count genes.

### See Also

**edgeR**

### Examples

```
## Not run:
  filtered_table <- cbcb_filter_counts(count_table)

## End(Not run)
```

---

choose_basic_dataset	<i>Attempt to ensure that input data to basic_pairwise() is suitable.</i>
----------------------	---

---

### Description

basic\_pairwise() assumes log2 data as input, use this to ensure that is true.

### Usage

```
choose_basic_dataset(input, force = FALSE, ...)
```



**Arguments**

input	An expressionset containing expt to test and/or modify.
force	If we want to try out other distributed data sets, force it in using me.
...	future options, I think currently unused.

**Value**

data ready for basic\_pairwise()

**See Also**

**Biobase**

**Examples**

```
## Not run:  
ready <- choose_basic_dataset(expt)  
  
## End(Not run)
```

---

choose_binom_dataset	<i>A sanity check that a given set of data is suitable for analysis by edgeR or DESeq2.</i>
----------------------	---

---

**Description**

Take an expt and poke at it to ensure that it will not result in troubled results.

**Usage**

```
choose_binom_dataset(input, force = FALSE, ...)
```

**Arguments**

input	Expressionset containing expt object.
force	Ignore every warning and just use this data.
...	Extra arguments passed to arglist.

**Details**

Invoked by `deseq_pairwise()` and `edger_pairwise()`.

**Value**

dataset suitable for limma analysis

**See Also**

**DESeq2 edgeR**

---

choose_dataset	<i>Choose a suitable data set for Edger/DESeq</i>
----------------	---

---

### Description

The `_pairwise` family of functions all demand data in specific formats. This tries to make that consistent.

### Usage

```
choose_dataset(input, choose_for = "limma", force = FALSE, ...)
```

### Arguments

<code>input</code>	Expt input.
<code>choose_for</code>	One of <code>limma</code> , <code>deseq</code> , <code>edger</code> , or <code>basic</code> . Defines the requested data state.
<code>force</code>	Force non-standard data?
<code>...</code>	More options for future expansion.

### Details

Invoked by `_pairwise()`.

### Value

List the data, conditions, and batches in the data.

### See Also

[choose\\_binom\\_dataset](#) [choose\\_limma\\_dataset](#) [choose\\_basic\\_dataset](#)

---

choose_limma_dataset	<i>A sanity check that a given set of data is suitable for analysis by limma.</i>
----------------------	---

---

### Description

Take an expt and poke at it to ensure that it will not result in troubled limma results.

### Usage

```
choose_limma_dataset(input, force = FALSE, which_voom = "limma", ...)
```

**Arguments**

input	Expressionset containing expt object.
force	Ignore warnings and use the provided data as is.
which_voom	Choose between limma's voom, voomWithQualityWeights, or the hpgl equivalents.
...	Extra arguments passed to arglist.

**Value**

dataset suitable for limma analysis

**See Also**

**limma**

---

choose_model	<i>Try out a few experimental models and return a likely working option.</i>
--------------	--

---

**Description**

The `_pairwise` family of functions all demand an experimental model. This tries to choose a consistent and useful model for all for them. This does not try to do multi-factor, interacting, nor dependent variable models, if you want those do them yourself and pass them off as `alt_model`.

**Usage**

```
choose_model(input, conditions, batches, model_batch = TRUE,
             model_cond = TRUE, model_intercept = TRUE, alt_model = NULL,
             alt_string = NULL, intercept = 0, reverse = FALSE, surrogates = "be",
             ...)
```

**Arguments**

input	Input data used to make the model.
conditions	Factor of conditions in the putative model.
batches	Factor of batches in the putative model.
model_batch	Try to include batch in the model?
model_cond	Try to include condition in the model? (Yes!)
model_intercept	Use an intercept model instead of cell-means?
alt_model	Use your own model.
alt_string	String describing an alternate model.
intercept	Choose an intercept for the model as opposed to 0.

reverse	Reverse condition/batch in the model? This shouldn't/doesn't matter but I wanted to test.
surrogates	Number of or method used to choose the number of surrogate variables.
...	Further options are passed to arglist.

### Details

Invoked by the `_pairwise()` functions.

### Value

List including a model matrix and strings describing cell-means and intercept models.

### See Also

`stats` [model.matrix](#)

---

choose\_orgdb

*Load the appropriate orgDb environment for a given species.*

---

### Description

Ok, so these are a bit more complex than I realized. The heirarchy as I now understand it (probably wrong) is that orgdb objects provide ID mappings among the various DBs. txdb objects provide the actual annotation information, and organismdbs acquire both (but only exist for a few species). Let's face it, I will never remember that the yeast orgdb is 'org.Sc.sgd.something'. This function is intended to make that process easier. Feed it a species name which makes sense: 'homo\_sapiens' and it will assume you mean orgdb.whatever and load that into your environment. This should also make a reasonable attempt at installing the appropriate orgdb if it is not already in your R library tree.

### Usage

```
choose_orgdb(species = "saccharomyces_cerevisiae")
```

### Arguments

species            Human readable species name

### Value

orgdb object for the relevant species, or an error if I don't have a mapping for it.

### See Also

`AnnotationDbi` [keytypes](#)

## Examples

```
## Not run:
object <- choose_orgdb("homo_sapiens")

## End(Not run)
```

---

choose\_txdb

*Load the appropriate TxDb environment for a given species.*

---

## Description

Ok, so these are a bit more complex than I realized. The heirarchy as I now understand it (probably wrong) is that orgdb objects provide ID mappings among the various DBs. txdb objects provide the actual annotation information, and organismdbs acquire both (but only exist for a few species). Let's face it, I will never remember that the yeast orgdb is 'org.Sc.sgd.something'. This function is intended to make that process easier. Feed it a species name which makes sense: 'homo\_sapiens' and it will assume you mean orgdb.whatever and load that into your environment. This should also make a reasonable attempt at installing the appropriate orgdb if it is not already in your R library tree.

## Usage

```
choose_txdb(species = "saccharomyces_cerevisiae")
```

## Arguments

species	Human readable species name
---------	-----------------------------

## Value

orgdb object for the relevant species, or an error if I don't have a mapping for it.

## See Also

**AnnotationDbi** [keytypes](#)

## Examples

```
## Not run:
object <- choose_txdb("homo_sapiens")

## End(Not run)
```

---

circos_arc	<i>Write arcs between chromosomes in circos.</i>
------------	--

---

## Description

Ok, so when I said I only do 1 chromosome images, I lied. This function tries to make writing arcs between chromosomes easier. It too works in 3 stages, It writes out a data file using cfgout as a basename and the data from df in the circos arc format into circos/data/bob\_arc.txt It then writes out a configuration plot stanza in circos/conf/bob\_arc.conf and finally adds an include to circos/bob.conf

## Usage

```
circos_arc(df, cfgout = "circos/conf/default.conf", first_col = "chr1",  
           second_col = "chr2", color = "blue", radius = 0.75, thickness = 3)
```

## Arguments

df	Dataframe with starts/ends and the floating point information.
cfgout	Master configuration file to write.
first_col	Name of the first chromosome.
second_col	Name of the second chromosome.
color	Color of the chromosomes.
radius	Outer radius at which to add the arcs.
thickness	Integer thickness of the arcs.

## Details

In its current implementation, this only understands two chromosomes. A minimal amount of logic and data organization will address this weakness.

## Value

The file to which the arc configuration information was written.

---

circos_heatmap	<i>Write tiles of arbitrary heat-mappable data in circos.</i>
----------------	---

---

### Description

This function tries to make the writing circos heatmaps easier. Like `circos_plus_minus()` and `circos_hist()` it works in 3 stages, It writes out a data file using `cfgout` as a basename and the data from `df` in the circos histogram format into `circos/data/bob_heatmap.txt` It then writes out a configuration plot stanza in `circos/conf/bob_heatmap.conf` and finally adds an include to `circos/bob.conf`

### Usage

```
circos_heatmap(df, annot_df, cfgout = "circos/conf/default.conf",
               colname = "logFC", chr = "chr1", colors = NULL, outer = 0.9,
               width = 0.08, spacing = 0)
```

### Arguments

<code>df</code>	Dataframe with starts/ends and the floating point information.
<code>annot_df</code>	Annotation data frame with starts/ends.
<code>cfgout</code>	Master configuration file to write.
<code>colname</code>	Name of the column with the data of interest.
<code>chr</code>	Name of the chromosome (This currently assumes a bacterial chromosome).
<code>colors</code>	Colors of the heat map.
<code>outer</code>	Floating point radius of the circle into which to place the heatmap.
<code>width</code>	Width of each tile in the heatmap.
<code>spacing</code>	Radial distance between outer, inner, and inner to whatever follows.

### Value

Radius after adding the histogram and the spacing.

---

circos_hist	<i>Write histograms of arbitrary floating point data in circos.</i>
-------------	---

---

### Description

This function tries to make the writing of histogram data in circos easier. Like `circos_plus_minus()` it works in 3 stages, It writes out a data file using `cfgout` as a basename and the data from `df` in the circos histogram format into `circos/data/bob_hist.txt` It then writes out a configuration plot stanza in `circos/conf/bob_hist.conf` and finally adds an include to `circos/bob.conf`

**Usage**

```
circos_hist(df, annot_df, cfgout = "circos/conf/default.conf",
            colname = "logFC", chr = "chr1", color = "blue", fill_color = "blue",
            outer = 0.9, width = 0.08, spacing = 0)
```

**Arguments**

df	Dataframe with starts/ends and the floating point information.
annot_df	Annotation data frame containing starts/ends.
cfgout	Master configuration file to write.
colname	Name of the column with the data of interest.
chr	Name of the chromosome (This currently assumes a bacterial chromosome).
color	Color of the plotted data.
fill_color	Guess!
outer	Floating point radius of the circle into which to place the data.
width	Radial width of each tile.
spacing	Distance between outer, inner, and inner to whatever follows.

**Value**

Radius after adding the histogram and the spacing.

---

circos_ideogram	<i>Create the description of chromosome markings.</i>
-----------------	---

---

**Description**

This function writes ideogram files for circos.

**Usage**

```
circos_ideogram(name = "default", conf_dir = "circos/conf",
               band_url = NULL)
```

**Arguments**

name	Name of the configuration file to which to add the ideogram.
conf_dir	Where does the configuration live?
band_url	Provide a url for making these imagemaps?

**Value**

The file to which the ideogram configuration was written.



---

circos_karyotype	<i>Create the description of (a)chromosome(s) for circos.</i>
------------------	---

---

### Description

This function tries to save me from having to get the lengths of arcs for bacterial chromosomes manually correct, and writes them as a circos compatible karyotype file. The outfile parameter was chosen to match the configuration directive outlined in `circos_prefix()`, however that will need to be changed in order for this to work in variable conditions. Next time I make one of these graphs I will do that I suspect. In addition, this currently only understands how to write bacterial chromosomes, that will likely be fixed when I am asked to write out a L.major karyotype. These defaults were chosen because I have a chromosome of this length that is correct.

### Usage

```
circos_karyotype(name = "default", conf_dir = "circos/conf",
  length = NULL, chr_name = "chr1", segments = 6, color = "white",
  chr_num = 1, fasta = NULL)
```

### Arguments

name	Name of the chromosome (This currently assumes a bacterial chromosome).
conf_dir	Where to put the circos configuration file(s).
length	Length of the chromosome (the default is mgas5005).
chr_name	Short name of the chromosome.
segments	How many segments to cut the chromosome into?
color	Color segments of the chromosomal arc?
chr_num	Number to record for each chromosome.
fasta	Fasta file to use to create the karyotype.

### Value

The output filename.

---

circos_make	<i>Write a simple makefile for circos.</i>
-------------	--

---

### Description

I regenerate all my circos pictures with `make(1)`. This is my makefile.

### Usage

```
circos_make(target = "", output = "circos/Makefile", circos = "circos")
```

**Arguments**

target	Default make target.
output	Makefile to write.
circos	Location of circos. I have a copy in home/bin/circos and use that sometimes.

**Value**

a kitten

---

circos_plus_minus	<i>Write tiles of bacterial ontology groups using the categories from microbesonline.org.</i>
-------------------	---

---

**Description**

This function tries to save me from writing out ontology definitions and likely making mistakes. It uses the start/ends from the gff annotation along with the 1 letter GO-like categories from microbesonline.org. It then writes two data files circos/data/bob\_plus\_go.txt, circos/data/bob\_minus\_go.txt along with two configuration files circos/conf/bob\_minus\_go.conf and circos/conf/bob\_plus\_go.conf and finally adds an include to circos/bob.conf

**Usage**

```
circos_plus_minus(go_table, cfgout = "circos/conf/default.conf",
  chr = "chr1", outer = 1, width = 0.08, spacing = 0)
```

**Arguments**

go_table	Dataframe with starts/ends and categories.
cfgout	Master configuration file to write.
chr	Name of the chromosome.
outer	Floating point radius of the circle into which to place the plus-strand data.
width	Radial width of each tile.
spacing	Radial distance between outer, inner, and inner to whatever follows.

**Value**

Radius after adding the plus/minus information and the spacing between them.

---

circos_prefix	<i>Write the beginning of a circos configuration file.</i>
---------------	--

---

## Description

A few parameters need to be set when starting circos. This sets some of them and gets ready for plot stanzas.

## Usage

```
circos_prefix(name = "mgas", conf_dir = "circos/conf", radius = 1800,
              band_url = NULL)
```

## Arguments

name	Name of the map, called with 'make name'.
conf_dir	Directory containing the circos configuration data.
radius	Size of the image.
band_url	Place to imagemap link.

## Details

In its current implementation, this really assumes that there will be no highlight stanzas and at most 1 link stanza. chromosomes. A minimal amount of logic and data organization will address these weaknesses.

## Value

The master configuration file name.

---

circos_suffix	<i>Write the end of a circos master configuration.</i>
---------------	--

---

## Description

circos configuration files need an ending. This writes it.

## Usage

```
circos_suffix(cfgout = "circos/conf/default.conf")
```

## Arguments

cfgout	Master configuration file to write.
--------	-------------------------------------

**Value**

The filename of the configuration.

---

circos_tile	<i>Write tiles of arbitrary categorical point data in circos.</i>
-------------	---

---

**Description**

This function tries to make the writing circos tiles easier. Like `circos_plus_minus()` and `circos_hist()` it works in 3 stages, It writes out a data file using `cfgout` as a basename and the data from `df` in the circos histogram format into `circos/data/bob_tile.txt` It then writes out a configuration plot stanza in `circos/conf/bob_tile.conf` and finally adds an include to `circos/bob.conf`

**Usage**

```
circos_tile(df, annot_df, cfgout = "circos/conf/default.conf",
            colname = "logFC", chr = "chr1", colors = NULL, outer = 0.9,
            width = 0.08, spacing = 0)
```

**Arguments**

<code>df</code>	Dataframe with starts/ends and the floating point information.
<code>annot_df</code>	Annotation data frame defining starts/stops.
<code>cfgout</code>	Master configuration file to write.
<code>colname</code>	Name of the column with the data of interest.
<code>chr</code>	Name of the chromosome (This currently assumes a bacterial chromosome)
<code>colors</code>	Colors of the data.
<code>outer</code>	Floating point radius of the circle into which to place the categorical data.
<code>width</code>	Width of each tile.
<code>spacing</code>	Radial distance between outer, inner, and inner to whatever follows.

**Value**

Radius after adding the histogram and the spacing.

---

cluster_trees	<i>Take clusterprofile group data and print it on a tree as per topGO.</i>
---------------	--

---

## Description

TopGO's ontology trees can be very illustrative. This function shoe-horns clusterProfiler data into the format expected by topGO and uses it to make those trees.

## Usage

```
cluster_trees(de_genes, cpdata, goid_map = "id2go.map", goids_df = NULL,  
  score_limit = 0.2, overwrite = FALSE, selector = "topDiffGenes",  
  pval_column = "adj.P.Val")
```

## Arguments

de_genes	List of genes deemed 'interesting'.
cpdata	Data from simple_clusterprofiler().
goid_map	Mapping file of IDs to GO ontologies.
goids_df	Dataframe of mappings used to build goid_map.
score_limit	Scoring limit above which to ignore genes.
overwrite	Overwrite an existing goid mapping file?
selector	Name of a function for applying scores to the trees.
pval_column	Name of the column in the GO table from which to extract scores.

## Value

plots! Trees! oh my!

## See Also

**Ramigo** [showSigOfNodes](#)

## Examples

```
## Not run:  
cluster_data <- simple_clusterprofiler(genes, stuff)  
ctrees <- cluster_trees(genes, cluster_data)  
  
## End(Not run)
```

---

combine_de_table	<i>Given a limma, edger, and deseq table, combine them into one.</i>
------------------	--

---

### Description

This combines the outputs from the various differential expression tools and formalizes some column names to make them a little more consistent.

### Usage

```
combine_de_table(li, ed, de, ba, table_name, annot_df = NULL,
  inverse = FALSE, adjp = TRUE, padj_type = "fdr", include_deseq = TRUE,
  include_edger = TRUE, include_limma = TRUE, include_basic = TRUE,
  fc_cutoff = 1, p_cutoff = 0.05, excludes = NULL)
```

### Arguments

li	Limma output table.
ed	Edger output table.
de	Deseq2 output table.
ba	Basic output table.
table_name	Name of the table to merge.
annot_df	Add some annotation information?
inverse	Invert the fold changes?
adjp	Use adjusted p-values?
include_deseq	Include tables from deseq?
include_edger	Include tables from edger?
include_limma	Include tables from limma?
include_basic	Include the basic table?
fc_cutoff	Preferred logfoldchange cutoff.
p_cutoff	Preferred pvalue cutoff.
excludes	Set of genes to exclude from the output.
adjp_type	Add this consistent p-adjustment.

### Value

List containing a) Dataframe containing the merged limma/edger/deseq/basic tables, and b) A summary of how many genes were observed as up/down by output table.

### See Also

**data.table** **openxlsx**

---

combine_de_tables	<i>Combine portions of deseq/limma/edger table output.</i>
-------------------	--

---

### Description

This hopefully makes it easy to compare the outputs from limma/DESeq2/EdgeR on a table-by-table basis.

### Usage

```
combine_de_tables(all_pairwise_result, extra_annot = NULL, excel = NULL,
  excel_title = "Table SXXX: Combined Differential Expression of YYY",
  keepers = "all", excludes = NULL, adjp = TRUE, include_limma = TRUE,
  include_edger = TRUE, include_deseq = TRUE, rownames = TRUE,
  include_basic = TRUE, add_plots = TRUE, loess = FALSE, plot_dim = 6,
  compare_plots = TRUE, padj_type = "fdr")
```

### Arguments

all_pairwise_result	Output from all_pairwise().
extra_annot	Add some annotation information?
excel	Filename for the excel workbook, or null if not printed.
excel_title	Title for the excel sheet(s). If it has the string 'YYY', that will be replaced by the contrast name.
keepers	List of reformatted table names to explicitly keep certain contrasts in specific orders and orientations.
excludes	List of columns and patterns to use for excluding genes.
adjp	Perhaps you do not want the adjusted p-values for plotting?
include_limma	Include limma analyses in the table?
include_edger	Include edger analyses in the table?
include_deseq	Include deseq analyses in the table?
include_basic	Include my stupid basic logFC tables?
add_plots	Add plots to the end of the sheets with expression values?
loess	Add time intensive loess estimation to plots?
plot_dim	Number of inches squared for the plot if added.
compare_plots	In an attempt to save memory when printing to excel, make it possible to
adjp_type	Add a consistent p adjustment of this type. exclude comparison plots in the summary sheet.

### Value

Table combining limma/edger/deseq outputs.

**See Also**[all\\_pairwise](#)**Examples**

```
## Not run:
pretty = combine_de_tables(big_result, table='t12_vs_t0')
pretty = combine_de_tables(big_result, table='t12_vs_t0', keepers=list("avsb" = c("a", "b")))
pretty = combine_de_tables(big_result, table='t12_vs_t0', keepers=list("avsb" = c("a", "b")),
                          excludes=list("description" = c("sno", "rRNA")))

## End(Not run)
```

---

compare_go_searches	<i>Compare the results from different ontology tools</i>
---------------------	--

---

**Description**

Combine the results from goseq, cluster profiler, topgo, and gostats; poke at them with a stick and see what happens. The general idea is to pull the p-value data from each tool and contrast that to the set of all possible ontologies. This allows one to do a correlation coefficient between them. In addition, take the 1-pvalue for each ontology for each tool. Thus for strong p-values the score will be near 1 and so we can sum the scores for all the tools. Since topgo has 4 tools, the total possible is 7 if everything has a p-value equal to 0.

**Usage**

```
compare_go_searches(goseq = NULL, cluster = NULL, topgo = NULL,
                    gostats = NULL)
```

**Arguments**

goseq	The goseq result from simple_goseq()
cluster	The result from simple_clusterprofiler()
topgo	Guess
gostats	Yep, ditto

**Value**

a summary of the similarities of ontology searches

**See Also**

**goseq clusterProfiler topGO goStats**



---

compare_logfc_plots	<i>Compare logFC values from limma and friends</i>
---------------------	--

---

**Description**

There are some peculiar discrepancies among these tools, what is up with that?

**Usage**

```
compare_logfc_plots(combined_tables)
```

**Arguments**

combined\_tables

The combined tables from limma et al.

**Details**

Invoked by combine\_de\_tables() in order to compare the results.

**Value**

Some plots

**See Also**

[plot\\_linear\\_scatter](#)

---

compare_surrogate_estimates
-----------------------------

*Perform a comparison of the surrogate estimators demonstrated by Jeff Leek.*

---

**Description**

This is entirely derivative, but seeks to provide similar estimates for one's own actual data and catch corner cases not taken into account in that document (for example if the estimators don't converge on a surrogate variable). This will attempt each of the surrogate estimators described by Leek: pca, sva supervised, sva unsupervised, ruv supervised, ruv residuals, ruv empirical. Upon completion it will perform the same limma expression analysis and plot the ranked t statistics as well as a correlation plot making use of the extracted estimators against condition/batch/whatever else. Finally, it does the same ranking plot against a linear fitting Leek performed and returns the whole pile of information as a list.

**Usage**

```
compare_surrogate_estimates(expt, extra_factors = NULL, do_catplots = FALSE,
  surrogates = "be")
```

**Arguments**

expt	Experiment containing a design and other information.
extra_factors	Character list of extra factors which may be included in the final plot of the data.
do_catplots	Include the catplots? They don't make a lot of sense yet, so probably no.
surrogates	Use 'be' or 'leek' surrogate estimates, or choose a number.

**Value**

List of the results.

**See Also**

[get\\_model\\_adjust](#)

---

compare\_tables

*See how similar are results from limma/deseq/edgeR.*

---

**Description**

limma, DEseq2, and EdgeR all make somewhat different assumptions. and choices about what makes a meaningful set of differentially. expressed genes. This seeks to provide a quick and dirty metric describing the degree to which they (dis)agree.

**Usage**

```
compare_tables(limma = NULL, deseq = NULL, edgeR = NULL, basic = NULL,
  include_basic = TRUE, annot_df = NULL, ...)
```

**Arguments**

limma	Data from limma_pairwise().
deseq	Data from deseq2_pairwise().
edgeR	Data from edgeR_pairwise().
basic	Data from basic_pairwise().
include_basic	include the basic data?
annot_df	Include annotation data?
...	More options!

**Details**

Invoked by `all_pairwise()`.

**Value**

Heatmap showing how similar they are along with some correlations between the three players.

**See Also**

[limma\\_pairwise](#) [edgeR\\_pairwise](#) [DESeq2\\_pairwise](#)

**Examples**

```
## Not run:
l = limma_pairwise(expt)
d = DESeq2_pairwise(expt)
e = edgeR_pairwise(expt)
fun = compare_tables(limma=l, DESeq2=d, edgeR=e)

## End(Not run)
```

---

concatenate_runs	<i>Sum the reads/gene for multiple sequencing runs of a single condition/batch.</i>
------------------	---

---

**Description**

On occasion we have multiple technical replicates of a sequencing run. This can use a column in the experimental design to identify those replicates and sum the counts into a single column in the count tables.

**Usage**

```
concatenate_runs(expt, column = "replicate")
```

**Arguments**

expt	Experiment class containing the requisite metadata and count tables.
column	Column of the design matrix used to specify which samples are replicates.

**Details**

Untested as of 2016-12-01, but used in a couple of projects where sequencing runs got repeated.

**Value**

Expt with the concatenated counts, new design matrix, batches, conditions, etc.

**See Also****Biobase** [exprs](#) [fData](#) [pData](#)**Examples**

```
## Not run:
compressed <- concatenate_runs(expt)

## End(Not run)
```

---

convert_counts	<i>Perform a cpm/rpkm/whatever transformation of a count table.</i>
----------------	---

---

**Description**

I should probably tell it to also handle a simple df/vector/list of gene lengths, but I haven't. `cp_seq_m` is a cpm conversion of the data followed by a rp-ish conversion which normalizes by the number of the given oligo. By default this oligo is 'TA' because it was used for tseq which should be normalized by the number of possible transposition sites by mariner. It could, however, be used to normalize by the number of methionines, for example – if one wanted to do such a thing.

**Usage**

```
convert_counts(data, convert = "raw", ...)
```

**Arguments**

<code>data</code>	Matrix of count data.
<code>convert</code>	Type of conversion to perform: <code>edgecpm</code> / <code>cpm</code> / <code>rpkm</code> / <code>cp_seq_m</code> .
<code>...</code>	Options I might pass from other functions are dropped into arglist, used by <code>rpkm</code> (gene lengths) and <code>divide_seq</code> (genome, pattern to match, and annotation type).

**Value**

Dataframe of `cpm/rpkm/whatever(counts)`

**See Also****edgeR** **Biobase** [cpm](#)**Examples**

```
## Not run:
converted_table = convert_counts(count_table, convert='cbcbcpm')

## End(Not run)
```

---

`counts_from_surrogates`*A single place to extract count tables from a set of surrogate variables.*

---

**Description**

Given an initial set of counts and a series of surrogates, what would the resulting count table look like? Hopefully this function answers that question.

**Usage**

```
counts_from_surrogates(data, adjust, design = NULL)
```

**Arguments**

<code>data</code>	Original count table, may be an expt/expressionset or df/matrix.
<code>adjust</code>	Surrogates with which to adjust the data.
<code>design</code>	Experimental design if it is not included in the expressionset.

**Value**

A data frame of adjusted counts.

**See Also**

**Biobase**

---

`count_nmer`*Count n-mers in a given data set using Biostrings*

---

**Description**

This just calls `PDict()` and `vcountPDict()` on a sequence database given a pattern and number of mismatches. This may be used by `divide_seq()` normalization.

**Usage**

```
count_nmer(genome, pattern = "ATG", mismatch = 0)
```

**Arguments**

<code>genome</code>	Sequence database, genome in this case.
<code>pattern</code>	Count off this string.
<code>mismatch</code>	How many mismatches are acceptable?

**Value**

Set of counts by sequence.

---

cp_options	<i>Set up appropriate option sets for clusterProfiler</i>
------------	---

---

**Description**

This hard-sets some defaults for orgdb/kegg databases when using clusterProfiler.

**Usage**

```
cp_options(species)
```

**Arguments**

species	Currently it only works for humans and fruit flies.
---------	---

---

create_expt	<i>Wrap bioconductor's expressionset to include some other extraneous information.</i>
-------------	--

---

**Description**

It is worth noting that this function has a lot of logic used to find the count tables in the local filesystem. This logic has been superceded by simply adding a field to the .csv file called 'file'. create\_expt() will then just read that filename, it may be a full pathname or local to the cwd of the project.

**Usage**

```
create_expt(metadata, gene_info = NULL, count_dataframe = NULL,
  sample_colors = NULL, title = NULL, notes = NULL,
  include_type = "all", include_gff = NULL, savefile = "expt",
  low_files = FALSE, ...)
```

**Arguments**

metadata	Comma separated file (or excel) describing the samples with information like condition, batch, count_filename, etc.
gene_info	Annotation information describing the rows of the data set, this often comes from a call to import.gff() or biomaRt or organismdbi.
count_dataframe	If one does not wish to read the count tables from the filesystem, they may instead be fed as a data frame here.

sample_colors	List of colors by condition, if not provided it will generate its own colors using colorBrewer.
title	Provide a title for the expt?
notes	Additional notes?
include_type	I have usually assumed that all gff annotations should be used, but that is not always true, this allows one to limit to a specific annotation type.
include_gff	Gff file to help in sorting which features to keep.
savefile	Rdata filename prefix for saving the data of the resulting expt.
low_files	Explicitly lowercase the filenames when searching the filesystem?
...	More parameters are fun!

**Value**

experiment an expressionset

**See Also**

[Biobase pData fData exprs expt\\_read\\_counts as.list.hash](#)

**Examples**

```
## Not run:
new_experiment = create_expt("some_csv_file.csv", color_hash)
## Remember that this depends on an existing data structure of gene annotations.

## End(Not run)
```

---

default_norm	<i>Perform a default normalization of some data</i>
--------------	---

---

**Description**

This just calls `normalize_expt` with the most common arguments except `log2` transformation, but that may be appended with `'transform=log2'`, so I don't feel bad. Indeed, it will allow you to overwrite any arguments if you wish. In our work, the most common normalization is: `quantile(cpm(low-filter(data)))`.

**Usage**

```
default_norm(expt, ...)
```

**Arguments**

expt	An expressionset containing expt object
...	More options to pass to <code>normalize_expt()</code>

**Value**

The normalized expt

**See Also**

[normalize\\_expt](#)

---

deparse\_go\_value

---

*Extract more easily readable information from a GOTERM datum.*


---

**Description**

The output from the GOTERM/GO.db functions is inconsistent, to put it nicely. This attempts to extract from that heterogeneous datatype something easily readable. Example: `Synonym()` might return any of the following: NA, NULL, "NA", "NULL", `c("NA",NA,"GO:00001")`, "GO:00002", `c("Some text",NA,NULL,"GO:00003")` This function will boil that down to 'not found', "", 'GO:00004', or "GO:0001, some text, GO:00004"

**Usage**

```
deparse_go_value(value)
```

**Arguments**

value	Result of <code>try(as.character(somefunction(GOTERM[id])), silent=TRUE)</code> . some-function would be 'Synonym' 'Secondary' 'Ontology', etc...
-------	---

**Value**

something more sane (hopefully).

**See Also**

**GO.db**

**Examples**

```
## Not run:
## goterms = GOTERM[ids]
## sane_goterms = deparse_go_value(goterms)

## End(Not run)
```



---

deseq2_pairwise	<i>Set up model matrices contrasts and do pairwise comparisons of all conditions using DESeq2.</i>
-----------------	--

---

## Description

Invoking DESeq2 is confusing, this should help.

## Usage

```
deseq2_pairwise(input = NULL, conditions = NULL, batches = NULL,
  model_cond = TRUE, model_batch = TRUE, model_intercept = FALSE,
  alt_model = NULL, extra_contrasts = NULL, annot_df = NULL,
  force = FALSE, deseq_method = "long", ...)
```

## Arguments

input	Dataframe/vector or expt class containing data, normalization state, etc.
conditions	Factor of conditions in the experiment.
batches	Factor of batches in the experiment.
model_cond	Is condition in the experimental model?
model_batch	Is batch in the experimental model?
model_intercept	Use an intercept model? DESeq seems to not be a fan of them.
alt_model	Provide an arbitrary model here.
extra_contrasts	Provide extra contrasts here.
annot_df	Include some annotation information in the results?
force	Force deseq to accept data which likely violates its assumptions.
deseq_method	The DESeq2 manual shows a few ways to invoke it, I make 2 of them available here.
...	Triple dots! Options are passed to arglist.

## Details

Tested in test\_24de\_deseq.R Like the other `_pairwise()` functions, this attempts to perform all pairwise contrasts in the provided data set. The details are of course slightly different when using DESeq2. Thus, this uses the function `choose_binom_dataset()` to try to ensure that the incoming data is appropriate for DESeq2 (if one normalized the data, it will attempt to revert to raw counts, for example). It continues on to extract the conditions and batches in the data, choose an appropriate experimental model, and run the DESeq analyses as described in the manual. It defaults to using an experimental batch factor, but will accept a string like 'sva' instead, in which case it will use sva to estimate the surrogates, and append them to the experimental design. The `deseq_method` parameter may be used to apply different DESeq2 code paths as outlined in the manual. If you want to play with non-standard data, the `force` argument will round the data and shoe-horn it into DESeq2.

**Value**

List including the following information: run = the return from calling DESeq() denominators = list of denominators in the contrasts numerators = list of the numerators in the contrasts conditions = the list of conditions in the experiment coefficients = list of coefficients making the contrasts all\_tables = list of DE tables

**See Also**

**DESeq2 Biobase stats**

**Examples**

```
## Not run:
pretend = deseq2_pairwise(data, conditions, batches)

## End(Not run)
```

---

deseq_pairwise	<i>deseq_pairwise()</i> Because I can't be trusted to remember '2'.
----------------	---

---

**Description**

This calls deseq2\_pairwise(...) because I am determined to forget typing deseq2.

**Usage**

```
deseq_pairwise(...)
```

**Arguments**

```
...           I like cats.
```

**Value**

stuff deseq2\_pairwise results.

**See Also**

[deseq2\\_pairwise](#)

---

de_venn	Create venn diagrams describing how well deseq/limma/edger agree.
---------	---

---

### Description

The sets of genes provided by limma and friends would ideally always agree, but they do not. Use this to see out how much the (dis)agree.

### Usage

```
de_venn(table, adjp = FALSE, euler = FALSE, p = 0.05, fc = 0, ...)
```

### Arguments

table	Which table to query?
adjp	Use adjusted p-values
euler	Perform a euler plot
p	p-value cutoff, I forget what for right now.
...	More arguments are passed to arglist.

### Value

A list of venn plots

### See Also

**venneuler** **Vennerable**

### Examples

```
## Not run:
bunchovenns <- de_venn(pairwise_result)

## End(Not run)
```

---

disjunct_pvalues	Test for infected/control/beads – a placebo effect?
------------------	---

---

### Description

The goal is therefore to find responses different than beads The null hypothesis is (H0): (infected == uninfected) || (infected == beads) The alt hypothesis is (HA): (infected != uninfected) && (infected != beads)

**Usage**

```
disjunct_pvalues(contrast_fit, cellmeans_fit, conj_contrasts, disj_contrast)
```

**Arguments**

contrast_fit	The result of lmFit.
coef1	The first coefficient to query.
coef2	And the second.
...	Extra arguments are passed to arglist, but basically ignored.

---

divide_seq	<i>Express a data frame of counts as reads per pattern per million.</i>
------------	---

---

**Description**

This uses a sequence pattern rather than length to normalize sequence. It is essentially fancy pants rpkm.

**Usage**

```
divide_seq(counts, ...)
```

**Arguments**

counts	Read count matrix.
...	Options I might pass from other functions are dropped into arglist.

**Value**

The RPseqM counts

**See Also**

**edgeR** **Rsamtools** [FaFile](#) [rpkm](#)

**Examples**

```
## Not run:
cptam <- divide_seq(cont_table, fasta="mgas_5005.fasta.xz", gff="mgas_5005.gff.xz")

## End(Not run)
```

---

`download_gbk`*A genbank accession downloader scurrilously stolen from ape.*

---

**Description**

This takes and downloads genbank accessions.

**Usage**

```
download_gbk(accessions = "AE009949", write = TRUE)
```

**Arguments**

<code>accessions</code>	An accession – actually a set of them.
<code>write</code>	Write the files? Otherwise return a list of the strings

**Details**

Tested in test\_40ann\_biomartgenbank.R In this function I stole the same functionality from the ape package and set a few defaults so that it hopefully fails less often.

**Value**

A list containing the number of files downloaded and the character strings acquired.

**See Also**

**ape**

**Examples**

```
## Not run:  
gbk_file <- download_gbk(accessions=c("AE009949", "AE009948"))  
  
## End(Not run)
```

---

`do_pairwise`*Generalize pairwise comparisons*

---

**Description**

I want to multithread my pairwise comparisons, this is the first step in doing so.

**Usage**

```
do_pairwise(type, ...)
```

**Arguments**

type	Which type of pairwise comparison to perform
...	The set of arguments intended for limma_pairwise(), edger_pairwise(), and friends.

**Details**

Used to make parallel operations easier.

**Value**

The result from limma/deseq/edger/basic

**See Also**

[limma\\_pairwise](#) [edger\\_pairwise](#) [deseq\\_pairwise](#) [basic\\_pairwise](#)

---

edger_pairwise	<i>Set up a model matrix and set of contrasts to do pairwise comparisons using EdgeR.</i>
----------------	---

---

**Description**

This function performs the set of possible pairwise comparisons using EdgeR.

**Usage**

```
edger_pairwise(input = NULL, conditions = NULL, batches = NULL,
  model_cond = TRUE, model_batch = TRUE, model_intercept = TRUE,
  alt_model = NULL, extra_contrasts = NULL, annot_df = NULL,
  force = FALSE, edger_method = "long", ...)
```

**Arguments**

input	Dataframe/vector or expt class containing data, normalization state, etc.
conditions	Factor of conditions in the experiment.
batches	Factor of batches in the experiment.
model_cond	Include condition in the experimental model?
model_batch	Include batch in the model? In most cases this is a good thing(tm).
model_intercept	Use cell means or intercept?
alt_model	Alternate experimental model to use?
extra_contrasts	Add some extra contrasts to add to the list of pairwise contrasts. This can be pretty neat, lets say one has conditions A,B,C,D,E and wants to do (C/B)/A and (E/D)/A or (E/D)/(C/B) then use this with a string like: "c_vs_b_ctrla = (C-B)-A, e_vs_d_ctrla = (E-D)-A, de_vs_cb = (E-D)-(C-B),"

annot_df	Annotation information to the data tables?
force	Force edgeR to accept inputs which it should not have to deal with.
edger_method	I found a couple/few ways of doing edger in the manual, choose with this.
...	The elipsis parameter is fed to write_edger() at the end.

### Details

Tested in test\_26de\_edger.R Like the other `_pairwise()` functions, this attempts to perform all pairwise contrasts in the provided data set. The details are of course slightly different when using EdgeR. Thus, this uses the function `choose_binom_dataset()` to try to ensure that the incoming data is appropriate for EdgeR (if one normalized the data, it will attempt to revert to raw counts, for example). It continues on to extract the conditions and batches in the data, choose an appropriate experimental model, and run the EdgeR analyses as described in the manual. It defaults to using an experimental batch factor, but will accept a string like 'sva' instead, in which case it will use sva to estimate the surrogates, and append them to the experimental design. The `edger_method` parameter may be used to apply different EdgeR code paths as outlined in the manual. If you want to play with non-standard data, the `force` argument will round the data and shoe-horn it into EdgeR.

### Value

List including the following information: `contrasts` = The string representation of the contrasts performed. `lrt` = A list of the results from calling `glmLRT()`, one for each contrast. `contrast_list` = The list of each call to `makeContrasts()` I do this to avoid running into the limit on # of contrasts addressable by `topTags()` `all_tables` = a list of tables for the contrasts performed.

### See Also

**edgeR**

### Examples

```
## Not run:
pretend = edger_pairwise(data, conditions, batches)

## End(Not run)
```

---

expt_exclude_genes	<i>Exclude some genes given a pattern match</i>
--------------------	---

---

### Description

Because I am too lazy to remember that expressionsets use matrix subsets for [gene,sample]

### Usage

```
expt_exclude_genes(expt, column = "txtype", method = "remove",
  patterns = c("snRNA", "tRNA", "rRNA"), ...)
```

**Arguments**

expt	Expressionset containing expt object.
column	fData column to use for subsetting.
method	Either remove explicit rows, or keep them.
patterns	Character list of patterns to remove/keep
...	Extra arguments are passed to arglist, currently unused.

**Value**

A smaller expt

**See Also**

[create\\_expt](#)

---

expt_read_counts	<i>Read a bunch of count tables and create a usable data frame from them.</i>
------------------	---

---

**Description**

It is worth noting that this function has some logic intended for the elsayed lab's data storage structure. It shouldn't interfere with other usages, but it attempts to take into account different ways the data might be stored.

**Usage**

```
expt_read_counts(ids, files, header = FALSE, include_summary_rows = FALSE,
  suffix = NULL, ...)
```

**Arguments**

ids	List of experimental ids.
files	List of files to read.
header	Whether or not the count tables include a header row.
include_summary_rows	Whether HTSeq summary rows should be included.
suffix	Optional suffix to add to the filenames when reading them.
...	More options for happy time!

**Details**

Used primarily in `create_expt()` This is responsible for reading count tables given a list of filenames. It tries to take into account upper/lowercase filenames and uses `data.table` to speed things along.



**Value**

Data frame of count tables.

**See Also**

`data.table` [create\\_expt](#)

**Examples**

```
## Not run:
count_tables <- hpgl_read_files(as.character(sample_ids), as.character(count_filenames))

## End(Not run)
```

---

expt_snp	<i>Gather snp information for an expt</i>
----------	---

---

**Description**

I have some initial code for working with snps, but it seems that it will be getting more use, so make it testable etc.

**Usage**

```
expt_snp(expt, input_dir = "preprocessing/outputs",
  file_suffix = "_parsed_ratio.txt", bam_suffix = "_accepted_paired.bam",
  tolower = TRUE)
```

**Arguments**

- expt            an expressionset from which to extract information.
- input\_dir      Directory to scan for snps output files.
- file\_suffix    What to add on the end of the files for the resulting output.
- bam\_suffix     How do we find the bam files?
- tolower        Lowercase stuff like 'HPGL'?

**Value**

some stuff

---

expt_subset	<i>Extract a subset of samples following some rule(s) from an experiment class.</i>
-------------	---

---

### Description

Sometimes an experiment has too many parts to work with conveniently, this operation allows one to break it into smaller pieces.

### Usage

```
expt_subset(expt, subset = NULL)
```

### Arguments

expt	Expt chosen to extract a subset of data.
subset	Valid R expression which defines a subset of the design to keep.

### Value

metadata Expt class which contains the smaller set of data.

### See Also

**Biobase** [pData](#) [exprs](#) [fData](#)

### Examples

```
## Not run:
smaller_expt = expt_subset(big_expt, "condition=='control'")
all_expt = expt_subset(expressionset, "") ## extracts everything

## End(Not run)
```

---

extract_abundant_genes	<i>Extract the sets of genes which are significantly more abundant than the rest.</i>
------------------------	---

---

### Description

Given the output of something\_pairwise(), pull out the genes for each contrast which are the most/least abundant. This is in contrast to extract\_significant\_genes(). That function seeks out the most changed, statistically significant genes.

**Usage**

```
extract_abundant_genes(pairwise, according_to = "all", n = 100, z = NULL,
  unique = FALSE, least = FALSE, excel = "excel/abundant_genes.xlsx")
```

**Arguments**

pairwise	Output from <code>_pairwise()</code> .
according_to	What tool(s) define 'most'? One may use <code>deseq</code> , <code>edger</code> , <code>limma</code> , <code>basic</code> , <code>all</code> .
n	How many genes to pull?
z	Instead take the distribution of abundances and pull those past the given z score.
unique	One might want the subset of unique genes in the top-n which are unique in the set of available conditions. This will attempt to provide that.
least	Instead of the most abundant, do the least.
excel	Excel file to write.

**Value**

The set of most/least abundant genes by contrast/tool.

**See Also**

**openxlsx**

---

`extract_coefficient_scatter`

*Perform a coefficient scatter plot of a limma/deseq/edger/basic table.*

---

**Description**

Plot the gene abundances for two coefficients in a differential expression comparison. By default, genes past 1.5 z scores from the mean are colored red/green.

**Usage**

```
extract_coefficient_scatter(output, toptable = NULL, type = "limma",
  x = 1, y = 2, z = 1.5, p = NULL, fc = NULL, n = NULL,
  loess = FALSE, color_low = "#DD0000", color_high = "#7B9F35", ...)
```

**Arguments**

output	Result from the <code>de_</code> family of functions, <code>all_pairwise</code> , or <code>combine_de_tables()</code> .
toptable	Chosen table to query for abundances.
type	Query <code>limma</code> , <code>deseq</code> , <code>edger</code> , or <code>basic</code> outputs.
x	The x-axis column to use, either a number of name.

y	The y-axis column to use.
z	Define the range of genes to color (FIXME: extend this to p-value and fold-change).
p	Set a p-value cutoff for coloring the scatter plot (currently not supported).
fc	Set a fold-change cutoff for coloring points in the scatter plot (currently not supported.)
n	Set a top-n fold-change for coloring the points in the scatter plot (this should work, actually).
loess	Add a loess estimation (This is slow.)
color_low	Color for the genes less than the mean.
color_high	Color for the genes greater than the mean.
...	More arguments are passed to arglist.

**See Also**

`ggplot2` [plot\\_linear\\_scatter](#)

**Examples**

```
## Not run:
scatter_plot <- extract_coefficient_scatter(pairwise_output, type="deseq", x="uninfected", y="infected")

## End(Not run)
```

---

extract_de_ma	<i>Make a MA plot of some limma output with pretty colors and shapes</i>
---------------	--

---

**Description**

Yay pretty colors and shapes!

**Usage**

```
extract_de_ma(pairwise, type = "edger", table = NULL, logfc = 1,
  pval_cutoff = 0.05, invert = FALSE, ...)
```

**Arguments**

pairwise	The result from <code>all_pairwise()</code> , which should be changed to handle other invocations too.
type	Type of table to use: <code>deseq</code> , <code>edger</code> , <code>limma</code> , <code>basic</code> .
table	Result from <code>edger</code> to use, left alone it chooses the first.
pval_cutoff	Cutoff to define 'significant' by p-value.
...	Extra arguments are passed to <code>arglist</code> .
fc	Cutoff for <code>log2(fold-change)</code> significant.

**Value**

a plot!

**See Also**

[plot\\_ma\\_de](#)

**Examples**

```
## Not run:
prettyplot <- edger_ma(all_aprwise) ## [sic, I'm witty! and can speel]

## End(Not run)
```

---

extract\_go

*Extract a set of geneID to GOID mappings from a suitable data source.*

---

**Description**

Like `extract_lengths` above, this is primarily intended to read gene ID and GO ID mappings from a `OrgDb/OrganismDbi` object.

**Usage**

```
extract_go(db, metadf = NULL, keytype = "ENTREZID")
```

**Arguments**

db	Data source containing mapping information.
metadf	Data frame containing extant information.
keytype	Keytype used for querying

**Value**

Dataframe of 2 columns: `geneID` and `goID`.

**See Also**

**`AnnotationDbi`**

---

extract_lengths	<i>Take gene/exon lengths from a suitable data source (gff/TxDb/OrganismDbi)</i>
-----------------	--

---

### Description

Primarily goseq, but also other tools on occasion require a set of gene IDs and lengths. This function is responsible for pulling that data from either a gff, or TxDb/OrganismDbi.

### Usage

```
extract_lengths(db = NULL, gene_list = NULL,
  type = "GenomicFeatures::transcripts", id = "TXID",
  possible_types = c("GenomicFeatures::genes", "GenomicFeatures::cds",
    "GenomicFeatures::transcripts"), ...)
```

### Arguments

db	Object containing data, if it is a string then a filename is assumed to a gff file.
gene_list	Set of genes to query.
type	Function name used for extracting data from TxDb objects.
id	Column from the resulting data structure to extract gene IDs.
possible_types	Character list of types I have previously used.
...	More arguments are passed to arglist.

### Value

Dataframe containing 2 columns: ID, length

### See Also

**GenomicFeatures**

---

extract_siggenes	<i>Alias for extract_significant_genes because I am dumb.</i>
------------------	---

---

### Description

Alias for extract\_significant\_genes because I am dumb.

### Usage

```
extract_siggenes(...)
```

**Arguments**

... The parameters for extract\_significant\_genes()

**Value**

It should return a reminder for me to remember my function names or change them to something not stupid.

---

extract\_significant\_genes

*Extract the sets of genes which are significantly up/down regulated from the combined tables.*

---

**Description**

Given the output from combine\_de\_tables(), extract the genes in which we have the greatest likely interest, either because they have the largest fold changes, lowest p-values, fall outside a z-score, or are at the top/bottom of the ranked list.

**Usage**

```
extract_significant_genes(combined, according_to = "all", fc = 1,
  p = 0.05, sig_bar = TRUE, z = NULL, n = NULL, ma = TRUE,
  p_type = "adj", invert_barplots = FALSE,
  excel = "excel/significant_genes.xlsx", siglfc_cutoffs = c(0, 1, 2))
```

**Arguments**

combined	Output from combine_de_tables().
according_to	What tool(s) decide 'significant?' One may use the deseq, edger, limma, basic, meta, or all.
fc	Log fold change to define 'significant'.
p	(Adjusted)p-value to define 'significant'.
sig_bar	Add bar plots describing various cutoffs of 'significant'?
z	Z-score to define 'significant'.
n	Take the top/bottom-n genes.
ma	Add ma plots to the sheets of 'up' genes?
p_type	use an adjusted p-value?
invert_barplots	Invert the significance barplots as per Najib's request?
excel	Write the results to this excel file, or NULL.
siglfc_cutoffs	Set of cutoffs used to define levels of 'significant.'

**Value**

The set of up-genes, down-genes, and numbers therein.

**See Also**

[combine\\_de\\_tables](#)

---

factor_rsquared	<i>Collect the <math>r^2</math> values from a linear model fitting between a singular value decomposition and factor.</i>
-----------------	---

---

**Description**

Collect the  $r^2$  values from a linear model fitting between a singular value decomposition and factor.

**Usage**

```
factor_rsquared(svd_v, fact, type = "factor")
```

**Arguments**

svd_v	$V' V = I$ portion of a fast.svd call.
fact	Experimental factor from the original data.
type	Make this categorical or continuous with factor/continuous.

**Value**

The  $r^2$  values of the linear model as a percentage.

**See Also**

[corpcor](#) [fast.svd](#)

---

features_greater_than	<i>Count the number of features(genes) greater than <math>x</math> in a data set.</i>
-----------------------	---

---

**Description**

Sometimes I am asked how many genes have  $\geq x$  counts. Well, here you go.

**Usage**

```
features_greater_than(data, cutoff = 1, hard = TRUE)
```



**Arguments**

data	A dataframe/exprs/matrix/whatever of counts.
cutoff	Minimum number of counts.
hard	Greater-than is hard, greater-than-equals is not.

**Details**

Untested as of 2016-12-01 but used with Lucia. I think it would be interesting to iterate this function from small to large cutoffs and plot how the number of kept genes decreases.

**Value**

Number of genes.

**See Also**

**Biobase**

**Examples**

```
## Not run:
features <- features_greater_than(expt)

## End(Not run)
```

---

filter_counts	<i>Call various count filters.</i>
---------------	------------------------------------

---

**Description**

This calls the various filtering functions in genefilter along with suggestions made in our lab meetings; defaulting to the threshold based filter suggested by Hector.

**Usage**

```
filter_counts(count_table, filter = "cbcb", p = 0.01, A = 1, k = 1,
              cv_min = 0.01, cv_max = 1000, thresh = 4, min_samples = 2, ...)
```

**Arguments**

count_table	Some counts to filter.
filter	Filtering method to apply (cbcb, pofa, kofa, cv right now).
p	Used by genefilter's pofa().
A	Also for pofa().
k	Used by genefilter's kofa().
cv_min	Used by genefilter's cv().

cv_max	Also used by cv().
thresh	Minimum threshold across samples for cbc.
min_samples	Minimum number of samples for cbc.
...	More options might be needed, especially if I fold cv/p/etc into ...

**Value**

Data frame of filtered counts.

**See Also**

**genefilter**

**Examples**

```
## Not run:
new <- filter_counts(old)

## End(Not run)
```

---

flanking_sequence	<i>Extract sequence flanking a set of annotations (generally coding sequences)</i>
-------------------	--

---

**Description**

Given a set of annotations and genome, one might want to get the set of adjacent sequences.

**Usage**

```
flanking_sequence(bsgenome, annotation, distance = 200, type = "gene",
  prefix = "")
```

**Arguments**

bsgenome	Genome sequence
annotation	Set of annotations
distance	How far from each annotation is desired?
type	What type of annotation is desired?
prefix	Provide a prefix to the names to distinguish them from the existing annotations.

**Value**

A list of sequences before and after each sequence.

---

gather_genes_orgdb	<i>Use the orgdb instances from clusterProfiler to gather annotation data for GO.</i>
--------------------	---

---

### Description

Since clusterProfiler no longer builds gomaps, I need to start understanding how to properly get information from orgDBs.

### Usage

```
gather_genes_orgdb(goseq_data, orgdb_go, orgdb_ensembl)
```

### Arguments

goseq_data	Some data from goseq and friends.
orgdb_go	The orgDb instance with GO data.
orgdb_ensembl	The orgDb instance with ensembl data.

### Value

a go mapping

### See Also

**clusterProfiler**

---

gather_goseq_genes	<i>Given a set of goseq data from simple_goseq(), make a list of genes represented in each ontology.</i>
--------------------	--

---

### Description

This function uses the GO2ALLEG data structure to reverse map ontology categories to a list of genes represented. It therefore assumes that the GO2ALLEG.rda data structure has been deposited in pwd(). This in turn may be generated by clusterProfilers buildGOMap() function if it doesn't exist. For some species it may also be auto-generated. With little work this can be made much more generic, and it probably should.

### Usage

```
gather_goseq_genes(goseq, ontology = NULL, pval = 0.1,  
  include_all = FALSE, ...)
```

**Arguments**

<code>goseq</code>	List of goseq specific results as generated by <code>simple_goseq()</code> .
<code>ontology</code>	Ontology to search (MF/BP/CC).
<code>pval</code>	Maximum accepted pvalue to include in the list of categories to cross reference.
<code>include_all</code>	Include all genes in the ontology search?
<code>...</code>	Extra options without a purpose just yet.

**Value**

Data frame of categories/genes.

**See Also**

**goseq** **clusterProfiler** [simple\\_goseq](#)

**Examples**

```
## Not run:
data <- simple_goseq(sig_genes=limma_output, lengths=annotation_df, goids=goids_df)
genes_in_cats <- gather_genes(data, ont='BP')

## End(Not run)
```

---

<code>gbk2txdb</code>	<i>Given a genbank accession, make a txDb object along with sequences, etc.</i>
-----------------------	---

---

**Description**

Let us admit it, sometimes biomart is a pain. It also does not have easily accessible data for microbes. Genbank does!

**Usage**

```
gbk2txdb(accession = "AE009949", savetxdb = FALSE)
```

**Arguments**

<code>accession</code>	Accession to download and import
<code>savetxdb</code>	Save a txdb package from this? FIXME THIS DOES NOT WORK.

**Details**

Tested in `test_40ann_biomartgenbank.R` and `test_70expt_spyogenes.R` This just sets some defaults for the genbankr service in order to facilitate downloading genomes and such from genbank and dumping them into a local txdb instance.

**Value**

List containing a txDb, sequences, and some other stuff which I haven't yet finalized.

**See Also**

**genbankr** **rentrez** [import](#)

**Examples**

```
## Not run:
txdb_result <- gbk2txdb(accession="AE009948", savetxdb=TRUE)

## End(Not run)
```

---

gbk_annotations	<i>Extract some useful information from a gbk imported as a txDb.</i>
-----------------	---

---

**Description**

Maybe this should get pulled into the previous function?

**Usage**

```
gbk_annotations(gbr)
```

**Arguments**

gbr	TxDb object to poke at.
-----	-------------------------

**Details**

Tested in test\_40ann\_biomartgenbank.R This function should provide a quick reminder of how to use the AnnotationDbi select function if it does nothing else. It also (hopefully helpfully) returns a granges object containing the essential information one might want for printing out a gff or whatever.

**Value**

Granges data

**See Also**

**AnnotationDbi** **GenomeInfoDb** **GenomicFeatures** [select](#)

**Examples**

```
## Not run:
annotations <- gbk_annotations("saureus_txdb")

## End(Not run)
```

---

genefilter\_cv\_counts     *Filter genes from a dataset outside a range of variance.*

---

### Description

This function from genefilter removes genes surpassing a variance cutoff. It is not therefore a low-count filter per se.

### Usage

```
genefilter_cv_counts(count_table, cv_min = 0.01, cv_max = 1000)
```

### Arguments

count_table	Input data frame of counts by sample.
cv_min	Minimum coefficient of variance.
cv_max	Maximum coefficient of variance.

### Value

Dataframe of counts without the high/low variance genes.

### See Also

**genefilter** [kOverA](#)

### Examples

```
## Not run:
  filtered_table = genefilter_kofa_counts(count_table)

## End(Not run)
```

---

genefilter\_kofa\_counts

*Filter low-count genes from a data set using genefilter's kOverA().*

---

### Description

This is the most similar to the function suggested by Hector I think.

### Usage

```
genefilter_kofa_counts(count_table, k = 1, A = 1)
```

**Arguments**

count_table	Input data frame of counts by sample.
k	Minimum number of samples to have >A counts.
A	Minimum number of counts for each gene's sample in kOverA().

**Value**

Dataframe of counts without the low-count genes.

**See Also**

**genefilter** [kOverA](#)

**Examples**

```
## Not run:
filtered_table = genefilter_kofa_counts(count_table)

## End(Not run)
```

---

genefilter\_pofa\_counts

*Filter low-count genes from a data set using genefilter's pOverA().*

---

**Description**

I keep thinking this function is pofa... oh well. Of the various tools in genefilter, this one to me is the most intuitive. Take the ratio of counts/samples and make sure it is  $\geq$  a score.

**Usage**

```
genefilter_pofa_counts(count_table, p = 0.01, A = 100)
```

**Arguments**

count_table	Input data frame of counts by sample.
p	Minimum proportion of each gene's counts/sample to be greater than a minimum(A).
A	Minimum number of counts in the above proportion.

**Value**

Dataframe of counts without the low-count genes.

**See Also**

**genefilter** [pOverA](#)

## Examples

```
## Not run:
  filtered_table = genefilter_pofa_counts(count_table)

## End(Not run)
```

---

```
generate_gene_kegg_mapping
```

*Generate GENE/KEGG mapping.*

---

## Description

This uses KEGGREST and related function `kegg_to_ensembl()` to associate genes to KEGG pathways.

## Usage

```
generate_gene_kegg_mapping(pathways, org_abbreviation, verbose = FALSE)
```

## Arguments

<code>pathways</code>	Vector of KEGG pathway IDs returned from call to <code>keggLink()</code> e.g. "path:mmu05134".
<code>org_abbreviation</code>	KEGG identifier for the species of interest (e.g. "hsa" for Homo sapiens).
<code>verbose</code>	talky talky?

## Value

Df mapping kegg and gene IDs.

## See Also

**KEGGREST** [keggLink](#)

## Examples

```
## Not run:
  kegg_df <- generate_gene_kegg_mapping(path, org)

## End(Not run)
```



---

`generate_kegg_pathway_mapping`*Generate a KEGG PATHWAY / description mapping.*

---

**Description**

Make an easier to use df of KEGG -> descriptions using keggGet.

**Usage**

```
generate_kegg_pathway_mapping(pathways, verbose = FALSE)
```

**Arguments**

pathways	Vector of KEGG pathway identifiers.
verbose	talk talk?

**Value**

Data frame describing some kegg pathways

**See Also**

**KEGGREST** [keggLink](#)

**Examples**

```
## Not run:  
mapping <- generate_kegg_pathway_mapping(c("hsa00040", "hsa00100"))  
  
## End(Not run)
```

---

`genoplot_chromosome`*Try plotting a chromosome (region)*

---

**Description**

genoplotr is cool, I don't yet understand it though

**Usage**

```
genoplot_chromosome(accession = "AE009949", start = NULL, end = NULL,  
  title = "Genome plot")
```

**Arguments**

accession	An accession to plot, this will download it.
start	First segment to plot (doesn't quite work yet).
end	Final segment to plot (doesn't quite work yet).
title	Put a title on the resulting plot.

**Value**

Hopefully a pretty plot of a genome

**See Also**

**genoPlotR**

---

getEdgeWeights	<i>Plot the ontology DAG.</i>
----------------	-------------------------------

---

**Description**

This function was stolen from topgo in order to figure out where it was failing.

**Usage**

```
getEdgeWeights(graph)
```

**Arguments**

graph	Graph from topGO
-------	------------------

**Value**

Weights!

---

get_abundant_genes	<i>Find the set of most/least abundant genes according to limma and friends following a differential expression analysis.</i>
--------------------	---

---

### Description

Given a data set provided by limma, deseq, edgeR, etc; one might want to know what are the most and least abundant genes, much like get\_sig\_genes() does to find the most significantly different genes for each contrast.

### Usage

```
get_abundant_genes(datum, type = "limma", n = NULL, z = NULL,  
  unique = FALSE, least = FALSE)
```

### Arguments

datum	Output from the _pairwise() functions.
type	Extract abundant genes according to what?
n	Perhaps take just the top/bottom n genes.
z	Or take genes past a given z-score.
unique	Unimplemented: take only the genes unique among the conditions surveyed.
least	When true, this finds the least abundant rather than most.

### Value

List of data frames containing the genes of interest.

### See Also

**stats limma DESeq2 edgeR**

---

get_biomart_annotations	<i>Extract annotation information from biomart.</i>
-------------------------	---

---

### Description

Biomart is an amazing resource of information, but using it is a bit annoying. This function hopes to alleviate some common headaches.

**Usage**

```
get_biomart_annotations(species = "hsapiens", overwrite = FALSE,
  do_save = TRUE, host = "dec2015.archive.ensembl.org",
  trymart = "ENSEMBL_MART_ENSEMBL", gene_requests = c("ensembl_gene_id",
    "ensembl_transcript_id", "description", "gene_biotype"),
  length_requests = c("ensembl_transcript_id", "cds_length",
    "chromosome_name", "strand", "start_position", "end_position"),
  include_lengths = TRUE)
```

**Arguments**

species	Choose a species.
overwrite	Overwrite an existing save file?
do_save	Create a savefile of annotations for future runs?
host	Ensembl hostname to use.
trymart	Biomart has become a circular dependency, this makes me sad, now to list the marts, you need to have a mart loaded...
gene_requests	Set of columns to query for description-ish annotations.
length_requests	Set of columns to query for location-ish annotations.
include_lengths	Also perform a search on structural elements in the genome?

**Details**

Tested in test\_40ann\_biomart.R This goes to some lengths to find the relevant tables in biomart. But biomart is incredibly complex and one should carefully inspect the output if it fails to see if there are more appropriate marts, datasets, and columns to download.

**Value**

Df of some (by default) human annotations.

**See Also**

**biomaRt** [listDatasets](#) [getBM](#)

**Examples**

```
## Not run:
tt = get_biomart_annotations()

## End(Not run)
```

---

`get_biomart_ontologies`*Extract gene ontology information from biomart.*

---

## Description

I perceive that every time I go to acquire annotation data from biomart, they have changed something important and made it more difficult for me to find what I want. I recently found the \*.archive.ensembl.org, and so this function uses that to try to keep things predictable, if not consistent.

## Usage

```
get_biomart_ontologies(species = "hsapiens", overwrite = FALSE,
  do_save = TRUE, host = "dec2015.archive.ensembl.org",
  trymart = "ENSEMBL_MART_ENSEMBL", secondtry = "_gene",
  dl_rows = c("ensembl_gene_id", "go_accession"),
  dl_rowsv2 = c("ensembl_gene_id", "go_id"))
```

## Arguments

<code>species</code>	Species to query.
<code>overwrite</code>	Overwrite existing savefile?
<code>do_save</code>	Create a savefile of the annotations? (if not false, then a filename.)
<code>host</code>	Ensembl hostname to use.
<code>trymart</code>	Default mart to try, newer marts use a different notation.
<code>secondtry</code>	The newer mart name.
<code>dl_rows</code>	List of rows from the final biomart object to download.
<code>dl_rowsv2</code>	A second list of potential rows.

## Details

Tested in test\_40ann\_biomart.R This function makes a couple of attempts to pick up the correct tables from biomart. It is worth noting that it uses the archive.ensembl host(s) because of changes in table organization after December 2015 as well as an attempt to keep the annotation sets relatively consistent.

## Value

Df of geneIDs and GOIDs.

## See Also

**biomaRt** [listMarts](#) [useDataset](#) [getBM](#)

**Examples**

```
## Not run:
  tt = get_biomart_ontologies()

## End(Not run)
```

---

get_eupath_config	<i>Grab some configuration data collated and used to make OrganismDbi/OrgDb/TxDb objects.</i>
-------------------	---

---

**Description**

This function uses some data copied into inst/ to decide some parameters used for generating the various packages generated here.

**Usage**

```
get_eupath_config(cfg = NULL)
```

**Arguments**

cfg	Optional data frame
-----	---------------------

**Details**

Tested in test\_46ann\_tritrypdb.R This function is sort of stupid and perhaps will be removed. I keep a small csv file of some TriTrypDB specific metadata, things like data base version number, URL schemes, etc. This reads that and extracts the relevant information.

**Value**

Dataframe of configuration data, a few columns are required, run it with no args to see which ones.

---

get_genelengths	<i>Grab gene lengths from a gff file.</i>
-----------------	---

---

**Description**

This function attempts to be robust to the differences in output from importing gff2/gff3 files. But it certainly isn't perfect.

**Usage**

```
get_genelengths(gff, type = "gene", key = "ID", ...)
```

**Arguments**

gff	Gff file with (hopefully) IDs and widths.
type	Annotation type to use (3rd column).
key	Identifier in the 10th column of the gff file to use.
...	Extra arguments likely for gff2df

**Value**

Data frame of gene IDs and widths.

**See Also**

**rtracklayer** [gff2df](#)

**Examples**

```
## Not run:
tt = get_genelengths('reference/fun.gff.gz')
head(tt)
##           ID width
## 1  YAL069W   312
## 2  YAL069W   315
## 3  YAL069W     3
## 4 YAL068W-A   252
## 5 YAL068W-A   255
## 6 YAL068W-A     3

## End(Not run)
```

---

get\_kegg\_genes

*Extract the set of geneIDs matching pathways for a given species.*

---

**Description**

This uses KEGGREST to extract the mappings for all genes for a species and pathway or 'all'. Because downloading them takes a while, it will save the results to kegg\_species.rda. When run interactively, it will give some information regarding the number of genes observed in each pathway.

**Usage**

```
get_kegg_genes(pathway = "all", abbreviation = NULL,
               species = "leishmania major", savefile = NULL)
```

**Arguments**

pathway	Either a single pathway kegg id or 'all'.
abbreviation	Optional 3 letter species kegg id.
species	Stringified species name used to extract the 3 letter abbreviation.
savefile	Filename to which to save the relevant data.

**Value**

Dataframe of the various kegg data for each pathway, 1 row/gene.

**See Also**

**KEGGREST**

**Examples**

```
## Not run:
kegg_info <- get_kegg_genes(species="Canis familiaris")

## End(Not run)
```

---

get_kegg_sub	<i>Provide a set of simple substitutions to convert geneIDs from KEGG-&gt;TriTryDB</i>
--------------	--

---

**Description**

This function should provide 2 character lists which, when applied sequentially, will result in a hopefully coherent set of mapped gene IDs matching the TriTryDB/KEGG specifications.

**Usage**

```
get_kegg_sub(species = "lma")
```

**Arguments**

species            3 letter abbreviation for a given kegg type

**Value**

2 character lists containing the patterns and replace arguments for gsub(), order matters!

**See Also**

**KEGGREST**



---

get_loci_go	<i>Extract the set of GO categories by microbesonline locus</i>
-------------	---

---

**Description**

The microbesonline is such a fantastic resource, it is a bit of a shame that it is such a pain to query.

**Usage**

```
get_loci_go(taxonid = "160490")
```

**Arguments**

taxonid	Which species to query.
---------	-------------------------

**Details**

Tested in test\_42ann\_microbes.R I am not 100 At the very least, it does return a large number of them, which is a start.

**Value**

data frame of GO terms from pub.microbesonline.org

**See Also**

**DBI** [dbSendQuery](#) [fetch](#)

**Examples**

```
## Not run:
go_df <- get_loci_go(taxonid="160490")

## End(Not run)
```

---

get_microbesonline_annotation	<i>Skip the db and download all the text annotations for a given species.</i>
-------------------------------	---

---

**Description**

Like I said, the microbesonline mysqldb is rather more complex than I prefer. This shortcuts that process and just grabs a tsv copy of everything and loads it into a dataframe.

**Usage**

```
get_microbesonline_annotation(ids = "160490", species = NULL)
```

**Arguments**

ids	List of ids to query.
species	Species name(s) to use instead.

**Details**

Tested in test\_70expt\_spyogenes.R There is so much awesome information in microbesonline, but damn is it annoying to download. This function makes that rather easier, or so I hope at least.

**Value**

List of dataframes with the annotation information.

**See Also**

**RCurl** [getURL](#)

**Examples**

```
## Not run:
  annotations <- get_microbesonline_annotation(ids=c("160490","160491"))

## End(Not run)
```

---

get\_microbesonline\_ids

*Use the publicly available microbesonline mysql instance to get species ids.*

---

**Description**

The microbesonline mysql instance is more complex than I like. Their id system is reminiscent of KEGG's and similarly annoying. Though I haven't figured out how the tables interact, a query to get ids is simple enough.

**Usage**

```
get_microbesonline_ids(name = "Escherichia", exact = FALSE)
```

**Arguments**

name	Text string containing some part of the species name of interest.
exact	Use an exact species name?

**Details**

Tested in test\_42ann\_microbes.R This function sets the defaults required for getting a quick and dirty connection to the public microbesonline database and returning the ids associated with a given name.

**Value**

Dataframe of ids and names.

**See Also**

**DBI** [dbSendQuery](#) [fetch](#)

**Examples**

```
## Not run:
microbes_ids <- get_microbesonline_ids(name="Streptococcus")

## End(Not run)
```

---

`get_microbesonline_name`

*Use the publicly available microbesonline mysql instance to get species name(s).*

---

**Description**

The microbesonline mysql instance is more complex than I like. Their id system is reminiscent of KEGG's and similarly annoying. Though I haven't figured out how the tables interact, a query to get ids is simple enough.

**Usage**

```
get_microbesonline_name(id = 316385)
```

**Arguments**

`id` Text string containing some part of the species name of interest.

**Details**

Tested in test\_42ann\_microbesonline.R This is essentially covered in `get_microbesonline_ids()`, but this works too.

**Value**

Dataframe of ids and names.

**See Also**

**DBI** [dbSendQuery](#) [fetch](#)

**Examples**

```
## Not run:
names <- get_microbesonline_name(id=316385)

## End(Not run)
```

---

get_model_adjust	<i>Extract some surrogate estimations from a raw data set using sva, ruv, and/or pca.</i>
------------------	---

---

**Description**

This applies the methodologies very nicely explained by Jeff Leek at <https://github.com/jtleek/svaseq/blob/master/recount.R> and attempts to use them to acquire estimates which may be applied to an experimental model by either EdgeR, DESeq2, or limma. In addition, it modifies the count tables using these estimates so that one may play with the modified counts and view the changes (with PCA or heatmaps or whatever). Finally, it prints a couple of the plots shown by Leek in his document. In other words, this is entirely derivative of someone much smarter than me.

**Usage**

```
get_model_adjust(input, design = NULL, estimate_type = "sva",
  surrogates = "be", expt_state = NULL, ...)
```

**Arguments**

input	Expt or data frame to manipulate.
design	If the data is not an expt, provide experimental design here.
estimate_type	One of: sva_supervised, sva_unsupervised, ruv_empirical, ruv_supervised, ruv_residuals, or pca.
surrogates	Choose a method for getting the number of surrogates, be or leek, or a number.
...	Parameters fed to arglist.

**Value**

List including the adjustments for a model matrix, a modified count table, and 3 plots of the known batch, surrogates, and batch/surrogate.

**See Also**

**Biobase** [sva](#) [EDASeq](#) [RUVseq](#) [edgeR](#)

---

get_ncbi_taxonid	<i>Use taxize to get ncbi taxon IDs</i>
------------------	---

---

**Description**

taxize looks like it might be awesome, but it is also pretty annoying

**Usage**

```
get_ncbi_taxonid(species = "Leishmania major")
```

**Arguments**

species	Human readable species name
---------	-----------------------------

**Value**

potential NCBI taxon IDs

**See Also**

**taxize**

**Examples**

```
## Not run:
taxonid <- get_ncbi_taxonid(species="Trypanosoma cruzi")

## End(Not run)
```

---

get_pairwise_gene_abundances	<i>A companion function for get_abundant_genes()</i>
------------------------------	--

---

**Description**

Instead of pulling to top/bottom abundant genes, get all abundances and variances or stderr.

**Usage**

```
get_pairwise_gene_abundances(datum, type = "limma", excel = NULL)
```

**Arguments**

datum	Output from _pairwise() functions.
type	According to deseq/limma/edgeR/basic?
excel	Print this to an excel file?

**Value**

A list containing the expression values and some metrics of variance/error.

**See Also**

**limma**

---

get_sig_genes	<i>Get a set of up/down differentially expressed genes.</i>
---------------	---

---

**Description**

Take one or more criteria (fold change, rank order, (adj)p-value, z-score from median FC) and use them to extract the set of genes which are defined as 'differentially expressed.' If no criteria are provided, it arbitrarily chooses all genes outside of 1-z.

**Usage**

```
get_sig_genes(table, n = NULL, z = NULL, fc = NULL, p = NULL,
  column = "logFC", fold = "plusminus", p_column = "adj.P.Val")
```

**Arguments**

table	Table from limma/edger/deseq.
n	Rank-order top/bottom number of genes to take.
z	Number of z-scores >/< the median to take.
fc	Fold-change cutoff.
p	P-value cutoff.
column	Table's column used to distinguish top vs. bottom.
fold	Identifier reminding how to get the bottom portion of a fold-change (plusminus says to get the negative of the positive, otherwise 1/positive is taken). This effectively tells me if this is a log fold change or not.
p_column	Table's column containing (adjusted or not)p-values.

**Details**

Tested in test\_29de\_shared.R

**Value**

Subset of the up/down genes given the provided criteria.

**See Also**

[extract\\_significant\\_genes](#)

---

gff2df*Extract annotation information from a gff file into a df*

---

## Description

Try to make `import.gff` a little more robust; I acquire (hopefully) valid gff files from various sources: `yeastgenome.org`, `microbesonline`, `tritypdb`, `ucsc`, `ncbi`. To my eyes, they all look like reasonably good gff3 files, but some of them must be loaded with `import.gff2`, `import.gff3`, etc. That is super annoying. Also, I pretty much always just do `as.data.frame()` when I get something valid from `rtracklayer`, so this does that for me, I have another function which returns the `iranges` etc. This function wraps `import.gff/import.gff3/import.gff2` calls in `try()` because sometimes those functions fail in unpredictable ways.

## Usage

```
gff2df(gff, type = NULL, id_col = "ID", second_id_col = "locus_tag",
      try = NULL)
```

## Arguments

<code>gff</code>	Gff filename.
<code>type</code>	Subset the gff file for entries of a specific type.
<code>id_col</code>	Column in a successful import containing the IDs of interest.
<code>second_id_col</code>	Second column to check.
<code>try</code>	Give your own function call to use for importing.

## Value

Dataframe of the annotation information found in the gff file.

## See Also

`rtracklayer` `GenomicRanges` `import.gff`

## Examples

```
## Not run:
funkytown <- gff2df('reference/gff/saccharomyces_cerevsiae.gff.xz')

## End(Not run)
```

---

**gff2irange***Extract annotation information from a gff file into an irange object.*

---

## Description

Try to make import.gff a little more robust; I acquire (hopefully) valid gff files from various sources: yeastgenome.org, microbesonline, tritrypdb, ucsc, ncbi. To my eyes, they all look like reasonably good gff3 files, but some of them must be loaded with import.gff2, import.gff3, etc. That is super annoying. Also, I pretty much always just do as.data.frame() when I get something valid from rtracklayer, so this does that for me, I have another function which returns the iranges etc. This function wraps import.gff/import.gff3/import.gff2 calls in try() because sometimes those functions fail in unpredictable ways.

## Usage

```
gff2irange(gff, type = NULL)
```

## Arguments

gff	Gff filename.
type	Subset to extract.

## Details

This is essentially gff2df(), but returns data suitable for getSet()

## Value

Iranges! (useful for getSeq().)

## See Also

**rtracklayer** [gff2df](#) **Biostrings** [import.gff](#)

## Examples

```
## Not run:
library(BSgenome.Tcruzi.clbrener.all)
tc_clb_all <- BSgenome.Tcruzi.clbrener.all
cds_ranges <- gff2irange('reference/gff/tcruzi_clbrener.gff.xz', type='CDS')
cds_sequences <- Biostrings::getSeq(tc_clb_all, cds_ranges)

## End(Not run)
```



---

`ggplot2_heatmap`*Taken from <https://plot.ly/ggplot2/ggdendro-dendrograms/>*

---

**Description**

Check out the following link for a neat dendrogram library. <http://www.sthda.com/english/wiki/beautiful-dendrogram-visualizations-in-r-5-must-known-methods-unsupervised-machine-learning>

**Usage**

```
ggplot2_heatmap(some_df)
```

**Arguments**

`some_df`            A data frame to heatmap using ggplot2.

**Value**

putatively a heatmap!

---

`godef`*Get a go long-form definition from an id.*

---

**Description**

Sometimes it is nice to be able to read the full definition of some GO terms.

**Usage**

```
godef(go = "GO:0032432")
```

**Arguments**

`go`                GO ID, this may be a character or list (assuming the elements are goids).

**Value**

Some text providing the long definition of each provided GO id.

**See Also**

**GOTermsAnnDbBimap**

### Examples

```
## Not run:
godef("GO:0032432")
## > GO:0032432
## > "An assembly of actin filaments that are on the same axis but may be oriented with the
## > same or opposite polarities and may be packed with different levels of tightness."

## End(Not run)
```

---

golev

*Get a go level approximation from an ID.*

---

### Description

Sometimes it is useful to know how far up/down the ontology tree a given id resides. This attmpts to answer that question.

### Usage

```
golev(go)
```

### Arguments

go                      GO id, this may be a character or list (assuming the elements are goids).

### Value

Set of numbers corresponding to approximate tree positions of the GO ids.

### See Also

**GOTermsAnnDbBimap**

### Examples

```
## Not run:
golev("GO:0032559")
## > 3

## End(Not run)
```

---

golevel	<i>Get a go level approximation from a set of IDs.</i>
---------	--

---

**Description**

This just wraps golev() in mapply.

**Usage**

```
golevel(go = c("GO:0032559", "GO:0000001"))
```

**Arguments**

go	Character list of IDs.
----	------------------------

**Value**

Set pf approximate levels within the onlogy.

**See Also**

**GOTermsAnnDbBimap**

**Examples**

```
## Not run:
golevel(c("GO:0032559", "GO:0000001"))
## > 3 4

## End(Not run)
```

---

golevel_df	<i>Extract a dataframe of golevels using getGOLevel() from clusterProfiler.</i>
------------	---

---

**Description**

This function is way faster than my previous iterative golevel function. That is not to say it is very fast, so it saves the result to ontlevel.rda for future lookups.

**Usage**

```
golevel_df(ont = "MF", savefile = "ontlevel.rda")
```

**Arguments**

ont                    the ontology to recurse.  
 savefile            a file to save the results for future lookups.

**Value**

golevels a dataframe of goids<->highest level

**See Also**

**clusterProfiler**

---

goont	<i>Get a go ontology name from an ID.</i>
-------	---

---

**Description**

Get a go ontology name from an ID.

**Usage**

```
goont(go = c("GO:0032432", "GO:0032433"))
```

**Arguments**

go                    GO id, this may be a character or list (assuming the elements are goids).

**Value**

The set of ontology IDs associated with the GO ids, thus 'MF' or 'BP' or 'CC'.

**See Also**

**GOTermsAnnDbBimap**

**Examples**

```
## Not run:
goont(c("GO:0032432", "GO:0032433"))
## > GO:0032432 GO:0032433
## > "CC" "CC"

## End(Not run)
```

---

`gosec`*Get a GO secondary ID from an id.*

---

**Description**

Unfortunately, GOTERM's returns for secondary IDs are not consistent, so this function has to have a whole bunch of logic to handle the various outputs.

**Usage**

```
gosec(go = "GO:0032432")
```

**Arguments**

<code>go</code>	GO ID, this may be a character or list(assuming the elements, not names, are goids).
-----------------	--

**Value**

Some text comprising the secondary GO id(s).

**See Also**

**GOTermsAnnDbBimap**

**Examples**

```
## Not run:
gosec("GO:0032432")
## > GO:0032432
## > "GO:0000141" "GO:0030482"

## End(Not run)
```

---

`goseq_table`*Enhance the goseq table of gene ontology information.*

---

**Description**

While goseq has some nice functionality, the table of outputs it provides is somewhat lacking. This attempts to increase that with some extra helpful data like ontology categories, definitions, etc.

While goseq has some nice functionality, the table of outputs it provides is somewhat lacking. This attempts to increase that with some extra helpful data like ontology categories, definitions, etc.

**Usage**

```
goseq_table(df, file = NULL)
```

```
goseq_table(df, file = NULL)
```

**Arguments**

df	Dataframe of ontology information. This is intended to be the output from goseq including information like numbers/category, GOids, etc. It requires a column 'category' which contains: GO:000001 and such.
file	Csv file to which to write the table.
df	Dataframe of ontology information. This is intended to be the output from goseq including information like numbers/category, GOids, etc. It requires a column 'category' which contains: GO:000001 and such.
file	Csv file to which to write the table.

**Value**

Ontology table with annotation information included.

Ontology table with annotation information included.

**See Also**

**goseq**

**goseq**

**Examples**

```
## Not run:
annotated_go = goseq_table(go_ids)
head(annotated_go, n=1)
## >      category numDEInCat numInCat over_represented_pvalue
## > 571  GO:0006364          9      26          4.655108e-08
## >      under_represented_pvalue      qvalue ontology
## > 571          1.0000000 6.731286e-05      BP
## >      term
## > 571      rRNA processing
## >      synonym
## > 571      "35S primary transcript processing, GO:0006365"
## >      secondary      definition
## > 571  GO:0006365  Any process involved in the conversion of a primary ribosomal
##      RNA (rRNA) transcript into one or more mature rRNA molecules.

## End(Not run)
## Not run:
annotated_go = goseq_table(go_ids)
head(annotated_go, n=1)
## >      category numDEInCat numInCat over_represented_pvalue
## > 571  GO:0006364          9      26          4.655108e-08
```

```
## >      under_represented_pvalue      qvalue ontology
## > 571      1.0000000 6.731286e-05      BP
## >      term
## > 571      rRNA processing
## >      synonym
## > 571      "35S primary transcript processing, GO:0006365"
## >      secondary definition
## > 571      GO:0006365 Any process involved in the conversion of a primary ribosomal
##      RNA (rRNA) transcript into one or more mature rRNA molecules.

## End(Not run)
```

goseq\_trees

*Make fun trees a la topgo from goseq data.*

## Description

This seeks to force goseq data into a format suitable for topGO and then use its tree plotting function to make it possible to see significantly increased ontology trees.

This seeks to force goseq data into a format suitable for topGO and then use its tree plotting function to make it possible to see significantly increased ontology trees.

## Usage

```
goseq_trees(goseq, goid_map = "id2go.map", score_limit = 0.01,
  overwrite = FALSE, selector = "topDiffGenes", pval_column = "adj.P.Val")

goseq_trees(goseq, goid_map = "id2go.map", score_limit = 0.01,
  overwrite = FALSE, selector = "topDiffGenes", pval_column = "adj.P.Val")
```

## Arguments

goseq	Data from goseq.
goid_map	File to save go id mapping.
score_limit	Score limit for the coloring.
overwrite	Overwrite the trees?
selector	Function for choosing genes.
pval_column	Column to acquire pvalues.
de_genes	Some differentially expressed genes.
godata	Data from goseq.
goids_df	Mapping of IDs to GO in the Ramigo expected format.
goid_map	File to save go id mapping.
score_limit	Score limit for the coloring.
overwrite	Overwrite the trees?
selector	Function for choosing genes.
pval_column	Column to acquire pvalues.

**Value**

A plot!

A plot!

**See Also**

**Ramigo**

**Ramigo**

---

gostats\_kegg

*Use gostats() against kegg pathways.*

---

**Description**

This sets up a GSEABase analysis using KEGG pathways rather than gene ontologies. Does this even work? I don't think I have ever tested it yet. oh, it sort of does, maybe if I export it I will rembmber it.

**Usage**

```
gostats_kegg(organism = "Homo sapiens", pathdb = "org.Hs.egPATH",  
             godb = "org.Hs.egGO")
```

**Arguments**

organism	The organism used to make the KEGG frame, human readable no taxonomic.
pathdb	Name of the pathway database for this organism.
godb	Name of the ontology database for this organism.

**Value**

Results from hyperGTest using the KEGG pathways.

**See Also**

**AnnotationDbi GSEABase Category**



---

gostats_trees	<i>Take gostats data and print it on a tree as topGO does.</i>
---------------	--

---

## Description

This shoeorns gostats data into a format acceptable by topgo and uses it to print pretty ontology trees showing the over represented ontologies.

## Usage

```
gostats_trees(de_genes, mf_over, bp_over, cc_over, mf_under, bp_under, cc_under,
  goid_map = "id2go.map", score_limit = 0.01, goids_df = NULL,
  overwrite = FALSE, selector = "topDiffGenes", pval_column = "adj.P.Val")
```

## Arguments

de_genes	Some differentially expressed genes.
mf_over	Mfover data.
bp_over	Bpover data.
cc_over	Ccover data.
mf_under	Mfunder data.
bp_under	Bpunder data.
cc_under	Ccunder expression data.
goid_map	Mapping of IDs to GO in the Ramigo expected format.
score_limit	Maximum score to include as 'significant'.
goids_df	Dataframe of available goids (used to generate goid_map).
overwrite	Overwrite the goid_map?
selector	Function to choose differentially expressed genes in the data.
pval_column	Column in the data to be used to extract pvalue scores.

## Value

plots! Trees! oh my!

## See Also

**topGO** **gostats**

---

**gosyn***Get a go synonym from an ID.*

---

**Description**

I think I will need to do similar parsing of the output for this function as per `gosec()` In some cases this also returns stuff like `c("some text", "GO:someID")` versus "some other text" versus `NULL` versus `NA`. This function just goes a `mapply(gosn, go)`.

**Usage**

```
gosyn(go = "GO:0000001")
```

**Arguments**

**go** GO id, this may be a character or list(assuming the elements are goids).

**Value**

Some text providing the synonyms for the given id(s).

**See Also**

**GOTermsAnnDbBimap**

**Examples**

```
## Not run:
text = gosyn("GO:0000001")
text
## > GO:000001
## > "mitochondrial inheritance"

## End(Not run)
```

---

**goterm***Get a go term from ID.*

---

**Description**

Get a go term from ID.

**Usage**

```
goterm(go = "GO:0032559")
```

**Arguments**

go                      GO id or a list thereof, this may be a character or list(assuming the elements, not names, are goids).

**Value**

Some text containing the terms associated with GO id(s).

**See Also**

**GOTermsAnnDbBimap**

**Examples**

```
## Not run:
goterm("GO:0032559")
## > GO:0032559
## > "adenyl ribonucleotide binding"

## End(Not run)
```

---

gotest

*Test GO ids to see if they are useful.*

---

**Description**

This just wraps gotst in mapply.

**Usage**

```
gotest(go)
```

**Arguments**

go                      go IDs as characters.

**Value**

Some text

**See Also**

**GOTermsAnnDbBimap**

**Examples**

```
## Not run:
gotest("G0:0032559")
## > 1
gotest("G0:0923429034823904")
## > 0

## End(Not run)
```

---

graph\_metrics

---

*Make lots of graphs!*


---

**Description**

Plot out a set of metrics describing the state of an experiment including library sizes, # non-zero genes, heatmaps, boxplots, density plots, pca plots, standard median distance/correlation, and qq plots.

**Usage**

```
graph_metrics(expt, cormethod = "pearson", distmethod = "euclidean",
  title_suffix = NULL, qq = NULL, ma = NULL, ...)
```

**Arguments**

expt	an expt to process
cormethod	the correlation test for heatmaps.
distmethod	define the distance metric for heatmaps.
title_suffix	text to add to the titles of the plots.
qq	include qq plots
ma	include pairwise ma plots
...	extra parameters optionally fed to the various plots

**Value**

a loooong list of plots including the following:

1. nonzero = a ggplot2 plot of the non-zero genes vs library size
2. libsize = a ggplot2 bar plot of the library sizes
3. boxplot = a ggplot2 boxplot of the raw data
4. corheat = a recordPlot(ed pairwise correlation heatmap of the raw data
5. smc = a recordPlot(ed view of the standard median pairwise correlation of the raw data
6. disheat = a recordPlot(ed pairwise euclidean distance heatmap of the raw data
7. smd = a recordPlot(ed view of the standard median pairwise distance of the raw data

8. pcaplot = a recordPlot()ed PCA plot of the raw samples
9. pccatble = a table describing the relative contribution of condition/batch of the raw data
10. pcars = a table describing the relative contribution of condition/batch of the raw data
11. pcavar = a table describing the variance of the raw data
12. qq = a recordPlotted() view comparing the quantile/quantiles between the mean of all data and every raw sample
13. density = a ggplot2 view of the density of each raw sample (this is complementary but more fun than a boxplot)

### See Also

**Biobase** **ggplot2** **grDevices** **gplots** **exprs** **hpgl\_norm** **plot\_nonzero** **plot\_libsize** **plot\_boxplot** **plot\_corheat** **plot\_sm** **plot\_disheat** **plot\_pca** **plot\_qq\_all** **plot\_pairwise\_ma**

### Examples

```
## Not run:
toomany_plots <- graph_metrics(expt)
toomany_plots$pcaplot
norm <- normalize_expt(expt, convert="cpm", batch=TRUE, filter_low=TRUE,
                      transform="log2", norm="rle")
holy_asscrackers <- graph_metrics(norm, qq=TRUE, ma=TRUE)
## good luck, you are going to be waiting a while for the ma plots to print!

## End(Not run)
```

---

heatmap.3

*a minor change to heatmap.2 makes heatmap.3*


---

### Description

heatmap.2 is the devil.

### Usage

```
heatmap.3(x, Rowv = TRUE, Colv = if (symm) "Rowv" else TRUE,
  distfun = dist, hclustfun = hclust, dendrogram = c("both", "row",
  "column", "none"), reorderfun = function(d, w) reorder(d, w),
  symm = FALSE, scale = c("none", "row", "column"), na.rm = TRUE,
  revC = identical(Colv, "Rowv"), add.expr, breaks, symbreaks = min(x < 0,
  na.rm = TRUE) || scale != "none", col = "heat.colors", colsep, rowsep,
  sepcolor = "white", sepwidth = c(0.05, 0.05), cellnote, notecex = 1,
  notecol = "cyan", na.color = par("bg"), trace = c("column", "row",
  "both", "none"), tracecol = "cyan", hline = median(breaks),
  vline = median(breaks), linecol = tracecol, margins = c(5, 5),
  ColSideColors, RowSideColors, cexRow = 0.2 + 1/log10(nr), cexCol = 0.2 +
  1/log10(nc), labRow = NULL, labCol = NULL, srtRow = NULL,
```

```

srtCol = NULL, adjRow = c(0, NA), adjCol = c(NA, 0), offsetRow = 0.5,
offsetCol = 0.5, key = TRUE, keysize = 1.5,
density.info = c("histogram", "density", "none"), denscol = tracecol,
symkey = min(x < 0, na.rm = TRUE) || symbreaks, densadj = 0.25,
key.title = NULL, key.xlab = NULL, key.ylab = NULL,
key.xtickfun = NULL, key.ytickfun = NULL, key.par = list(),
main = NULL, xlab = NULL, ylab = NULL, lmat = NULL, lhei = NULL,
lwid = NULL, extrafun = NULL, linewidth = 1, ...)

```

### Arguments

x	data
Rowv	add rows?
Colv	add columns?
distfun	distance function to use
hclustfun	clustering function to use
dendrogram	which axes to put trees on
reorderfun	reorder the rows/columns?
symm	symmetrical?
scale	add the scale?
na.rm	remove nas from the data?
revC	reverse the columns?
add.expr	no clue
breaks	also no clue
symbreaks	still no clue
col	colors!
colsep	column separator
rowsep	row separator
sepcolor	color to put between columns/rows
sepwidth	how much to separate
cellnote	mur?
notecex	size of the notes
notecol	color of the notes
na.color	a parameter call to bg
trace	do a trace for rows/columns?
tracecol	color of the trace
hline	the hline
vline	the vline
linecol	the line color
margins	margins are good

ColSideColors	colors for the columns as annotation
RowSideColors	colors for the rows as annotation
cexRow	row size
cexCol	column size
labRow	hmmmm
labCol	still dont know
srtRow	srt the row?
srtCol	srt the column?
adjRow	adj the row?
adjCol	adj the column?
offsetRow	how far to place the text from the row
offsetCol	how far to place the text from the column
key	add a key?
keysize	if so, how big?
density.info	for the key, what information to add
denscol	tracecol hmm ok
symkey	I like keys
densadj	adj the dens?
key.title	title for the key
key.xlab	text for the x axis of the key
key.ylab	text for the y axis of the key
key.xtickfun	add text to the ticks of the key x axis
key.ytickfun	add text to the ticks of the key y axis
key.par	parameters for the key
main	the main title of the plot
xlab	main x label
ylab	main y label
lmat	the lmat
lhei	the lhei
lwid	the lwid
extrafun	I do enjoy me some extra fun
linewidth	the width of lines
...	because this function did not already have enough options

**Value**

a heatmap!

**See Also**

[heatmap.2](#)

---

hpgltools

*hpgltools: a suite of tools to make our analyses easier*


---

## Description

This provides a series of helpers for working with sequencing data

## Details

It falls under a few main topics

- Data exploration, look for trends in sequencing data and identify batch effects or skewed distributions.
- Differential expression analyses, use DESeq2/limma/EdgeR in a hopefully robust and flexible fashion.
- Ontology analyses, use goseq/clusterProfiler/topGO/GOStats/gProfiler in hopefully robust ways.
- Perform some simple TnSeq analyses.

To see examples of this inaction, check out the vignettes: `browseVignettes(package = 'hpgltools')`

---

hpgl\_arescore

*Implement the arescan function in R*


---

## Description

This function was taken almost verbatim from AREScore() in SeqTools Available at: <https://github.com/lianos/seqtools.git> At least on my computer I could not make that implementation work So I rewrapped its apply() calls and am now hoping to extend its logic a little to make it more sensitive and get rid of some of the spurious parameters or at least make them more transparent.

## Usage

```
hpgl_arescore(x, basal = 1, overlapping = 1.5, d1.3 = 0.75, d4.6 = 0.4,
  d7.9 = 0.2, within.AU = 0.3, aub.min.length = 10,
  aub.p.to.start = 0.8, aub.p.to.end = 0.55)
```

## Arguments

x	DNA/RNA StringSet containing the UTR sequences of interest
basal	I dunno.
overlapping	default=1.5
d1.3	default=0.75 These parameter names are so stupid, lets be realistic
d4.6	default=0.4



```

d7.9          default=0.2
within.AU     default=0.3
aub.min.length default=10
aub.p.to.start default=0.8
aub.p.to.end  default=0.55

```

## Details

Note that I did this two months ago and haven't touched it since...

## Value

a DataFrame of scores

## See Also

**IRanges Biostrings**

## Examples

```

## Not run:
## Extract all the genes from my genome, pull a static region 120nt following the stop
## and test them for potential ARE sequences.
## FIXME: There may be an error in this example, another version I have handles the +/- strand
## genes separately, I need to return to this and check if it is providing the 5' UTR for 1/2
## the genome, which would be unfortunate -- but the logic for testing remains the same.
are_candidates <- hpgl_arescore(genome)
utr_genes <- subset(lmajor_annotations, type == 'gene')
threep <- GenomicRanges::GRanges(seqnames=Rle(utr_genes[,1]),
                                ranges=IRanges(utr_genes[,3], end=(utr_genes[,3] + 120)),
                                strand=Rle(utr_genes[,5]),
                                name=Rle(utr_genes[,10]))
threep_seqstrings <- Biostrings::getSeq(lm, threep)
are_test <- hpgltools::hpgl_arescore(x=threep_seqstrings)
are_genes <- rownames(are_test[ which(are_test$score > 0), ])

## End(Not run)

```

---

hpgl\_combatMod

*A modified version of comBatMod.*


---

## Description

This is a hack of Kwame Okrah's `combatMod` to make it not fail on corner-cases. This was mostly copy/pasted from <https://github.com/kokrah/cbcbSEQ/blob/master/R/transform.R>

## Usage

```
hpgl_combatMod(dat, batch, mod, noScale = TRUE, prior.plots = FALSE, ...)
```

**Arguments**

<code>dat</code>	Df to modify.
<code>batch</code>	Factor of batches.
<code>mod</code>	Factor of conditions.
<code>noScale</code>	The normal 'scale' option squishes the data too much, so this defaults to TRUE.
<code>prior.plots</code>	Print out prior plots?
<code>...</code>	Extra options are passed to <code>arglist</code>

**Value**

Df of batch corrected data

**See Also**

`sva` [ComBat](#)

**Examples**

```
## Not run:
df_new = hpgl_combatMod(df, batches, model)

## End(Not run)
```

---

`hpgl_cor`

*Wrap `cor()` to include robust correlations.*

---

**Description**

Take `covRob`'s robust correlation coefficient and add it to the set of correlations available when one calls `cor()`.

**Usage**

```
hpgl_cor(df, method = "pearson", ...)
```

**Arguments**

<code>df</code>	Data frame to test.
<code>method</code>	Correlation method to use. Includes <code>pearson</code> , <code>spearman</code> , <code>kendal</code> , <code>robust</code> .
<code>...</code>	Other options to pass to <code>stats::cor()</code> .

**Value**

Some fun correlation statistics.

**See Also****robust** [cor](#) [cov](#) [covRob](#)**Examples**

```
## Not run:
  hpgl_cor(df=df)
  hpgl_cor(df=df, method="robust")

## End(Not run)
```

hpgl\_GOplot

*A minor hack of the topGO GOplot function.***Description**

This allows me to change the line widths from the default.

**Usage**

```
hpgl_GOplot(dag, sigNodes, dag.name = "GO terms", edgeTypes = TRUE,
  nodeShape.type = c("box", "circle", "ellipse", "plaintext")[3],
  genNodes = NULL, wantedNodes = NULL, showEdges = TRUE,
  useFullNames = TRUE, oldSigNodes = NULL, nodeInfo = NULL,
  maxchars = 30)
```

**Arguments**

<code>dag</code>	DAG tree of ontologies.
<code>sigNodes</code>	Set of significant ontologies (with p-values).
<code>dag.name</code>	Name for the graph.
<code>edgeTypes</code>	Types of the edges for graphviz.
<code>nodeShape.type</code>	Shapes on the tree.
<code>genNodes</code>	Generate the nodes?
<code>wantedNodes</code>	Subset of the ontologies to plot.
<code>showEdges</code>	Show the arrows?
<code>useFullNames</code>	Full names of the ontologies (they can get long).
<code>oldSigNodes</code>	I dunno.
<code>nodeInfo</code>	Hmm.
<code>maxchars</code>	Maximum characters per line inside the shapes.

**Value**

Topgo plot!

**See Also****topGO**

---

hpgl_GroupDensity	<i>A hack of topGO's groupDensity()</i>
-------------------	---

---

**Description**

This just adds a couple wrappers to avoid errors in groupDensity.

**Usage**

```
hpgl_GroupDensity(object, whichGO, ranks = TRUE, rm.one = FALSE)
```

**Arguments**

object	TopGO enrichment object.
whichGO	Individual ontology group to compare against.
ranks	Rank order the set of ontologies?
rm.one	Remove pvalue=1 groups?

**Value**

plot of group densities.

---

hpgl_log2cpm	<i>Converts count matrix to log2 counts-per-million reads.</i>
--------------	--

---

**Description**

Based on the method used by limma as described in the Law et al. (2014) voom paper.

**Usage**

```
hpgl_log2cpm(counts, lib.size = NULL)
```

**Arguments**

counts	Read count matrix.
lib.size	Library size.

**Value**

log2-CPM read count matrix.

**See Also****edgeR****Examples**

```
## Not run:
l2cpm <- hpgl_log2cpm(counts)

## End(Not run)
```

hpgl\_norm

*Normalize a dataframe/expt, express it, and/or transform it***Description**

There are many possible options to this function. Refer to `normalize_expt()` for a more complete list.

**Usage**

```
hpgl_norm(data, ...)
```

**Arguments**

<code>data</code>	Some data as a df/expt/whatever.
<code>...</code>	I should put all those other options here

**Value**

edgeR's DGEList expression of a count table. This seems to me to be the easiest to deal with.

**See Also**

[edgeR](#) [DESeq2](#) [cpm](#) [rpkm](#) [hpgl\\_rpkm](#) [DESeqDataSetFromMatrix](#) [estimateSizeFactors](#) [DGEList](#) [calcNormFactors](#)

**Examples**

```
## Not run:
df_raw = hpgl_norm(expt=expt) ## Only performs low-count filtering
df_raw = hpgl_norm(df=a_df, design=a_design) ## Same, but using a df
df_ql2rpkm = hpgl_norm(expt=expt, norm='quant', transform='log2',
                      convert='rpkm') ## Quantile, log2, rpkm
count_table = df_ql2rpkm$counts

## End(Not run)
```

---

`hpgl_qshrink`*A hacked copy of Kwame's qsmooth/qstats code.*

---

### Description

I made a couple small changes to Kwame's `qstats()` function to make it not fail when on corner-cases. I sent him a diff, but haven't checked to see if it was useful yet.

### Usage

```
hpgl_qshrink(data = NULL, groups = NULL, refType = "mean",  
             groupLoc = "mean", window = 99, groupCol = NULL, plot = TRUE, ...)
```

### Arguments

<code>data</code>	Count table to modify
<code>groups</code>	Factor of the experimental conditions
<code>refType</code>	Method for grouping conditions
<code>groupLoc</code>	Method for grouping groups
<code>window</code>	Window, for looking!
<code>groupCol</code>	Column to define conditions
<code>plot</code>	Plot the quantiles?
<code>...</code>	More options

### Value

New data frame of normalized counts

### See Also

**qsmooth**

### Examples

```
## Not run:  
df <- hpgl_qshrink(data)  
  
## End(Not run)
```

---

hpgl_qstats	<i>A hacked copy of Kwame's qsmooth/qstats code.</i>
-------------	--

---

## Description

I made a couple small changes to Kwame's qstats() function to make it not fail when on corner-cases. I sent him a diff, but haven't checked to see if it was useful yet.

## Usage

```
hpgl_qstats(data, groups, refType = "mean", groupLoc = "mean",  
            window = 99)
```

## Arguments

data	Initial count data
groups	Experimental conditions as a factor.
refType	Method to separate groups, mean or median.
groupLoc	I don't remember what this is for.
window	Window for basking!

## Value

Some new data.

## See Also

**matrixStats**

## Examples

```
## Not run:  
qstatted <- hpgl_qstats(data, conditions)  
  
## End(Not run)
```

---

hpgl_rpk	<i>Reads/(kilobase(gene) * million reads)</i>
----------	---

---

### Description

Express a data frame of counts as reads per kilobase(gene) per million(library). This function wraps EdgeR's rpk in an attempt to make sure that the required gene lengths get sent along.

### Usage

```
hpgl_rpk(df, ...)
```

### Arguments

df	Data frame of counts, alternately an edgeR DGEList.
...	extra options including annotations for defining gene lengths.

### Value

Data frame of counts expressed as rpk.

### See Also

[edgeR cpm rpk](#)

### Examples

```
## Not run:
rpk_df = hpgl_rpk(df, annotations=gene_annotations)

## End(Not run)
```

---

hpgl_voom	<i>A slight modification of limma's voom().</i>
-----------	---

---

### Description

Estimate mean-variance relationship between samples and generate 'observational-level weights' in preparation for linear modeling RNAseq data. This particular implementation was primarily scabbed from cbcSEQ, but changes the mean-variance plot slightly and attempts to handle corner cases where the sample design is confounded by setting the coefficient to 1 for those samples rather than throwing an unhelpful error. Also, the Elist output gets a 'plot' slot which contains the plot rather than just printing it.



**Usage**

```
hpgl_voom(dataframe, model = NULL, libsize = NULL,
  normalize.method = "none", span = 0.5, stupid = FALSE, logged = FALSE,
  converted = FALSE, ...)
```

**Arguments**

dataframe	Dataframe of sample counts which have been normalized and log transformed.
model	Experimental model defining batches/conditions/etc.
libsize	Size of the libraries (usually provided by edgeR).
normalize.method	Normalization method used in voom().
span	The span used in voom().
stupid	Cheat when the resulting matrix is not solvable?
logged	Is the input data is known to be logged?
converted	Is the input data is known to be cpm converted?
...	Extra arguments are passed to arglist.

**Value**

EList containing the following information: E = The normalized data weights = The weights of said data design = The resulting design lib.size = The size in pseudocounts of the library plot = A ggplot of the mean/variance trend with a blue loess fit and red trend fit

**See Also**

**limma ggplot2**

**Examples**

```
## Not run:
funkytown = hpgl_voom(samples, model)

## End(Not run)
```

---

hpgl_voomweighted	<i>A minor change to limma's voom with quality weights to attempt to address some corner cases.</i>
-------------------	---

---

**Description**

This copies the logic employed in hpgl\_voom(). I suspect one should not use it.

**Usage**

```
hpgl_voomweighted(data, fun_model, libsize = NULL,  
  normalize.method = "none", plot = TRUE, span = 0.5, var.design = NULL,  
  method = "genebygene", maxiter = 50, tol = 1e-10, trace = FALSE,  
  replace.weights = TRUE, col = NULL, ...)
```

**Arguments**

data	Some data!
fun_model	A model for voom() and arrayWeights()
libsize	Library sizes passed to voom().
normalize.method	Passed to voom()
plot	Do the plot of mean variance?
span	yes
var.design	maybe
method	kitty!
maxiter	50 is good
tol	I have no tolerance.
trace	no trace for you.
replace.weights	Replace the weights?
col	yay columns!
...	more arguments!

**Value**

a voom return

**See Also**

**limma**

**Examples**

```
## Not run:  
## No seriously, dont run this, I think it is wiser to use the functions provided by limma.  
## But this provides a place to test stuff out.  
voom_result <- hpgl_voomweighted(dataset, model)  
  
## End(Not run)
```

---

kegg_get_orgn	<i>Search KEGG identifiers for a given species name.</i>
---------------	--

---

**Description**

KEGG identifiers do not always make sense. For example, how am I supposed to remember that *Leishmania major* is lmj? This takes in a human readable string and finds the KEGG identifiers that match it.

**Usage**

```
kegg_get_orgn(species = "Leishmania", short = TRUE)
```

**Arguments**

species	Search string (Something like 'Homo sapiens').
short	Only pull the orgid?

**Value**

Data frame of possible KEGG identifier codes, genome ID numbers, species, and phylogenetic classifications.

**See Also**

**RCurl**

**Examples**

```
## Not run:
fun = kegg_get_orgn('Canis')
## >   Tid   orgid   species   phylogeny
## >  17 T01007   cfa Canis familiaris (dog) Eukaryotes;Animals;Vertebrates;Mammals

## End(Not run)
```

---

kegg_to_ensembl	<i>Maps KEGG identifiers to ENSEMBL gene ids.</i>
-----------------	---

---

**Description**

Takes a list of KEGG gene identifiers and returns a list of ENSEMBL ids corresponding to those genes.

**Usage**

```
kegg_to_ensembl(kegg_ids)
```

**Arguments**

kegg\_ids            List of KEGG identifiers to be mapped.

**Value**

Ensembl IDs as a character list.

**See Also**

**KEGGREST** [keggGet](#)

**Examples**

```
## Not run:
ensembl_list <- kegg_to_ensembl("a")

## End(Not run)
```

---

kmeans_testing	<i>This is for the moment just a code dump of some arbitrarily chosen kmeans clustering stuff</i>
----------------	---

---

**Description**

Fill this in asap with real code for Ginger's search of gene sets which have similar profiles over time.

**Usage**

```
kmeans_testing(gene_ids = get0("gene_ids"))
```

**Arguments**

gene\_ids            A set of gene IDs to query.

---

limma_pairwise	<i>Set up a model matrix and set of contrasts for pairwise comparisons using voom/limma.</i>
----------------	--

---

## Description

Creates the set of all possible contrasts and performs them using voom/limma.

## Usage

```
limma_pairwise(input = NULL, conditions = NULL, batches = NULL,
  model_cond = TRUE, model_batch = TRUE, model_intercept = TRUE,
  alt_model = NULL, extra_contrasts = NULL, annot_df = NULL,
  libsize = NULL, force = FALSE, ...)
```

## Arguments

input	Dataframe/vector or expt class containing count tables, normalization state, etc.
conditions	Factor of conditions in the experiment.
batches	Factor of batches in the experiment.
model_cond	Include condition in the model?
model_batch	Include batch in the model? This is hopefully TRUE.
model_intercept	Perform a cell-means or intercept model? A little more difficult for me to understand. I have tested and get the same answer either way.
alt_model	Separate model matrix instead of the normal condition/batch.
extra_contrasts	Some extra contrasts to add to the list. This can be pretty neat, lets say one has conditions A,B,C,D,E and wants to do (C/B)/A and (E/D)/A or (E/D)/(C/B) then use this with a string like: "c_vs_b_ctrla = (C-B)-A, e_vs_d_ctrla = (E-D)-A, de_vs_cb = (E-D)-(C-B),"
annot_df	Data frame for annotations.
libsize	I've recently figured out that libsize is far more important than I previously realized. Play with it here.
force	Force data which may not be appropriate for limma into it?
...	Use the elipsis parameter to feed options to write_limma().

## Value

List including the following information: macb = the mashing together of condition/batch so you can look at it macb\_model = The result of calling model.matrix(~0 + macb) macb\_fit = The result of calling lmFit(data, macb\_model) voom\_result = The result from voom() voom\_design = The design from voom (redundant from voom\_result, but convenient) macb\_table = A table of the number of times each condition/batch pairing happens cond\_table = A table of the number of times

each condition appears (the denominator for the identities) batch\_table = How many times each batch appears identities = The list of strings defining each condition by itself all\_pairwise = The list of strings defining all the pairwise contrasts contrast\_string = The string making up the makeContrasts() call pairwise\_fits = The result from calling contrasts.fit() pairwise\_comparisons = The result from eBayes() limma\_result = The result from calling write\_limma()

### See Also

**limma** **Biobase** [write\\_limma](#)

### Examples

```
## Not run:
pretend <- limma_pairwise(expt)

## End(Not run)
```

---

limma_scatter	<i>Plot arbitrary data from limma as a scatter plot.</i>
---------------	--

---

### Description

Extract the adjusted abundances for the two conditions used in the pairw

### Usage

```
limma_scatter(all_pairwise_result, first_table = 1, first_column = "logFC",
              second_table = 2, second_column = "logFC", type = "linear_scatter", ...)
```

### Arguments

all_pairwise_result	Result from calling balanced_pairwise().
first_table	First table from all_pairwise_result\$limma_result to look at (may be a name or number).
first_column	Name of the column to plot from the first table.
second_table	Second table inside all_pairwise_result\$limma_result (name or number).
second_column	Column to compare against.
type	Type of scatter plot (linear model, distance, vanilla).
...	Use the elipsis to feed options to the html graphs.

### Value

plot\_linear\_scatter() set of plots comparing the chosen columns. If you forget to specify tables to compare, it will try the first vs the second.

**See Also**[limma plot\\_linear\\_scatter](#)**Examples**

```
## Not run:
compare_logFC <- limma_scatter(all_pairwise, first_table="wild_type", second_column="mutant",
                             first_table="AveExpr", second_column="AveExpr")
compare_B <- limma_scatter(all_pairwise, first_column="B", second_column="B")

## End(Not run)
```

---

loadme*Load a backup rdata file*

---

**Description**

I often use R over a sshfs connection, sometimes with significant latency, and I want to be able to save/load my R sessions relatively quickly. Thus this function uses my backup directory to load its R environment.

**Usage**

```
loadme(directory = "savefiles", filename = "Rdata.rda.xz")
```

**Arguments**

directory	Directory containing the RData.rda.xz file.
filename	Filename to which to save.

**Value**

a bigger global environment

**See Also**[saveme load save](#)**Examples**

```
## Not run:
loadme()

## End(Not run)
```

---

load\_host\_annotations *Load organism annotation data (mouse/human).*

---

## Description

Creates a dataframe gene and transcript information for a given set of gene ids using the OrganismDbi interface.

## Usage

```
load_host_annotations(orgdb, gene_ids = NULL, keytype = "ENSEMBL",  
  fields = c("TXCHROM", "GENENAME", "TXSTRAND", "TXSTART", "TXEND"),  
  biomaRt_dataset = "hsapiens_gene_ensembl")
```

## Arguments

orgdb	OrganismDb instance.
gene_ids	Gene identifiers for retrieving annotations.
keytype	a, umm keytype? I need to properly read this code.
fields	Columns to include in the output.
biomaRt_dataset	Name of the biomaRt dataset to query for gene type.

## Value

a table of gene information

## See Also

**AnnotationDbi** **dplyr** **biomaRt** [select keytypes](#)

## Examples

```
## Not run:  
host <- load_host_annotations(org, c("a","b"))  
  
## End(Not run)
```



---

load_kegg_pathways	<i>Creates a KEGG pathway/description mapping dataframe.</i>
--------------------	--

---

**Description**

Use AnnotationDbi to map descriptions of KEGG pathways to gene IDs.

**Usage**

```
load_kegg_pathways(orgdb, gene_ids, keytype = "ENSEMBL")
```

**Arguments**

orgdb	OrganismDb instance.
gene_ids	Identifiers of the genes to retrieve annotations.
keytype	as per the previous functions, I don't know what this does yet

**Value**

Character list of pathways.

**See Also**

**AnnotationDbi**

**Examples**

```
## Not run:  
pathnames <- load_kegg_pathways(org, c("a","b","c"))  
  
## End(Not run)
```

---

load_orgdb_annotations	<i>Load organism annotation data (parasite).</i>
------------------------	--

---

**Description**

Creates a dataframe gene and transcript information for a given set of gene ids using the OrganismDbi interface.

**Usage**

```
load_orgdb_annotations(orgdb, gene_ids = NULL, include_go = FALSE,  
  keytype = "ENSEMBL", fields = NULL, sum_exons = FALSE)
```

**Arguments**

orgdb	OrganismDb instance.
gene_ids	Gene identifiers for retrieving annotations.
include_go	Ask the Dbi for gene ontology information?
keytype	mmm the key type used?
fields	Columns included in the output.
sum_exons	Perform a sum of the exons in the data set?

**Details**

Tested in test\_45ann\_organdb.R This defaults to a few fields which I have found most useful, but the brave can pass it 'all'.

**Value**

Table of geneids, chromosomes, descriptions, strands, types, and lengths.

**See Also**

**AnnotationDbi GenomicFeatures BiocGenerics** [columns](#) [keytypes](#) [select](#) [exonsBy](#)

**Examples**

```
## Not run:
one_gene <- load_annotations(org, c("LmJF.01.0010"))

## End(Not run)
```

---

load_orgdb_go	<i>Retrieve GO terms associated with a set of genes.</i>
---------------	--

---

**Description**

AnnotationDbi provides a reasonably complete set of GO mappings between gene ID and ontologies. This will extract that table for a given set of gene IDs.

**Usage**

```
load_orgdb_go(orgdb, gene_ids = NULL, keytype = "ENSEMBL",
  columns = c("GO", "GOALL", "GOID"))
```

**Arguments**

orgdb	OrganismDb instance.
gene_ids	Identifiers of the genes to retrieve annotations.
keytype	the mysterious keytype returns yet again to haunt my dreams

### Details

Tested in test\_45ann\_organdb.R This is a nice way to extract GO data primarily because the Orgdb data sets are extremely fast and flexible, thus by changing the keytype argument, one may use a lot of different ID types and still score some useful ontology data.

### Value

Data frame of gene IDs, go terms, and names.

### See Also

**AnnotationDbi** **GO.db** **magrittr** [select tbl\\_df](#)

### Examples

```
## Not run:
go_terms <- load_go_terms(org, c("a","b"))

## End(Not run)
```

---

load_orgdb_kegg	<i>Creates a gene/KEGG mapping dataframe.</i>
-----------------	---

---

### Description

In much the same way AnnotationDbi provides GO data, it also provides KEGG data.

### Usage

```
load_orgdb_kegg(orgdb, gene_ids = NULL, keytype = "ENSEMBL",
  columns = c("KEGG_PATH"))
```

### Arguments

orgdb	OrganismDb instance.
gene_ids	Identifiers of the genes to retrieve annotations.
keytype	The keytype, eg. the primary key used to query the orgdb.
columns	Columns to extract.

### Details

Tested in test\_45ann\_organdb.R Perhaps this function should be merged with the GO above?

### Value

Df of kegg mappings

See Also

AnnotationDbi dplyr [select tbl\\_df](#)

Examples

```
## Not run:
kegg_data <- load_kegg_mapping(org, c("a","b"))

## End(Not run)
```

---

load_parasite_annotations	<i>I see no reason to have load_host_annotations and load_parasite_annotations.</i>
---------------------------	---

---

Description

Thus I am making them both into aliases to load\_annotations.

Usage

```
load_parasite_annotations(...)
```

Arguments

... Arguments to be passed to load\_annotations.

---

local_get_value	<i>Perform a get_value for delimited files</i>
-----------------	--

---

Description

Keith wrote this as .get\_value() but functions which start with . trouble me.

Usage

```
local_get_value(x, delimiter = ": ")
```

Arguments

x                   Some stuff to split  
delimiter           The tritrypdb uses ':' ergo the default.

Value

A value!

---

make_exempladata	<i>Small hack of limma's exampleData() to allow for arbitrary data set sizes.</i>
------------------	---

---

**Description**

exampleData has a set number of genes/samples it creates. This relaxes that restriction.

**Usage**

```
make_exempladata(ngenes = 1000, columns = 5)
```

**Arguments**

ngenes	How many genes in the fictional data set?
columns	How many samples in this data set?

**Value**

Matrix of pretend counts.

**See Also**

**limma stats DESeq**

**Examples**

```
## Not run:
pretend = make_exempladata()

## End(Not run)
```

---

make_id2gomap	<i>Make a go mapping from IDs in a format suitable for topGO.</i>
---------------	---

---

**Description**

When using a non-supported organism, one must write out mappings in the format expected by topgo. This handles that process and gives a summary of the new table.

**Usage**

```
make_id2gomap(goid_map = "reference/go/id2go.map", goids_df = NULL,
  overwrite = FALSE)
```

**Arguments**

<code>goid_map</code>	TopGO mapping file.
<code>goids_df</code>	If there is no <code>goid_map</code> , create it with this data frame.
<code>overwrite</code>	Rewrite the mapping file?

**Value**

Summary of the new goid table.

**See Also**

**topGO**

---

<code>make_limma_tables</code>	<i>Writes out the results of a limma search using <code>toptable()</code>.</i>
--------------------------------	--

---

**Description**

However, this will do a couple of things to make one's life easier: 1. Make a list of the output, one element for each comparison of the contrast matrix 2. Write out the `toptable()` output for them in separate .csv files and/or sheets in excel 3. Since I have been using qvalues a lot for other stuff, add a column for them.

**Usage**

```
make_limma_tables(data, adjust = "BH", n = 0, coef = NULL,
  annot_df = NULL)
```

**Arguments**

<code>data</code>	Output from <code>eBayes()</code> .
<code>adjust</code>	Pvalue adjustment chosen.
<code>n</code>	Number of entries to report, 0 says do them all.
<code>coef</code>	Which coefficients/contrasts to report, NULL says do them all.
<code>annot_df</code>	Optional data frame including annotation information to include with the tables.

**Value**

List of data frames comprising the `toptable` output for each coefficient, I also added a qvalue entry to these `toptable()` outputs.

**See Also**

**limma** `qvalue` [write\\_xls](#) [topTable](#)

## Examples

```
## Not run:
finished_comparison = eBayes(limma_output)
table = make_limma_tables(finished_comparison, adjust="fdr")

## End(Not run)
```

---

make_organ	Create an organismDbi object by joining a txdb and orgdb together.
------------	--

---

## Description

This function is a bit more fragile than I would like.

## Usage

```
make_organ(txdb, keytype = NA, orgdb = NA)
```

## Arguments

txdb	Txdb input to merge
keytype	When merging to an orgdb, what key to use?
orgdb	The orgdb to help create the OrganismDbi instance.

## Value

An OrganismDb instance

## See Also

**S4Vectors** **GenomicFeatures** **AnnotationDbi** **OrganismDbi** [makePackageName](#)

## Examples

```
## Not run:
orgdbi <- make_organ(Tcruzi_txdb, orgdb=Tcruzi_orgdb)

## End(Not run)
```

---

make_organismdbi	<i>Create an OrganismDbi for a species at the TriTrypDb</i>
------------------	---

---

## Description

OrganismDbi instances are pretty neat, they pull together OrgDb and TxDb. With any luck, this function provides the ability to pull together all the data from the TriTrypDb, GO.db, and KEGGREST in order to accomplish these peculiar tasks.

## Usage

```
make_organismdbi(id = "lmajor_friedlin", cfg = NULL,  
  output_dir = "organdb/tritryp", ...)
```

## Arguments

id	Unique tritrypdb identifier.
cfg	A configuration dataframe, when null it will be replaced by reading a csv file in inst/extdata.
output_dir	The directory into which to put the various intermediate files, including downloads from the TriTrypdb, the created OrgDb and TxDb instances, and the final OrganismDbi.
...	Extra arguments including a boolean for whether to include kegg.

## Value

A path, some data files, and a kitty!

## See Also

**AnnotationForge OrganismDbi**

## Examples

```
## Not run:  
  crazytown <- make_organismdbi() ## wait a loong time  
  
## End(Not run)
```



---

make_orgdb	<i>Make an orgDb object from some information provided by make_orgdb_info()</i>
------------	---

---

## Description

An orgDb object should provide some useful annotation data including fun stuff like gene ontology, kegg, etc. In the case of the species at the TriTrypDb, much of this information is available in the species .txt file. This function takes that data and collates it into the final orgDb objects using AnnotationForge. It then makes some attempts to ensure that the resulting material created in the filesystem conforms to specifications which allow one to have multiple strains, etc. Finally, if everything goes according to plan, it calls devtools::install() and installs the resulting package.

## Usage

```
make_orgdb(orgdb_info, id = "lmajor_friedlin", cfg = NULL, kegg = TRUE,  
  output_dir = "organismdbi", ...)
```

## Arguments

orgdb_info	List of data frames generated by make_orgdb_info()
id	Human readable species identifier, keys off the cfg data frame.
cfg	Configuration data extracted either from inst/eupath_configuration.csv or provided by the user.
kegg	Attempt adding kegg data?
output_dir	Base output directory for the resulting packages.
...	Args to pass through.

## Value

List of the resulting package name(s) and whether they installed.

## See Also

**AnnotationForge** devtools [makeOrgPackage](#)

## Examples

```
## Not run:  
  orgdb_installedp <- make_orgdb(id="tcruzi_clbrener")  
  
## End(Not run)
```

---

make_orgdb_info	<i>Generate the (large) set of data frames required to make functional OrgDb/TxDb/OrganismDbi objects.</i>
-----------------	--

---

### Description

This function should probably be split into a few more pieces as it is pretty unwieldy at the moment.

### Usage

```
make_orgdb_info(gff, txt, kegg = TRUE)
```

### Arguments

gff	File to read gff annotations from.
txt	File to read txt annotations from.
kegg	Boolean deciding whether to try for KEGG data.

### Value

List containing gene information (likely from the txt file), chromosome information (gff file), gene types (gff file), gene ontology information, and potentially kegg information.

### See Also

**rtracklayer GenomicRanges**

### Examples

```
## Not run:
orgdb_data <- make_orgdb_info(gff="lmajor.gff", txt="lmajor.txt")

## End(Not run)
```

---

make_pairwise_contrasts	<i>Run makeContrasts() with all pairwise comparisons.</i>
-------------------------	---

---

### Description

In order to have uniformly consistent pairwise contrasts, I decided to avoid potential human errors(sic) by having a function generate all contrasts.

### Usage

```
make_pairwise_contrasts(model, conditions, do_identities = TRUE,
  do_pairwise = TRUE, extra_contrasts = NULL)
```

**Arguments**

model	Describe the conditions/batches/etc in the experiment.
conditions	Factor of conditions in the experiment.
do_identities	Include all the identity strings? Limma can use this information while edgeR can not.
do_pairwise	Include all pairwise strings? This shouldn't need to be set to FALSE, but just in case.
extra_contrasts	Optional string of extra contrasts to include.

**Details**

Invoked by the `_pairwise()` functions.

**Value**

List including the following information:

1. `all_pairwise_contrasts` = the result from `makeContrasts(...)`
2. `identities` = the string identifying each condition alone
3. `all_pairwise` = the string identifying each pairwise comparison alone
4. `contrast_string` = the string passed to R to call `makeContrasts(...)`
5. `names` = the names given to the identities/contrasts

**See Also**

**limma** [makeContrasts](#)

**Examples**

```
## Not run:
pretend = make_pairwise_contrasts(model, conditions)

## End(Not run)
```

---

make\_report

---

*Make a knitr report with some defaults set a priori.*


---

**Description**

I keep forgetting to set appropriate options for knitr. This tries to set them.

**Usage**

```
make_report(name = "report", type = "pdf")
```

**Arguments**

name	Name the document!
type	Html or pdf reports?

**Value**

Dated report file.

**See Also**

**knitr rmarkdown knitrBootstrap**

---

make_tooltips	<i>Create a simple df from a gff which contains tooltips usable in google-Vis graphs.</i>
---------------	---

---

**Description**

The tooltip column is a handy proxy for more thorough annotations information when it would otherwise be too troublesome to acquire.

**Usage**

```
make_tooltips(annotations, desc_col = "description", type = "gene",
  id_col = "ID", ...)
```

**Arguments**

annotations	Either a gff file or annotation data frame (which likely came from a gff file.).
desc_col	Gff column from which to gather data.
type	Gff type to use as the master key.
id_col	Which annotation column to cross reference against?
...	Extra arguments dropped into arglist.

**Value**

Df of tooltip information or name of a gff file.

**See Also**

**googleVis** [gff2df](#)

**Examples**

```
## Not run:
  tooltips <- make_tooltips('reference/gff/saccharomyces_cerevisiae.gff.gz')

## End(Not run)
```

---

make_txdb	<i>Create a TxDb object given data provided by make_orgdb_info()</i>
-----------	--

---

## Description

Much like make\_orgdb() above, this uses the same data to generate a TxDb object.

## Usage

```
make_txdb(orgdb_info, cfg_line, gff = NULL, from_gff = FALSE,  
          output_dir = "organismdbi", ...)
```

## Arguments

orgdb_info	List of data frames generated by make_orgdb_info().
cfg_line	Configuration data frame as per make_orgdb.
gff	File to read
from_gff	Use a gff file?
output_dir	Place to put rda intermediates.
...	Extra arguments to pass through.

## Value

List of the resulting txDb package and whether it installed.

## See Also

**GenomicFeatures** **Biobase** **devtools** [createPackage](#)

## Examples

```
## Not run:  
txdb <- make_txdb(orgdb_output)  
  
## End(Not run)
```

---

mdesc\_table

*Get the description of a microbesonline genomics table*


---

### Description

This at least in theory is only used by `get_microbesonline`, but if one needs a quick and dirty SQL query it might prove useful.

### Usage

```
mdesc_table(table = "Locus2Go")
```

### Arguments

table            Choose a table to query.

### Value

Data frame describing the relevant table

### See Also

**DBI** [dbSendQuery](#) [fetch](#)

### Examples

```
## Not run:
description <- mdesc_table(table="Locus2Go")

## End(Not run)
```

---

median\_by\_factor

*Create a data frame of the medians of rows by a given factor in the data.*


---

### Description

This assumes of course that (like `expressionsets`) there are separate columns for each replicate of the conditions. This will just iterate through the levels of a factor describing the columns, extract them, calculate the median, and add that as a new column in a separate data frame.

### Usage

```
median_by_factor(data, fact = "condition")
```

**Arguments**

data	Data frame, presumably of counts.
fact	Factor describing the columns in the data.

**Details**

Used in write\_expt() as well as a few random collaborations.

**Value**

Data frame of the medians.

**See Also**

**Biobase matrixStats**

**Examples**

```
## Not run:
compressed = median_by_factor(data, experiment$condition)

## End(Not run)
```

---

model_test	<i>Make sure a given experimental factor and design will play together.</i>
------------	---

---

**Description**

Have you ever wanted to set up a differential expression analysis and after minutes of the computer churning away it errors out with some weird error about rank? Then this is the function for you!

**Usage**

```
model_test(design, goal = "condition", factors = NULL, ...)
```

**Arguments**

design	Dataframe describing the design of the experiment.
goal	Experimental factor you actually want to learn about.
factors	Experimental factors you rather wish would just go away.
...	I might decide to add more options from other functions.

**Value**

List of booleans telling if the factors + goal will work.

**See Also**

[model.matrix.qr](#)

---

mytaxIdToOrgDb	Create an orgdb from an taxonID
----------------	---------------------------------

---

### Description

This function is a bit more fragile than I would like. I am not completely sold on AnnotationHub yet.

### Usage

```
mytaxIdToOrgDb(taxid)
```

### Arguments

taxid	TaxonID from AnnotationHub
-------	----------------------------

### Value

An Orgdb instance

### See Also

**AnnotationHub S4Vectors**

### Examples

```
## Not run:  
orgdbi <- mytaxIdToOrgDb(taxid)  
  
## End(Not run)
```

---

my_identifyAUBlocks	copy/paste the function from SeqTools and figure out where it falls on its ass.
---------------------	---

---

### Description

Yeah, I do not remember what I changed in this function.

### Usage

```
my_identifyAUBlocks(x, min.length = 20, p.to.start = 0.8, p.to.end = 0.55)
```



**Arguments**

x	Sequence object
min.length	I dunno.
p.to.start	P to start of course
p.to.end	The p to end – wtf who makes names like this?

**Value**

a list of IRanges which contain a bunch of As and Us.

---

normalize_counts	<i>Perform a simple normalization of a count table.</i>
------------------	---

---

**Description**

This provides shortcut interfaces for normalization functions from `deseq2`/`edger` and friends.

**Usage**

```
normalize_counts(data, design = NULL, norm = "raw", ...)
```

**Arguments**

data	Matrix of count data.
design	Dataframe describing the experimental design. (conditions/batches/etc)
norm	Normalization to perform: 'sflquantlqsmoothltmmlupperquartileltmmlrle' I keep wishy-washing on whether design is a required argument.
...	More arguments might be necessary.

**Value**

Dataframe of normalized(counts)

**See Also**

**edgeR limma DESeq2**

**Examples**

```
## Not run:
norm_table = normalize_counts(count_table, design=design, norm='qsmooth')

## End(Not run)
```

---

normalize_expt	<i>Normalize the data of an expt object. Save the original data, and note what was done.</i>
----------------	--

---

## Description

It is the responsibility of `normalize_expt()` to perform any arbitrary normalizations desired as well as to ensure that the data integrity is maintained. In order to do this, it writes the actions performed in `expt$state` and saves the intermediate steps of the normalization in `expt$intermediate_counts`. Furthermore, it should tell you every step of the normalization process, from count filtering, to normalization, conversion, transformation, and batch correction.

## Usage

```
normalize_expt(expt, transform = "raw", norm = "raw", convert = "raw",
  batch = "raw", filter = FALSE, annotations = NULL, fasta = NULL,
  entry_type = "gene", use_original = FALSE, batch1 = "batch",
  batch2 = NULL, batch_step = 5, low_to_zero = FALSE, thresh = 2,
  min_samples = 2, p = 0.01, A = 1, k = 1, cv_min = 0.01,
  cv_max = 1000, ...)
```

## Arguments

<code>expt</code>	Original expt.
<code>transform</code>	Transformation desired, usually log2.
<code>norm</code>	How to normalize the data? (raw, quant, sf, upperquartile, tmm, rle)
<code>convert</code>	Conversion to perform? (raw, cpm, rpkm, cp_seq_m)
<code>batch</code>	Batch effect removal tool to use? (limma sva fsva ruv etc)
<code>filter</code>	Filter out low/undesired features? (cbcb, pofa, kofa, others?)
<code>annotations</code>	Used for rpkm – probably not needed as this is in fData now.
<code>fasta</code>	Fasta file for cp_seq_m counting of oligos.
<code>entry_type</code>	For getting genelengths by feature type (rpkm or cp_seq_m).
<code>use_original</code>	Use the backup data in the expt class?
<code>batch1</code>	Experimental factor to extract first.
<code>batch2</code>	Second factor to remove (only with limma's <code>removebatcheffect()</code> ).
<code>batch_step</code>	From step 1-5, when should batch correction be applied?
<code>low_to_zero</code>	When log transforming, change low numbers (< 0) to 0 to avoid NaN?
<code>thresh</code>	Used by <code>cbcb_lowfilter()</code> .
<code>min_samples</code>	Also used by <code>cbcb_lowfilter()</code> .
<code>p</code>	Used by <code>genefilter</code> 's <code>pofa()</code> .
<code>A</code>	Also used by <code>genefilter</code> 's <code>pofa()</code> .

k	Used by genefilter's kofa().
cv_min	Used by genefilter's cv().
cv_max	Also used by genefilter's cv().
...	more options

**Value**

Expt object with normalized data and the original data saved as 'original\_expressionset'

**See Also**

**genefilter limma sva edgeR DESeq2**

**Examples**

```
## Not run:
normed <- normalize_expt(exp, transform='log2', norm='rle', convert='cpm',
                        batch='raw', filter='pofa')
normed_batch <- normalize_expt(exp, transform='log2', norm='rle', convert='cpm',
                              batch='sva', filter='pofa')

## End(Not run)
```

---

orgdb_idmap	<i>Load organism annotation data (mouse/human).</i>
-------------	---

---

**Description**

Creates a dataframe gene and transcript information for a given set of gene ids using the OrganismDbi interface.

**Usage**

```
orgdb_idmap(orgdb, gene_ids = NULL, mapto = c("ensembl"),
            keytype = "geneid")
```

**Arguments**

orgdb	OrganismDb instance.
gene_ids	Gene identifiers for retrieving annotations.
mapto	Key to map the IDs against.
keytype	Choose a keytype, this will yell if it doesn't like your choice.

**Value**

a table of gene information

**See Also**

**AnnotationDbi** [select keytypes](#)

**Examples**

```
## Not run:  
host <- load_host_annotations(org, c("a","b"))  
  
## End(Not run)
```

---

parse_gene_go_terms	<i>TriTrypDB gene information table GO term parser</i>
---------------------	--

---

**Description**

TriTrypDB gene information table GO term parser

**Usage**

```
parse_gene_go_terms(filepath, verbose = FALSE)
```

**Arguments**

filepath	Location of TriTrypDB gene information table.
verbose	Whether or not to enable verbose output.

**Value**

Returns a dataframe where each line includes a gene/GO terms pair along with some addition information about the GO term. Note that because each gene may have multiple GO terms, a single gene ID may appear on multiple lines.

**Author(s)**

Keith Hughitt



**Value**

Returns a dataframe where each line includes a gene/GO terms pair along with some addition information about the GO term. Note that because each gene may have multiple GO terms, a single gene ID may appear on multiple lines.

**Author(s)**

Keith Hughitt

---

parse_interpro_domains	<i>EuPathDB gene information table InterPro domain parser</i>
------------------------	---

---

**Description**

EuPathDB gene information table InterPro domain parser

**Usage**

```
parse_interpro_domains(filepath)
```

**Arguments**

filepath            Location of TriTrypDB gene information table.

**Value**

Returns a dataframe where each line includes a gene/domain pairs.

**Author(s)**

Keith Hughitt

---

pattern_count_genome	<i>Find how many times a given pattern occurs in every gene of a genome.</i>
----------------------	--

---

**Description**

There are times when knowing how many times a given string appears in a genome/CDS is helpful. This function provides that information and is primarily used by cp\_seq\_m().

**Usage**

```
pattern_count_genome(fasta, gff = NULL, pattern = "TA", type = "gene",  
                      key = "locus_tag")
```

**Arguments**

fasta	Genome sequence.
gff	Gff of annotation information from which to acquire CDS (if not provided it will just query the entire genome).
pattern	What to search for? This was used for tnseq and TA is the mariner insertion point.
type	Column to use in the gff file.
key	What type of entry of the gff file to key from?

**Value**

Data frame of gene names and number of times the pattern appears/gene.

**See Also**

**Biostrings** **Rsamtools** **Rsamtools** [FaFile](#) [getSeq](#) [PDict](#) [vcountPDict](#)

**Examples**

```
## Not run:
num_pattern = pattern_count_genome('mgas_5005.fasta', 'mgas_5005.gff')

## End(Not run)
```

---

pca_highscores	<i>Get the highest/lowest scoring genes for every principle component.</i>
----------------	--

---

**Description**

This function uses princomp to acquire a principle component biplot for some data and extracts a dataframe of the top n genes for each component by score.

**Usage**

```
pca_highscores(df = NULL, conditions = NULL, batches = NULL, n = 20)
```

**Arguments**

df	a dataframe of (pseudo)counts
conditions	a factor or character of conditions in the experiment.
batches	a factor or character of batches in the experiment.
n	the number of genes to extract.

**Value**

a list including the princomp biplot, histogram, and tables of top/bottom n scored genes with their scores by component.

**See Also**

`stats princomp`

**Examples**

```
## Not run:
information <- pca_highscores(df=df, conditions=cond, batches=bat)
information$pca_bitplot ## oo pretty

## End(Not run)
```

---

pca\_information

*Gather information about principle components.*

---

**Description**

Calculate some information useful for generating PCA plots. `pca_information` seeks to gather together interesting information to make principle component analyses easier, including: the results from `(fast.)svd`, a table of the  $r^2$  values, a table of the variances in the data, coordinates used to make a pca plot for an arbitrarily large set of PCs, correlations and `fstats` between experimental factors and the PCs, and heatmaps describing these relationships. Finally, it will provide a plot showing how much of the variance is provided by the top-n genes and (optionally) the set of all PCA plots with respect to one another. (PCx vs. PCy)

**Usage**

```
pca_information(expt_data, expt_design = NULL, expt_factors = c("condition",
  "batch"), num_components = NULL, plot_pcas = FALSE)
```

**Arguments**

<code>expt_data</code>	the data to analyze (usually <code>exprs(somedataset)</code> ).
<code>expt_design</code>	a dataframe describing the experimental design, containing columns with useful information like the conditions, batches, number of cells, whatever...
<code>expt_factors</code>	a character list of experimental conditions to query for $R^2$ against the <code>fast.svd</code> of the data.
<code>num_components</code>	a number of principle components to compare the design factors against. If left null, it will query the same number of components as factors asked for.
<code>plot_pcas</code>	plot the set of PCA plots for every pair of PCs queried.



**Value**

a list of fun pca information: svd\_u/d/v: The u/d/v parameters from fast.svd rsquared\_table: A table of the rsquared values between each factor and principle component pca\_variance: A table of the pca variances pca\_data: Coordinates for a pca plot pca\_cor: A table of the correlations between the factors and principle components anova\_fstats: the sum of the residuals with the factor vs without (manually calculated) anova\_f: The result from performing anova(withfactor, withoutfactor), the F slot anova\_p: The p-value calculated from the anova() call anova\_sums: The RSS value from the above anova() call cor\_heatmap: A heatmap from recordPlot() describing pca\_cor.

**Warning**

This function has gotten too damn big and needs to be split up.

**See Also**

**corpcor** **stats** [fast.svd](#), [lm](#)

**Examples**

```
## Not run:
pca_info = pca_information(exprs(some_expt$expressionset), some_design, "all")
pca_info

## End(Not run)
```

---

pcRes

*Compute variance of each principal component and how they correlate with batch and cond*

---

**Description**

This was copy/pasted from cbcSEQ <https://github.com/kokrah/cbcbSEQ/blob/master/R/explore.R>

**Usage**

```
pcRes(v, d, condition = NULL, batch = NULL)
```

**Arguments**

v	from makeSVD
d	from makeSVD
condition	factor describing experiment
batch	factor describing batch

**Value**

A dataframe containig variance, cum. variance, cond.R-sqrd, batch.R-sqrd

See Also

[plot\\_pca](#)

---

pct_all_kegg	<i>Extract the percent differentially expressed genes for all KEGG pathways.</i>
--------------	--

---

Description

KEGGgraph provides some interesting functionality for mapping KEGGids and examining the pieces. This attempts to use that in order to evaluate how many 'significant' genes are in a given pathway.

Usage

```
pct_all_kegg(all_ids, sig_ids, organism = "dme", pathways = "all",  
  pathdir = "kegg_pathways", verbose = FALSE, ...)
```

Arguments

all_ids	Set of all gene IDs in a given analysis.
sig_ids	Set of significant gene IDs.
organism	KEGG organism identifier.
pathways	What pathways to look at?
pathdir	Directory into which to copy downloaded pathway files.
verbose	Talky talky?
...	Options I might pass from other functions are dropped into arglist.

Value

Dataframe including the filenames, percentages, nodes included, and differential nodes.

See Also

**KEGGgraph** **KEGGREST**

---

pct_kegg_diff	<i>Extract the percent differentially expressed genes in a given KEGG pathway.</i>
---------------	--

---

### Description

KEGGgraph provides some interesting functionality for mapping KEGGids and examining the pieces. This attempts to use that in order to evaluate how many 'significant' genes are in a given pathway.

### Usage

```
pct_kegg_diff(all_ids, sig_ids, pathway = "00500", organism = "dme",
  pathdir = "kegg_pathways", ...)
```

### Arguments

all_ids	Set of all gene IDs in a given analysis.
sig_ids	Set of significant gene IDs.
pathway	Numeric pathway identifier.
organism	KEGG organism identifier.
pathdir	Directory into which to copy downloaded pathway files.
...	Options I might pass from other functions are dropped into arglist.

### Value

Percent genes/pathway deemed significant.

### See Also

**KEGGgraph KEGGREST**

---

pkg_cleaner	<i>Cleans up illegal characters in packages generated by make_organismdbi(), make_orgdb(), and make_txdb(). This attempts to fix some of the common problems therein.</i>
-------------	---

---

### Description

OrganismDbi instances are pretty neat, they pull together OrgDb and TxDb. With any luck, this function provides the ability to pull together all the data from the TriTrypDb, GO.db, and KEGGREST in order to accomplish these peculiar tasks.

**Usage**

```
pkg_cleaner(path, removal = "-like", replace = "")
```

**Arguments**

path	Location for the original Db/Dbi instance.
removal	String to remove from the instance.
replace	What to replace removal with, when necessary.

**Value**

A new OrgDb/TxDb/OrganismDbi

**Examples**

```
## Not run:
crazytown <- make_organismdbi() ## wait a loong time

## End(Not run)
```

---

plot_batchsv	<i>Make a dotplot of known batches vs. SVs.</i>
--------------	---

---

**Description**

This should make a quick df of the factors and surrogates and plot them. Maybe it should be folded into plot\_svfactor? Hmm, I think first I will write this and see if it is better.

**Usage**

```
plot_batchsv(expt, svs, batch_column = "batch", factor_type = "factor")
```

**Arguments**

expt	Experiment from which to acquire the design, counts, etc.
svs	Set of surrogate variable estimations from sva/svg or batch estimates.
batch_column	Which experimental design column to use?
factor_type	This may be a factor or range, it is intended to plot a scatterplot if it is a range, a dotplot if a factor.

**Value**

Plot of batch vs surrogate variables as per Leek's work.

**See Also**

**sva** **ggplot2**

**Examples**

```
## Not run:
  estimate_vs_snps <- plot_batchsv(start, surrogate_estimate, "snpcategory")

## End(Not run)
```

---

plot\_bcv

*Steal edgeR's plotBCV() and make it a ggplot2.*

---

**Description**

This was written primarily to understand what that function is doing in edgeR.

**Usage**

```
plot_bcv(data)
```

**Arguments**

data                    A dataframe/expt/exprs with count data

**Value**

a plot! of the BCV a la ggplot2.

**See Also**

**edgeR** [plotBCV](#)

**Examples**

```
## Not run:
  bcv <- plot_bcv(expt)
  summary(bcv$data)
  bcv$plot

## End(Not run)
```

---

plot\_boxplot

---

*Make a ggplot boxplot of a set of samples.*


---

### Description

Boxplots and density plots provide complementary views of data distributions. The general idea is that if the box for one sample is significantly shifted from the others, then it is likely an outlier in the same way a density plot shifted is an outlier.

### Usage

```
plot_boxplot(data, colors = NULL, names = NULL, title = NULL,
  scale = NULL, ...)
```

### Arguments

data	Expt or data frame set of samples.
colors	Color scheme, if not provided will make its own.
names	Another version of the sample names for printing.
title	A title!
scale	Whether to log scale the y-axis.
...	More parameters are more fun!

### Value

Ggplot2 boxplot of the samples. Each boxplot contains the following information: a centered line describing the median value of counts of all genes in the sample, a box around the line describing the inner-quartiles around the median (quartiles 2 and 3 for those who are counting), a vertical line above/below the box which shows 1.5x the inner quartile range (a common metric of the non-outliers), and single dots for each gene which is outside that range. A single dot is transparent.

### See Also

**ggplot2** [reshape2](#) [geom\\_boxplot](#) [melt](#) [scale\\_x\\_discrete](#)

### Examples

```
## Not run:
a_boxplot <- plot_boxplot(expt)
a_boxplot ## ooo pretty boxplot look at the lines

## End(Not run)
```

plot\_corheat

*Make a heatmap.3 description of the correlation between samples.***Description**

Given a set of count tables and design, this will calculate the pairwise correlations and plot them as a heatmap. It attempts to standardize the inputs and eventual output.

**Usage**

```
plot_corheat(expt_data, expt_colors = NULL, expt_design = NULL,
  method = "pearson", expt_names = NULL, batch_row = "batch",
  title = NULL, ...)
```

**Arguments**

expt_data	Dataframe, expt, or expressionset to work with.
expt_colors	Color scheme for the samples, not needed if this is an expt.
expt_design	Design matrix describing the experiment, not needed if this is an expt.
method	Correlation statistic to use. (pearson, spearman, kendall, robust).
expt_names	Alternate names to use for the samples.
batch_row	Name of the design row used for 'batch' column colors.
title	Title for the plot.
...	More options are wonderful!

**Value**

Gplots heatmap describing describing how the samples are clustering vis a vis pairwise correlation.

**See Also**

**grDevice** [hpgl\\_cor](#) [brewer.pal](#) [recordPlot](#)

**Examples**

```
## Not run:
corheat_plot <- hpgl_corheat(expt=expt, method="robust")

## End(Not run)
```

---

plot_density	Create a density plot, showing the distribution of each column of data.
--------------	---

---

## Description

Density plots and boxplots are cousins and provide very similar views of data distributions. Some people like one, some the other. I think they are both colorful and fun!

## Usage

```
plot_density(data, colors = NULL, sample_names = NULL,  
             position = "identity", fill = NULL, title = NULL, scale = NULL,  
             colors_by = "condition")
```

## Arguments

data	Expt, expressionset, or data frame.
colors	Color scheme to use.
sample_names	Names of the samples.
position	How to place the lines, either let them overlap (identity), or stack them.
fill	Fill the distributions? This might make the plot unreasonably colorful.
title	Title for the plot.
scale	Plot on the log scale?
colors_by	Factor for coloring the lines

## Value

Ggplot2 density plot!

## See Also

**ggplot2** [geom\\_density](#)

## Examples

```
## Not run:  
funkytown <- plot_density(data)  
  
## End(Not run)
```



---

plot_disheat	<i>Make a heatmap.<sup>3</sup> description of the distances (euclidean by default) between samples.</i>
--------------	---

---

## Description

Given a set of count tables and design, this will calculate the pairwise distances and plot them as a heatmap. It attempts to standardize the inputs and eventual output.

## Usage

```
plot_disheat(expt_data, expt_colors = NULL, expt_design = NULL,  
             method = "euclidean", expt_names = NULL, batch_row = "batch",  
             title = NULL, ...)
```

## Arguments

expt_data	Dataframe, expt, or expressionset to work with.
expt_colors	Color scheme (not needed if an expt is provided).
expt_design	Design matrix (not needed if an expt is provided).
method	Distance metric to use.
expt_names	Alternate names to use for the samples.
batch_row	Name of the design row used for 'batch' column colors.
title	Title for the plot.
...	More parameters!

## Value

a recordPlot() heatmap describing the distance between samples.

## See Also

**RColorBrewer** [brewer.pal](#) [heatmap.2](#) [recordPlot](#)

## Examples

```
## Not run:  
disheat_plot = plot_disheat(expt=expt, method="euclidean")  
  
## End(Not run)
```

---

plot_dist_scatter	<i>Make a scatter plot between two sets of numbers with a cheesy distance metric and some statistics of the two sets.</i>
-------------------	---

---

## Description

The distance metric should be codified and made more intelligent. Currently it creates a dataframe of distances which are absolute distances from each axis, multiplied by each other, summed by axis, then normalized against the maximum.

## Usage

```
plot_dist_scatter(df, tooltip_data = NULL, gvis_filename = NULL, size = 2)
```

## Arguments

df	Dataframe likely containing two columns.
tooltip_data	Df of tooltip information for gvis graphs.
gvis_filename	Filename to write a fancy html graph.
size	Size of the dots.

## Value

Ggplot2 scatter plot. This plot provides a "bird's eye" view of two data sets. This plot assumes the two data structures are not correlated, and so it calculates the median/mad of each axis and uses these to calculate a stupid, home-grown distance metric away from both medians. This distance metric is used to color dots which are presumed the therefore be interesting because they are far from 'normal.' This will make a fun clicky googleVis graph if requested.

## See Also

**ggplot2** [plot\\_gvis\\_scatter](#) [geom\\_point](#) [plot\\_linear\\_scatter](#)

## Examples

```
## Not run:
  dist_scatter(lotsofnumbers_intwo_columns, tooltip_data=tooltip_dataframe,
              gvis_filename="html/fun_scatterplot.html")

## End(Not run)
```

---

plot_epitrochoid	<i>Make epitrochoid plots!</i>
------------------	--------------------------------

---

**Description**

7, 2, 6, 7 should give a pretty result.

**Usage**

```
plot_epitrochoid(radius_a = 7, radius_b = 2, dist_b = 6,  
  revolutions = 7, increments = 6480)
```

**Arguments**

radius_a	Radius of the major circle
radius_b	And the smaller circle.
dist_b	between b and the drawing point.
revolutions	How many times to revolve through the spirograph.
increments	How many dots to lay down while writing.

---

plot_essentiality	<i>Plot the essentiality of a library as per DeJesus et al.</i>
-------------------	---

---

**Description**

This provides a plot of the essentiality metrics 'zbar' with respect to gene.

**Usage**

```
plot_essentiality(file)
```

**Arguments**

file	a file created using the perl script 'essentiality_tas.pl'
------	--

**Value**

A couple of plots

**See Also**

**ggplot2**

---

`plot_fun_venn`*A quick wrapper around venneuler to help label stuff*

---

**Description**

venneuler makes pretty venn diagrams, but no labels!

**Usage**

```
plot_fun_venn(ones = c(), twos = c(), threes = c(), fours = c(),  
             fives = c(), factor = 0.9)
```

**Arguments**

<code>ones</code>	Character list of singleton categories
<code>twos</code>	Character list of doubleton categories
<code>threes</code>	Character list of tripletone categories
<code>fours</code>	Character list of quad categories
<code>fives</code>	Character list of quint categories
<code>factor</code>	Currently unused, but intended to change the radial distance to the label from the center of each circle.

**Value**

Two element list containing the venneuler data and the plot.

**See Also**

**venneuler**

---

`plot_goseq_pval`*Make a pvalue plot from goseq data.*

---

**Description**

With minor changes, it is possible to push the goseq results into a clusterProfiler-ish pvalue plot. This handles those changes and returns the ggplot results.

With minor changes, it is possible to push the goseq results into a clusterProfiler-ish pvalue plot. This handles those changes and returns the ggplot results.

**Usage**

```
plot_goseq_pval(goterms, wrapped_width = 30, cutoff = 0.1, n = 30,
  mincat = 5, level = NULL)
```

```
plot_goseq_pval(goterms, wrapped_width = 30, cutoff = 0.1, n = 30,
  mincat = 5, level = NULL)
```

**Arguments**

goterms	Some data from goseq!
wrapped_width	Number of characters before wrapping to help legibility.
cutoff	Pvalue cutoff for the plot.
n	How many groups to include?
mincat	Minimum size of the category for inclusion.
level	Levels of the ontology tree to use.
goterms	Some data from goseq!
wrapped_width	Number of characters before wrapping to help legibility.
cutoff	Pvalue cutoff for the plot.
n	How many groups to include?
mincat	Minimum size of the category for inclusion.
level	Levels of the ontology tree to use.

**Value**

Plots!

Plots!

**See Also**

[goseq clusterProfiler plot\\_ontpval](#)

[goseq clusterProfiler goseq plot\\_ontpval](#)

---

plot_gostats_pval	<i>Make a pvalue plot similar to that from clusterProfiler from gostats data.</i>
-------------------	---

---

**Description**

clusterProfiler provides beautiful plots describing significantly overrepresented categories. This function attempts to expand the repertoire of data available to them to include data from gostats. The pval\_plot function upon which this is based now has a bunch of new helpers now that I understand how the ontology trees work better, this should take advantage of that, but currently does not.

**Usage**

```
plot_gostats_pval(gs_result, wrapped_width = 20, cutoff = 0.1, n = 12,
  group_minsize = 5)
```

**Arguments**

gs_result	Ontology search results.
wrapped_width	Make the text large enough to read.
cutoff	What is the maximum pvalue allowed?
n	How many groups to include in the plot?
group_minsize	Minimum group size before inclusion.

**Value**

Plots!

**See Also**

**clusterProfiler** [plot\\_ontpval](#)

---

plot_gprofiler_pval	<i>Make a pvalue plot from gprofiler data.</i>
---------------------	--

---

**Description**

The p-value plots from clusterProfiler are pretty, this sets the gprofiler data into a format suitable for plotting in that fashion and returns the resulting plots of significant ontologies.

**Usage**

```
plot_gprofiler_pval(gp_result, wrapped_width = 30, cutoff = 0.1, n = 30,
  group_minsize = 5, scorer = "recall", ...)
```

**Arguments**

gp_result	Some data from gProfiler.
wrapped_width	Maximum width of the text names.
cutoff	P-value cutoff for the plots.
n	Maximum number of ontologies to include.
group_minsize	Minimum ontology group size to include.
scorer	Which column to use for scoring the data.
...	Options I might pass from other functions are dropped into arglist.

**Value**

List of MF/BP/CC pvalue plots.

**See Also**

[topgo](#) [clusterProfiler](#)

---

plot_gvis_ma	<i>Make an html version of an MA plot: <math>M(\log \text{ ratio of conditions}) / A(\text{mean average})</math>.</i>
--------------	---

---

**Description**

A fun snippet from wikipedia: "In many microarray gene expression experiments, an underlying assumption is that most of the genes would not see any change in their expression therefore the majority of the points on the y-axis (M) would be located at 0, since  $\text{Log}(1)$  is 0. If this is not the case, then a normalization method such as LOESS should be applied to the data before statistical analysis. If the median line is not straight, the data should be normalized.

**Usage**

```
plot_gvis_ma(df, tooltip_data = NULL, filename = "html/gvis_ma_plot.html",
  base_url = "", ...)
```

**Arguments**

df	Data frame of counts which have been normalized counts by sample-type, which is to say the output from <code>voom/voomMod/hpql_voom()</code> .
tooltip_data	Df of tooltip information (gene names, etc).
filename	Filename to write a fancy html graph.
base_url	String with a basename used for generating URLs for clicking dots on the graph.
...	more options are more options!

**Value**

NULL, but along the way an html file is generated which contains a googleVis MA plot. See `plot_de_ma()` for details.

**See Also**

[googleVis](#) [plot\\_ma\\_de](#)

**Examples**

```
## Not run:
plot_gvis_ma(df, filename="html/fun_ma_plot.html",
             base_url="http://yeastgenome.org/accession?")

## End(Not run)
```

---

plot_gvis_scatter	<i>Make an html version of a scatter plot.</i>
-------------------	--

---

**Description**

Given an arbitrary scatter plot, we can make it pretty and javascript-tacular using this function.

**Usage**

```
plot_gvis_scatter(df, tooltip_data = NULL,
                  filename = "html/gvis_scatter.html", base_url = "", trendline = NULL)
```

**Arguments**

df	Df of two columns to compare.
tooltip_data	Df of tooltip information for gvis graphs.
filename	Filename to write a fancy html graph.
base_url	Url to send click events which will be suffixed with the gene name.
trendline	Add a trendline?

**Value**

NULL, but along the way an html file is generated which contains a googleVis scatter plot. See plot\_scatter() for details.

**See Also**

**googleVis** [gvisScatterChart](#)

**Examples**

```
## Not run:
gvis_scatter(a_dataframe_twocolumns, filename="html/fun_scatter_plot.html",
             base_url="http://yeastgenome.org/accession?")

## End(Not run)
```



---

plot_gvis_volcano	<i>Make an html version of an volcano plot.</i>
-------------------	---

---

## Description

Volcano plots provide some visual clues regarding the success of a given contrast. For our data, it has the  $-\log_{10}(\text{pvalue})$  on the y-axis and fold-change on the x. Here is a neat snippet from wikipedia describing them generally: "The concept of volcano plot can be generalized to other applications, where the x-axis is related to a measure of the strength of a statistical signal, and y-axis is related to a measure of the statistical significance of the signal."

## Usage

```
plot_gvis_volcano(toptable_data, fc_cutoff = 0.8, p_cutoff = 0.05,  
  tooltip_data = NULL, filename = "html/gvis_vol_plot.html",  
  base_url = "", ...)
```

## Arguments

toptable_data	Df of toptable() data.
fc_cutoff	Fold change cutoff.
p_cutoff	Maximum p value to allow.
tooltip_data	Df of tooltip information.
filename	Filename to write a fancy html graph.
base_url	String with a basename used for generating URLs for clicking dots on the graph.
...	more options

## Value

NULL, but along the way an html file is generated which contains a googleVis volcano plot.

## See Also

**googleVis** [plot\\_volcano](#)

## Examples

```
## Not run:  
plot_gvis_volcano(voomed_data, toptable_data, filename="html/fun_ma_plot.html",  
  base_url="http://yeastgenome.org/accession?")  
  
## End(Not run)
```

---

plot_heatmap	<i>Make a heatmap.3 plot, does the work for plot_disheat and plot_corheat.</i>
--------------	--

---

## Description

This does what is says on the tin. Sets the colors for correlation or distance heatmaps, handles the calculation of the relevant metrics, and plots the heatmap.

## Usage

```
plot_heatmap(expt_data, expt_colors = NULL, expt_design = NULL,  
  method = "pearson", expt_names = NULL, type = "correlation",  
  batch_row = "batch", title = NULL, ...)
```

## Arguments

expt_data	Dataframe, expt, or expressionset to work with.
expt_colors	Color scheme for the samples.
expt_design	Design matrix describing the experiment vis a vis conditions and batches.
method	Distance or correlation metric to use.
expt_names	Alternate names to use for the samples.
type	Defines the use of correlation, distance, or sample heatmap.
batch_row	Name of the design row used for 'batch' column colors.
title	Title for the plot.
...	I like ellipses!

## Value

a recordPlot() heatmap describing the distance between samples.

## See Also

**RColorBrewer** [brewer.pal](#) [recordPlot](#)

---

plot_heatplus	<i>Potential replacement for heatmap.2 based plots.</i>
---------------	---

---

### Description

Heatplus is an interesting tool, I have a few examples of using it and intend to include them here.

### Usage

```
plot_heatplus(fundata)
```

### Arguments

fundata	A data frame to plot.
---------	-----------------------

---

plot_histogram	<i>Make a pretty histogram of something.</i>
----------------	--

---

### Description

A shortcut to make a ggplot2 histogram which makes an attempt to set reasonable bin widths and set the scale to log if that seems a good idea.

### Usage

```
plot_histogram(df, binwidth = NULL, log = FALSE, bins = 500,
  fillcolor = "darkgrey", color = "black")
```

### Arguments

df	Dataframe of lots of pretty numbers.
binwidth	Width of the bins for the histogram.
log	Replot on the log scale?
bins	Number of bins for the histogram.
fillcolor	Change the fill colors of the plotted elements?
color	Change the color of the lines of the plotted elements?

### Value

Ggplot histogram.

### See Also

**ggplot2** [geom\\_histogram](#) [geom\\_density](#)

**Examples**

```
## Not run:
kittytime = plot_histogram(df)

## End(Not run)
```

---

plot_hypotrochoid	<i>Make hypotrochoid plots!</i>
-------------------	---------------------------------

---

**Description**

3,7,1 should give the classic 7 leaf clover

**Usage**

```
plot_hypotrochoid(radius_a = 3, radius_b = 7, dist_b = 1,
  revolutions = 7, increments = 6480)
```

**Arguments**

radius_a	Radius of the major circle
radius_b	And the smaller circle.
dist_b	between b and the drawing point.
revolutions	How many times to revolve through the spirograph.
increments	How many dots to lay down while writing.

---

plot_legend	<i>Scab the legend from a PCA plot and print it alone</i>
-------------	---

---

**Description**

This way I can have a legend object to move about.

**Usage**

```
plot_legend(stuff)
```

**Arguments**

stuff	This can take either a ggplot2 pca plot or some data from which to make one.
-------	--

**Value**

A legend!

---

plot_libsize	<i>Make a ggplot graph of library sizes.</i>
--------------	--

---

## Description

It is often useful to have a quick view of which samples have more/fewer reads. This does that and maintains one's favorite color scheme and tries to make it pretty!

## Usage

```
plot_libsize(data, condition = NULL, colors = NULL, names = NULL,  
             text = TRUE, title = NULL, yscale = NULL, ...)
```

## Arguments

data	Expt, dataframe, or expressionset of samples.
condition	vector of sample condition names.
colors	Color scheme if the data is not an expt.
names	Alternate names for the x-axis.
text	Add the numeric values inside the top of the bars of the plot?
title	Title for the plot.
yscale	Whether or not to log10 the y-axis.
...	More parameters for your good time!

## Value

a ggplot2 bar plot of every sample's size

## See Also

**ggplot2** [geom\\_bar](#) [geom\\_text](#) [prettyNum](#) [scale\\_y\\_log10](#)

## Examples

```
## Not run:  
  libsize_plot <- plot_libsize(expt=expt)  
  libsize_plot  ## ooo pretty bargraph  
  
## End(Not run)
```

---

plot_linear_scatter	<i>Make a scatter plot between two groups with a linear model superimposed and some supporting statistics.</i>
---------------------	--

---

## Description

Make a scatter plot between two groups with a linear model superimposed and some supporting statistics.

## Usage

```
plot_linear_scatter(df, tooltip_data = NULL, gvis_filename = NULL,
  cormethod = "pearson", size = 2, loess = FALSE, identity = FALSE,
  gvis_trendline = NULL, first = NULL, second = NULL, base_url = NULL,
  pretty_colors = TRUE, color_high = NULL, color_low = NULL, ...)
```

## Arguments

df	Dataframe likely containing two columns.
tooltip_data	Df of tooltip information for gvis graphs.
gvis_filename	Filename to write a fancy html graph.
cormethod	What type of correlation to check?
size	Size of the dots on the plot.
loess	Add a loess estimation?
identity	Add the identity line?
gvis_trendline	Add a trendline to the gvis plot? There are a couple possible types, I think linear is the most common.
first	First column to plot.
second	Second column to plot.
base_url	Base url to add to the plot.
pretty_colors	Colors!
color_high	Chosen color for points significantly above the mean.
color_low	Chosen color for points significantly below the mean.
...	Extra args likely used for choosing significant genes.

## Value

List including a ggplot2 scatter plot and some histograms. This plot provides a "bird's eye" view of two data sets. This plot assumes a (potential) linear correlation between the data, so it calculates the correlation between them. It then calculates and plots a robust linear model of the data using an 'SMDM' estimator (which I don't remember how to describe, just that the document I was reading said it is good). The median/mad of each axis is calculated and plotted as well. The distance from the linear model is finally used to color the dots on the plot. Histograms of each axis are plotted separately and then together under a single cdf to allow tests of distribution similarity. This will make a fun clicky googleVis graph if requested.

**See Also**

**robust stats** [ggplot2](#) [lmRob](#) [weights](#) [plot\\_histogram](#)

**Examples**

```
## Not run:
plot_linear_scatter(lotsofnumbers_intwo_columns, tooltip_data=tooltip_dataframe,
                    gvis_filename="html/fun_scatterplot.html")

## End(Not run)
```

---

plot\_ma\_de

---

*Make a pretty MA plot from one of limma, deseq, edger, or basic.*


---

**Description**

Because I can never remember, the following from wikipedia: "An MA plot is an application of a Bland-Altman plot for visual representation of two channel DNA microarray gene expression data which has been transformed onto the M (log ratios) and A (mean average) scale."

**Usage**

```
plot_ma_de(table, expr_col = "logCPM", fc_col = "logFC", p_col = "qvalue",
           pval_cutoff = 0.05, alpha = 0.4, logfc_cutoff = 1,
           label_numbers = TRUE, size = 2, tooltip_data = NULL,
           gvis_filename = NULL, invert = FALSE, ...)
```

**Arguments**

table	Df of linear-modelling, normalized counts by sample-type,
expr_col	Column showing the average expression across genes.
fc_col	Column showing the logFC for each gene.
p_col	Column containing the relevant p values.
pval_cutoff	Name of the pvalue column to use for cutoffs.
alpha	How transparent to make the dots.
logfc_cutoff	Fold change cutoff.
label_numbers	Show how many genes were 'significant', 'up', and 'down'?
size	How big are the dots?
tooltip_data	Df of tooltip information for gvis.
gvis_filename	Filename to write a fancy html graph.
...	More options for you

**Value**

ggplot2 MA scatter plot. This is defined as the rowmeans of the normalized counts by type across all sample types on the x axis, and the log fold change between conditions on the y-axis. Dots are colored depending on if they are 'significant.' This will make a fun clicky googleVis graph if requested.

**See Also**

[limma](#) [googleVis](#) [DESeq2](#) [edgeR](#) [plot\\_gvis\\_ma](#) [toptable](#) [voom](#) [hpgl\\_voom](#) [lmFit](#) [makeContrasts](#) [contrasts.fit](#)

**Examples**

```
## Not run:
plot_ma(voomed_data, toptable_data, gvis_filename="html/fun_ma_plot.html")
## Currently this assumes that a variant of toptable was used which
## gives adjusted p-values. This is not always the case and I should
## check for that, but I have not yet.

## End(Not run)
```

---

plot\_multihistogram     *Make a pretty histogram of multiple datasets.*

---

**Description**

If there are multiple data sets, it might be useful to plot them on a histogram together and look at the t.test results between distributions.

**Usage**

```
plot_multihistogram(data, log = FALSE, binwidth = NULL, bins = NULL)
```

**Arguments**

data	Dataframe of lots of pretty numbers, this also accepts lists.
log	Plot the data on the log scale?
binwidth	Set a static bin width with an unknown # of bins? If neither of these are provided, then bins is set to 500, if both are provided, then bins wins.
bins	Set a static # of bins of an unknown width?

**Value**

List of the ggplot histogram and some statistics describing the distributions.

**See Also**

[ggplot2](#) [pairwise.t.test](#) [ddply](#)



**Examples**

```
## Not run:
kittytime = plot_multihistogram(df)

## End(Not run)
```

---

plot_multiplot	<i>Make a grid of plots.</i>
----------------	------------------------------

---

**Description**

Make a grid of plots.

**Usage**

```
plot_multiplot(plots, file, cols = NULL, layout = NULL)
```

**Arguments**

plots	a list of plots
file	a file to write to
cols	the number of columns in the grid
layout	set the layout specifically

**Value**

a multiplot!

---

plot_nonzero	<i>Make a ggplot graph of the number of non-zero genes by sample.</i>
--------------	---

---

**Description**

This puts the number of genes with > 0 hits on the y-axis and CPM on the x-axis. Made by Ramzi Temanni <temanni at umd dot edu>.

**Usage**

```
plot_nonzero(data, design = NULL, colors = NULL, labels = NULL,
             title = NULL, ...)
```

Arguments

data	Expt, expressionset, or dataframe.
design	Eesign matrix.
colors	Color scheme.
labels	How do you want to label the graph? 'fancy' will use directlabels() to try to match the labels with the positions without overlapping anything else will just stick them on a 45' offset next to the graphed point.
title	Add a title?
...	rawr!

Value

a ggplot2 plot of the number of non-zero genes with respect to each library's CPM.

See Also

`ggplot2` [geom\\_point](#) [geom\\_dl](#)

Examples

```
## Not run:
nonzero_plot = plot_nonzero(expt=expt)
nonzero_plot ## ooo pretty

## End(Not run)
```

---

plot_num_siggenes	<i>Given a DE table with fold changes and p-values, show how 'significant' changes with changing cutoffs.</i>
-------------------	---

---

Description

Sometimes one might want to know how many genes are deemed significant while shifting the bars which define significant. This provides that metrics as a set of tables of numbers of significant up/down genes when p-value is held constant, as well as number when fold-change is held constant.

Usage

```
plot_num_siggenes(table, p_column = "limma_adjp", fc_column = "limma_logfc",
  bins = 100, constant_p = 0.05, constant_fc = 0)
```

**Arguments**

table	DE table to examine.
p_column	Column in the DE table defining the changing p-value cutoff.
fc_column	Column in the DE table defining the changing +/- log fold change.
bins	Number of incremental changes in p-value/FC to examine.
constant_p	When plotting changing FC, where should the p-value be held?
constant_fc	When plotting changing p, where should the FC be held?

**Value**

Plots and dataframes describing the changing definition of 'significant.'

**See Also**

**ggplot2**

**Examples**

```
## Not run:
crazy_sigplots <- plot_num_siggenes(pairwise_result)

## End(Not run)
```

---

plot_ontpval	<i>Make a pvalue plot from a df of IDs, scores, and p-values.</i>
--------------	---

---

**Description**

This function seeks to make generating pretty pvalue plots as shown by clusterprofiler easier.

**Usage**

```
plot_ontpval(df, ontology = "MF", fontsize = 16)
```

**Arguments**

df	Some data from topgo/goseq/clusterprofiler.
ontology	Ontology to plot (MF,BP,CC).
fontsize	Fiddling with the font size may make some plots more readable.

**Value**

Ggplot2 plot of pvalues vs. ontology.

**See Also**

**goseq** **ggplot2** [goseq](#)

---

plot_pairwise_ma	<i>Plot all pairwise MA plots in an experiment.</i>
------------------	---

---

**Description**

Use affy's `ma.plot()` on every pair of columns in a data set to help diagnose problematic samples.

**Usage**

```
plot_pairwise_ma(data, log = NULL, ...)
```

**Arguments**

<code>data</code>	Expt expressionset or data frame.
<code>log</code>	Is the data in log format?
<code>...</code>	Options are good and passed to <code>arglist()</code> .

**Value**

List of `affy::maplots`

**See Also**

`affy` [ma.plot](#)

**Examples**

```
## Not run:
ma_plots = plot_pairwise_ma(expt=some_expt)

## End(Not run)
```

---

plot_pca	<i>Make a ggplot PCA plot describing the samples' clustering.</i>
----------	---

---

**Description**

Make a ggplot PCA plot describing the samples' clustering.

**Usage**

```
plot_pca(data, design = NULL, plot_colors = NULL, plot_labels = NULL,
  plot_title = NULL, plot_size = 5, size_column = NULL, ...)
```

**Arguments**

data	an expt set of samples.
design	a design matrix and.
plot_colors	a color scheme.
plot_labels	add labels? Also, what type? FALSE, "default", or "fancy".
plot_title	a title for the plot.
plot_size	size for the glyphs on the plot.
size_column	use an experimental factor to size the glyphs of the plot
...	arglist from elipsis!

**Value**

a list containing the following:

1. pca = the result of fast.svd()
2. plot = ggplot2 pca\_plot describing the principle component analysis of the samples.
3. table = a table of the PCA plot data
4. res = a table of the PCA res data
5. variance = a table of the PCA plot variance

**See Also**

**directlabels** [geom\\_dl](#) [plot\\_pcs](#)

**Examples**

```
## Not run:
pca_plot <- plot_pca(expt=expt)
pca_plot

## End(Not run)
```

---

plot_pcfactor	<i>make a dotplot of some categorised factors and a set of principle components.</i>
---------------	--

---

**Description**

This should make a quick df of the factors and PCs and plot them.

**Usage**

```
plot_pcfactor(pc_df, expt, exp_factor = "condition", component = "PC1")
```

**Arguments**

pc_df	Df of principle components.
expt	Expt containing counts, metadata, etc.
exp_factor	Experimental factor to compare against.
component	Which principal component to compare against?

**Value**

Plot of principle component vs factors in the data

**See Also**

**ggplot2**

**Examples**

```
## Not run:
estimate_vs_pcs <- plot_pcfactor(pcs, times)

## End(Not run)
```

---

plot_pcs	<i>A quick and dirty PCA plotter of arbitrary components against one another.</i>
----------	---

---

**Description**

A quick and dirty PCA plotter of arbitrary components against one another.

**Usage**

```
plot_pcs(pca_data, first = "PC1", second = "PC2", variances = NULL,
  design = NULL, plot_title = TRUE, plot_labels = NULL, plot_size = 5,
  size_column = NULL, ...)
```

**Arguments**

pca_data	a dataframe of principle components PC1 .. PCN with any other arbitrary information.
first	principle component PCx to put on the x axis.
second	principle component PCy to put on the y axis.
variances	a list of the percent variance explained by each component.
design	the experimental design with condition batch factors.
plot_title	a title for the plot.
plot_labels	a parameter for the labels on the plot.

plot_size	The size of the dots on the plot
size_column	an experimental factor to use for sizing the glyphs
...	extra arguments dropped into arglist

**Value**

a ggplot2 PCA plot

**See Also**

`ggplot2` [geom\\_dl](#)

**Examples**

```
## Not run:
pca_plot = plot_pcs(pca_data, first="PC2", second="PC4", design=expt$design)

## End(Not run)
```

---

plot_qq_all	<i>Quantile/quantile comparison of the mean of all samples vs. each sample.</i>
-------------	---

---

**Description**

This allows one to visualize all individual data columns against the mean of all columns of data in order to see if any one is significantly different than the cloud.

**Usage**

```
plot_qq_all(data, labels = "short")
```

**Arguments**

data	Expressionset, expt, or dataframe of samples.
labels	What kind of labels to print?

**Value**

List containing: logs = a recordPlot() of the pairwise log qq plots. ratios = a recordPlot() of the pairwise ratio qq plots. means = a table of the median values of all the summaries of the qq plots.

**See Also**

**Biobase**

---

plot_qq_all_pairwise	<i>Perform qq plots of every column against every other column of a dataset.</i>
----------------------	--

---

### Description

This function is stupid, don't use it. It makes more sense to just use plot\_qq, however I am not quite read to delete this function yet.

### Usage

```
plot_qq_all_pairwise(data)
```

### Arguments

data	Dataframe to perform pairwise qqplots with.
------	---

### Value

List containing the recordPlot() output of the ratios, logs, and means among samples.

### See Also

**Biobase**

---

plot_qq_plot	<i>Perform a qqplot between two columns of a matrix.</i>
--------------	--

---

### Description

Given two columns of data, how well do the distributions match one another? The answer to that question may be visualized through a qq plot!

### Usage

```
plot_qq_plot(data, x = 1, y = 2, labels = TRUE)
```

### Arguments

data	Data frame/expt/expressionset.
x	First column to compare.
y	Second column to compare.
labels	Include the labels?



**Value**

a list of the logs, ratios, and mean between the plots as ggplots.

**See Also**

**Biobase**

---

plot_rpm	<i>Make relatively pretty bar plots of coverage in a genome.</i>
----------	--

---

**Description**

This was written for ribosome profiling coverage / gene. It should however, work for any data with little or no modification.

**Usage**

```
plot_rpm(input, workdir = "images", output = "01.svg",  
         name = "LmjF.01.0010", start = 1000, end = 2000, strand = 1,  
         padding = 100)
```

**Arguments**

input	Coverage / position filename.
workdir	Where to put the resulting images.
output	Output image filename.
name	Gene name to print at the bottom of the plot.
start	Relative to 0, where is the gene's start codon.
end	Relative to 0, where is the gene's stop codon.
strand	Is this on the + or - strand? (+1/-1)
padding	How much space to provide on the sides?

**Value**

coverage plot surrounding the ORF of interest

**See Also**

**ggplot2**

---

plot_sample_heatmap	<i>Make a heatmap.3 description of the similarity of the genes among samples.</i>
---------------------	---

---

### Description

Sometimes you just want to see how the genes of an experiment are related to each other. This can handle that. These heatmap functions should probably be replaced with neatmaps or heatplus or whatever it is, as the annotation dataframes in them are pretty awesome.

### Usage

```
plot_sample_heatmap(data, colors = NULL, design = NULL, names = NULL,
  title = NULL, Rowv = TRUE, ...)
```

### Arguments

data	Expt/expressionset/dataframe set of samples.
colors	Color scheme of the samples (not needed if input is an expt).
design	Design matrix describing the experiment (gotten for free if an expt).
names	Alternate samples names.
title	Title of the plot!
Rowv	Reorder the rows by expression?
...	More parameters for a good time!

### Value

a recordPlot() heatmap describing the samples.

### See Also

**RColorBrewer** [brewer.pal](#) [recordPlot](#)

---

plot_scatter	<i>Make a pretty scatter plot between two sets of numbers.</i>
--------------	--

---

### Description

This function tries to supplement a normal scatterplot with some information describing the relationship between the columns of data plotted.

### Usage

```
plot_scatter(df, tooltip_data = NULL, color = "black",
  gvis_filename = NULL, size = 2)
```

**Arguments**

df	Dataframe likely containing two columns.
tooltip_data	Df of tooltip information for gvis.
color	Color of the dots on the graph.
gvis_filename	Filename to write a fancy html graph.
size	Size of the dots on the graph.

**Value**

Ggplot2 scatter plot.

**See Also**

**ggplot2** **googleVis** [plot\\_gvis\\_scatter](#) [geom\\_point](#) [plot\\_linear\\_scatter](#)

**Examples**

```
## Not run:
plot_scatter(lotsofnumbers_intwo_columns, tooltip_data=tooltip_dataframe,
             gvis_filename="html/fun_scatterplot.html")

## End(Not run)
```

---

`plot_significant_bar`    *Make a bar plot of the numbers of significant genes by contrast. These plots are quite difficult to describe.*

---

**Description**

Make a bar plot of the numbers of significant genes by contrast. These plots are quite difficult to describe.

**Usage**

```
plot_significant_bar(ups, downs, maximum = NULL, text = TRUE,
  color_list = c("lightcyan", "lightskyblue", "dodgerblue", "plum1", "orchid",
    "purple4"), color_names = c("a_up_inner", "b_up_middle", "c_up_outer",
    "a_down_inner", "b_down_middle", "c_down_outer"))
```

**Arguments**

ups	Set of up-regulated genes.
downs	Set of down-regulated genes.
maximum	Maximum/minimum number of genes to display.
text	Add text at the ends of the bars describing the number of genes $>/< 0$ fc.
color_list	Set of colors to use for the bars.
color_names	Categories associated with aforementioned colors.

**Value**

weird significance bar plots

**See Also**

**ggplot2** [extract\\_significant\\_genes](#)

---

plot_sm	<i>Make an R plot of the standard median correlation or distance among samples.</i>
---------	---

---

**Description**

This was written by a mix of Kwame Okrah <kokrah at gmail dot com>, Laura Dillon <dillonl at umd dot edu>, and Hector Corrada Bravo <hcorrada at umd dot edu> I reimplemented it using ggplot2 and tried to make it a little more flexible. The general idea is to take the pairwise correlations/distances of the samples, then take the medians, and plot them.

**Usage**

```
plot_sm(data, colors = NULL, method = "pearson", names = NULL,
        title = NULL, ...)
```

**Arguments**

data	Expt, expressionset, or data frame.
colors	Color scheme if data is not an expt.
method	Correlation or distance method to use.
names	Use pretty names for the samples?
title	Title for the graph.
...	More parameters to make you happy!

**Value**

ggplot of the standard median something among the samples. This will also write to an open device. The resulting plot measures the median correlation of each sample among its peers. It notes 1.5\* the interquartile range among the samples and makes a horizontal line at that correlation coefficient. Any sample which falls below this line is considered for removal because it is much less similar to all of its peers.

**See Also**

**matrixStats** **grDevices** [hpgl\\_cor](#) [rowMedians](#) [quantile](#) [diff](#) [recordPlot](#)

**Examples**

```
## Not run:
smc_plot = hpgl_smc(expt=expt)

## End(Not run)
```

---

plot_spirograph	<i>Make spirographs!</i>
-----------------	--------------------------

---

**Description**

Taken (with modifications) from: <http://menuget.blogspot.com/2012/12/spirograph-with-r.html#more>  
 A positive value for 'B' will result in a epitrochoid, while a negative value will result in a hypotrochoid.

**Usage**

```
plot_spirograph(radius_a = 1, radius_b = -4, dist_bc = -2,
  revolutions = 158, increments = 3160, center_a = list(x = 0, y = 0))
```

**Arguments**

radius_a	The radius of the primary circle.
radius_b	The radius of the circle travelling around a.
dist_bc	A point relative to the center of 'b' which rotates with the turning of 'b'.
revolutions	How many revolutions to perform in the plot
increments	The number of radial increments to be calculated per revolution
center_a	The position of the center of 'a'.

**Value**

something which I don't yet know.

---

plot_svfactor	<i>Make a dotplot of some categorised factors and a set of SVs (for other factors).</i>
---------------	---

---

**Description**

This should make a quick df of the factors and surrogates and plot them.

**Usage**

```
plot_svfactor(expt, svest, chosen_factor = "snpcategory",
  factor_type = "factor")
```

**Arguments**

expt	Experiment from which to acquire the design, counts, etc.
svest	Set of surrogate variable estimations from sva/svg or batch estimates.
chosen_factor	Factor to compare against.
factor_type	This may be a factor or range, it is intended to plot a scatterplot if it is a range, a dotplot if a factor.

**Value**

surrogate variable plot as per Leek's work

**See Also**

**ggplot2**

**Examples**

```
## Not run:
estimate_vs_snps <- plot_svfactor(start, surrogate_estimate, "snpcategory")

## End(Not run)
```

---

plot\_topgo\_densities    *Plot the density of categories vs. the possibilities of all categories.*

---

**Description**

This can make a large number of plots.

**Usage**

```
plot_topgo_densities(godata, table)
```

**Arguments**

godata	Result from topgo.
table	Table of genes.

**Value**

density plot as per topgo

**See Also**

**topGO**

---

plot_topgo_pval	<i>Make a pvalue plot from topgo data.</i>
-----------------	--

---

### Description

The p-value plots from clusterProfiler are pretty, this sets the topgo data into a format suitable for plotting in that fashion and returns the resulting plots of significant ontologies.

### Usage

```
plot_topgo_pval(topgo, wrapped_width = 20, cutoff = 0.1, n = 12,
  type = "fisher")
```

### Arguments

topgo	Some data from topgo!
wrapped_width	Maximum width of the text names.
cutoff	P-value cutoff for the plots.
n	Maximum number of ontologies to include.
type	Type of score to use.

### Value

List of MF/BP/CC pvalue plots.

### See Also

**topgo** [clusterProfiler](#)

---

plot_volcano	<i>Make a pretty Volcano plot!</i>
--------------	------------------------------------

---

### Description

Volcano plots and MA plots provide quick and easy methods to view the set of (in)significantly differentially expressed genes. In the case of a volcano plot, it places the  $-\log_{10}$  of the p-value estimate on the y-axis and the fold-change between conditions on the x-axis. Here is a neat snippet from wikipedia: "The concept of volcano plot can be generalized to other applications, where the x-axis is related to a measure of the strength of a statistical signal, and y-axis is related to a measure of the statistical significance of the signal."

### Usage

```
plot_volcano(toptable_data, tooltip_data = NULL, gvis_filename = NULL,
  fc_cutoff = 0.8, p_cutoff = 0.05, size = 2, alpha = 0.6,
  xaxis_column = "logFC", yaxis_column = "P.Value", ...)
```

**Arguments**

<code>toptable_data</code>	Dataframe from limma's toptable which includes log(fold change) and an adjusted p-value.
<code>tooltip_data</code>	Df of tooltip information for gvis.
<code>gvis_filename</code>	Filename to write a fancy html graph.
<code>fc_cutoff</code>	Cutoff defining the minimum/maximum fold change for interesting. This is log, so I went with +/- 0.8 mostly arbitrarily as the default.
<code>p_cutoff</code>	Cutoff defining significant from not.
<code>size</code>	How big are the dots?
<code>alpha</code>	How transparent to make the dots.
<code>xaxis_column</code>	Column from the data to use on the x axis (logFC)
<code>yaxis_column</code>	Column from the data to use on the y axis (p-value)
<code>...</code>	I love parameters!

**Value**

Ggplot2 volcano scatter plot. This is defined as the  $-\log_{10}(\text{p-value})$  with respect to log(fold change). The cutoff values are delineated with lines and mark the boundaries between 'significant' and not. This will make a fun clicky googleVis graph if requested.

**See Also**

[limma](#) [plot\\_gvis\\_ma](#) [toptable](#) [voom](#) [hpgl\\_voom](#) [lmFit](#) [makeContrasts](#) [contrasts.fit](#)

**Examples**

```
## Not run:
plot_volcano(toptable_data, gvis_filename="html/fun_ma_plot.html")
## Currently this assumes that a variant of toptable was used which
## gives adjusted p-values. This is not always the case and I should
## check for that, but I have not yet.

## End(Not run)
```

---

pp

---

*png() shortcut*


---

**Description**

I hate remembering my options for png()

**Usage**

```
pp(file, width = 9, height = 9, res = 180)
```



**Arguments**

file	a filename to write
width	How wide?
height	How high?
res	The chosen resolution.

**Value**

a png with height=width=9 inches and a high resolution

---

print_ups_downs	<i>Reprint the output from extract_significant_genes().</i>
-----------------	---

---

**Description**

I found myself needing to reprint these excel sheets because I added some new information. This shortcuts that process for me.

**Usage**

```
print_ups_downs(upsdowns, wb = NULL, excel = "excel/significant_genes.xlsx",  
  according = "limma", summary_count = 1, ma = FALSE)
```

**Arguments**

upsdowns	Output from extract_significant_genes().
wb	Workbook object to use for writing, or start a new one.
excel	Filename for writing the data.
according	Use limma, deseq, or edger for defining 'significant'.
summary_count	For spacing sequential tables one after another.
ma	Include ma plots?

**Value**

Return from write\_xls.

**See Also**

[combine\\_de\\_tables](#)

---

read_metadata	<i>Given a table of meta data, read it in for use by create_expt().</i>
---------------	---

---

### Description

Reads an experimental design in a few different formats in preparation for creating an expt.

### Usage

```
read_metadata(file, ...)
```

### Arguments

file	Csv/xls file to read.
...	Arguments for arglist, used by sep, header and similar read.csv/read.table parameters.

### Value

Df of metadata.

### See Also

**tools openxlsx XLConnect**

---

recolor_points	<i>Quick point-recolorizer given an existing plot, df, list of rownames to recolor, and a color</i>
----------------	---

---

### Description

This function should make it easy to color a family of genes in any of the point plots.

### Usage

```
recolor_points(plot, df, ids, color = "red", ...)
```

### Arguments

plot	Geom_point based plot
df	Data frame used to create the plot
ids	Set of ids which must be in the rownames of df to recolor
color	Chosen color for the new points.
...	Extra arguments are passed to arglist.

**Value**

prettier plot.

---

replot\_varpart\_percent

*A shortcut for replotting the percent plots from variancePartition.*

---

**Description**

In case I wish to look at different numbers of genes from variancePartition and/or different columns to sort from.

**Usage**

```
replot_varpart_percent(varpart_output, n = 30, column = NULL,  
  decreasing = TRUE)
```

**Arguments**

varpart_output	List returned by varpart()
n	How many genes to plot.
column	The df column to use for sorting.
decreasing	high->low or vice versa?

**Value**

The percent variance bar plots from variancePartition!

**See Also**

**variancePartition** [plotPercentBars](#)

---

require.auto

*Automatic loading and/or installing of packages.*

---

**Description**

Load a library, install it first if necessary.

**Usage**

```
require.auto(lib, update = FALSE)
```

**Arguments**

lib	String name of a library to check/install.
update	Update packages?

**Details**

This was taken from: <http://sbamin.com/2012/11/05/tips-for-working-in-r-automatically-install-missing-package/>

**Value**

0 or 1, whether a package was installed or not.

**See Also**

**BiocInstaller** [biocLite](#) [install.packages](#)

**Examples**

```
## Not run:  
require.auto("ggplot2")  
  
## End(Not run)
```

---

rex	<i>Resets the display and xauthority variables to the new computer I am using so that plot() works.</i>
-----	---

---

**Description**

This function assumes a line in the .profile which writes the DISPLAY variable to \$HOME/.displays/\$(hostname).last

**Usage**

```
rex(display = ":0")
```

**Arguments**

display	DISPLAY variable to use, if NULL it looks in ~/.displays/(host).last
---------	--

---

saveme	<i>Make a backup rdata file for future reference</i>
--------	--

---

**Description**

I often use R over a sshfs connection, sometimes with significant latency, and I want to be able to save/load my R sessions relatively quickly. Thus this function uses pxz to compress the R session maximally and relatively fast. This assumes you have pxz installed and  $\geq 4$  CPUs.

**Usage**

```
saveme(directory = "savefiles", backups = 4, filename = "Rdata.rda.xz")
```

**Arguments**

directory	Directory to save the Rdata file.
backups	How many revisions?
filename	Choose a filename.

**Value**

Command string used to save the global environment.

**See Also**

[save pipe](#)

**Examples**

```
## Not run:  
saveme()  
  
## End(Not run)
```

---

semantic_copynumber_extract	<i>Extract multicopy genes from up/down gene expression lists.</i>
-----------------------------	--

---

**Description**

The function `semantic_copynumber_filter()` is the inverse of this.

**Usage**

```
semantic_copynumber_extract(de_list, min_copies = 2, semantic = c("mucin",  
  "sialidase", "RHS", "MASP", "DGF", "GP63"), semantic_column = "1.tooltip")
```

**Arguments**

de_list	List of sets of genes deemed significantly up/down with a column expressing approximate count numbers.
min_copies	Keep only those genes with $\geq n$ putative copies.
semantic	Set of strings with gene names to exclude.
semantic_column	Column in the DE table used to find the semantic strings for removal.

**Details**

Currently untested, used for Trypanosome analyses primarily, thus the default strings.

**Value**

Smaller list of up/down genes.

**See Also**

[semantic\\_copynumber\\_filter](#)

---

semantic\_copynumber\_filter

*Remove multicopy genes from up/down gene expression lists.*

---

**Description**

In our parasite data, there are a few gene types which are consistently obnoxious. Multi-gene families primarily where the coding sequences are divergent, but the UTRs nearly identical. For these genes, our sequence based removal methods fail and so this just excludes them by name.

**Usage**

```
semantic_copynumber_filter(de_list, max_copies = 2, use_files = FALSE,
  semantic = c("mucin", "sialidase", "RHS", "MASP", "DGF", "GP63"),
  semantic_column = "1.tooltip")
```

**Arguments**

de_list	List of sets of genes deemed significantly up/down with a column expressing approximate count numbers.
max_copies	Keep only those genes with $\leq n$ putative copies.
use_files	Use a set of sequence alignments to define the copy numbers?
semantic	Set of strings with gene names to exclude.
semantic_column	Column in the DE table used to find the semantic strings for removal.

**Details**

Currently untested, used for Trypanosome analyses primarily, thus the default strings.

**Value**

Smaller list of up/down genes.

**See Also**

[semantic\\_copynumber\\_extract](#)

---

sequence_attributes	<i>Gather some simple sequence attributes.</i>
---------------------	--

---

**Description**

This extends the logic of the pattern searching in `pattern_count_genome()` to search on some other attributes.

**Usage**

```
sequence_attributes(fasta, gff = NULL, type = "gene", key = "locus_tag")
```

**Arguments**

fasta	Genome encoded as a fasta file.
gff	Optional gff of annotations (if not provided it will just ask the whole genome).
type	Column of the gff file to use.
key	What type of entry of the gff file to key from?

**Value**

List of data frames containing gc/at/gt/ac contents.

**See Also**

**Biostrings** **Rsamtools** [FaFile](#) [getSeq](#)

**Examples**

```
## Not run:  
num_pattern = sequence_attributes('mgas_5005.fasta', 'mgas_5005.gff')  
  
## End(Not run)
```

---

set_expt_batch	<i>Change the batches of an expt.</i>
----------------	---------------------------------------

---

**Description**

When exploring differential analyses, it might be useful to play with the conditions/batches of the experiment. Use this to make that easier.

**Usage**

```
set_expt_batch(expt, fact, ids = NULL, ...)
```

**Arguments**

expt	Expt to modify.
fact	Batches to replace using this factor.
ids	Specific samples to change.
...	Extra options are like spinach.

**Value**

The original expt with some new metadata.

**See Also**

```
create\_expt set\_expt\_condition
```

**Examples**

```
## Not run:
  expt = set_expt_batch(big_expt, factor=c(some,stuff,here))

## End(Not run)
```

---

set_expt_colors	<i>Change the colors of an expt</i>
-----------------	-------------------------------------

---

**Description**

When exploring differential analyses, it might be useful to play with the conditions/batches of the experiment. Use this to make that easier.

**Usage**

```
set_expt_colors(expt, colors = TRUE, chosen_palette = "Dark2",
  change_by = "condition")
```



**Arguments**

expt	Expt to modify
colors	colors to replace
chosen_palette	I usually use Dark2 as the RColorBrewer palette.
change_by	Assuming a list is passed, cross reference by condition or sample?

**Value**

expt Send back the expt with some new metadata

**See Also**

[set\\_expt\\_condition](#) [set\\_expt\\_batch](#)

**Examples**

```
## Not run:
unique(esmer_expt$design$conditions)
chosen_colors <- list(
  "cl14_epi" = "#FF8D59",
  "clbr_epi" = "#962F00",
  "cl14_tryr" = "#D06D7F",
  "clbr_tryr" = "#A4011F",
  "cl14_late" = "#6BD35E",
  "clbr_late" = "#1E7712",
  "cl14_mid" = "#7280FF",
  "clbr_mid" = "#000D7E")
esmer_expt <- set_expt_colors(expt=esmer_expt, colors=chosen_colors)

## End(Not run)
```

---

set_expt_condition	<i>Change the condition of an expt</i>
--------------------	--

---

**Description**

When exploring differential analyses, it might be useful to play with the conditions/batches of the experiment. Use this to make that easier.

**Usage**

```
set_expt_condition(expt, fact = NULL, ids = NULL, ...)
```

**Arguments**

expt	Expt to modify
fact	Conditions to replace
ids	Specific sample IDs to change.
...	Extra arguments are given to arglist.

**Value**

expt Send back the expt with some new metadata

**See Also**

[set\\_expt\\_batch](#) [create\\_expt](#)

**Examples**

```
## Not run:
  expt = set_expt_condition(big_expt, factor=c(some,stuff,here))

## End(Not run)
```

---

set_expt_factors	<i>Change the factors (condition and batch) of an expt</i>
------------------	--

---

**Description**

When exploring differential analyses, it might be useful to play with the conditions/batches of the experiment. Use this to make that easier.

**Usage**

```
set_expt_factors(expt, condition = NULL, batch = NULL, ids = NULL, ...)
```

**Arguments**

expt	Expt to modify
condition	New condition factor
batch	New batch factor
ids	Specific sample IDs to change.
...	Arguments passed along (likely colors)

**Value**

expt Send back the expt with some new metadata

**See Also**

[set\\_expt\\_condition](#) [set\\_expt\\_batch](#)

**Examples**

```
## Not run:
  expt = set_expt_factors(big_expt, condition="column", batch="another_column")

## End(Not run)
```

---

set_expt_samplenames	<i>Change the sample names of an expt.</i>
----------------------	--

---

**Description**

Sometimes one does not like the hpgl identifiers, so provide a way to change them on-the-fly.

**Usage**

```
set_expt_samplenames(expt, newnames)
```

**Arguments**

expt	Expt to modify
newnames	New names, currently only a character vector.

**Value**

expt Send back the expt with some new metadata

**See Also**

[set\\_expt\\_condition](#) [set\\_expt\\_batch](#)

**Examples**

```
## Not run:  
expt = set_expt_samplenames(expt, c("a","b","c","d","e","f"))  
  
## End(Not run)
```

---

significant_barplots	<i>Given the set of significant genes from combine_de_tables(), provide a view of how many are significant up/down.</i>
----------------------	---

---

**Description**

These plots are pretty annoying, and I am certain that this function is not well written, but it provides a series of bar plots which show the number of genes/contrast which are up and down given a set of fold changes and p-value.

**Usage**

```
significant_barplots(combined, fc_cutoffs = c(0, 1, 2),  
  fc_column = "limma_logfc", p_type = "adj", invert = FALSE, p = 0.05,  
  z = NULL, order = NULL, maximum = NULL, ...)
```

**Arguments**

combined	Result from combine_de_tables and/or extract_significant_genes().
fc_cutoffs	Choose 3 fold changes to define the queries. 0, 1, 2 mean greater/less than 0 followed by 2 fold and 4 fold cutoffs.
fc_column	The column in the master-table to use for FC cutoffs.
p_type	Adjusted or not?
invert	Reverse the order of contrasts for readability?
p	Chosen p-value cutoff.
z	Choose instead a z-score cutoff.
order	Choose a specific order for the plots.
maximum	Set a specific limit on the number of genes on the x-axis.
...	More arguments are passed to arglist.

**Value**

list containing the significance bar plots and some information to hopefully help interpret them.

**See Also**

**ggplot2**

**Examples**

```
## Not run:
## Damn I wish I were smrt enough to make this elegant and easily comprehensible, but I cannot.
barplots <- significant_barplots(combined_result)

## End(Not run)
```

---

sillydist

---

*Calculate a simplistic distance function of a point against two axes.*


---

**Description**

Sillydist provides a distance of any point vs. the axes of a plot. This just takes the abs(distances) of each point to the axes, normalizes them against the largest point on the axes, multiplies the result, and normalizes against the max of all point.

**Usage**

```
sillydist(firstterm, secondterm, firstaxis = 0, secondaxis = 0)
```

**Arguments**

firstterm	X-values of the points.
secondterm	Y-values of the points.
firstaxis	X-value of the vertical axis.
secondaxis	Y-value of the second axis.

**Value**

Dataframe of the distances.

**See Also**

**ggplot2**

**Examples**

```
## Not run:
mydist <- sillydist(df[,1], df[,2], first_median, second_median)
first_vs_second <- ggplot2::ggplot(df, ggplot2::aes_string(x="first", y="second"),
                                environment=hpgl_env) +
  ggplot2::xlab(paste("Expression of", df_x_axis)) +
  ggplot2::ylab(paste("Expression of", df_y_axis)) +
  ggplot2::geom_vline(color="grey", xintercept=(first_median - first_mad), size=line_size) +
  ggplot2::geom_vline(color="grey", xintercept=(first_median + first_mad), size=line_size) +
  ggplot2::geom_vline(color="darkgrey", xintercept=first_median, size=line_size) +
  ggplot2::geom_hline(color="grey", yintercept=(second_median - second_mad), size=line_size) +
  ggplot2::geom_hline(color="grey", yintercept=(second_median + second_mad), size=line_size) +
  ggplot2::geom_hline(color="darkgrey", yintercept=second_median, size=line_size) +
  ggplot2::geom_point(colour=grDevices::hsv(mydist$dist, 1, mydist$dist),
                    alpha=0.6, size=size) +
  ggplot2::theme(legend.position="none")
first_vs_second ## dots get colored according to how far they are from the medians
## replace first_median, second_median with 0,0 for the axes

## End(Not run)
```

---

simple\_clusterprofiler

*Perform the array of analyses in the 2016-04 version of clusterProfiler*

---

**Description**

The new version of clusterProfiler has a bunch of new toys. However, it is more stringent in terms of input in that it now explicitly expects to receive annotation data in terms of a orgdb object. This is mostly advantageous, but will probably cause some changes in the other ontology functions in the near future. This function is an initial pass at making something similar to my previous 'simple\_clusterprofiler()' but using these new toys.

**Usage**

```
simple_clusterprofiler(sig_genes, all_genes, orgdb = "org.Dm.eg.db",
  orgdb_from = "FLYBASE", orgdb_to = "ENTREZID", internal = TRUE,
  go_level = 3, pcutoff = 0.05, qcutoff = 0.1, fc_column = "logFC",
  updown = "up", permutations = 100, min_groupsize = 5,
  kegg_prefix = "Dmel_", mings = 5, kegg_organism = "dme",
  categories = 12, parallel = TRUE)
```

**Arguments**

<code>sig_genes</code>	Dataframe of genes deemed 'significant.'
<code>all_genes</code>	Dataframe of all genes in the analysis, primarily for gse analyses.
<code>orgdb</code>	Name of the orgDb used for gathering annotation data.
<code>orgdb_from</code>	Name of a key in the orgdb used to cross reference to entrez IDs.
<code>orgdb_to</code>	List of keys to grab from the orgdb for cross referencing ontologies.
<code>internal</code>	Used by the 'use_internal_data' flag.
<code>go_level</code>	How deep into the ontology tree should this dive for over expressed categories.
<code>pcutoff</code>	P-value cutoff for 'significant' analyses.
<code>qcutoff</code>	Q-value cutoff for 'significant' analyses.
<code>fc_column</code>	When extracting vectors of all genes, what column should be used?
<code>updown</code>	Include the less than expected ontologies?
<code>permutations</code>	How many permutations for GSEA-ish analyses?
<code>min_groupsize</code>	Minimum size of an ontology before it is included.
<code>kegg_prefix</code>	Many KEGG ids need a prefix before they will cross reference.
<code>mings</code>	What is the minimum ontology group's size?
<code>kegg_organism</code>	Choose the 3 letter KEGG organism name here.
<code>categories</code>	How many categories should be plotted in bar/dot plots?
<code>parallel</code>	Perform slow operations in parallel?

**Value**

a list

**See Also**

**clusterProfiler**

**Examples**

```
## Not run:
  holyasscrackers <- simple_clusterprofiler(gene_list, all_genes, "org.Dm.eg.db")

## End(Not run)
```

---

simple_cp_enricher	<i>Generic enrichment using clusterProfiler.</i>
--------------------	--

---

**Description**

clusterProfiler::enricher provides a quick and easy enrichment analysis given a set of significant genes and a data frame which connects each gene to a category.

**Usage**

```
simple_cp_enricher(sig_genes, de_table, goids_df = NULL)
```

**Arguments**

sig_genes	Set of 'significant' genes as a table.
de_table	All genes from the original analysis.
goids_df	Dataframe of GO->ID matching the gene names of sig_genes to GO categories.

**Value**

Table of 'enriched' categories.

---

simple_filter_counts	<i>Filter low-count genes from a data set only using a simple threshold and number of samples.</i>
----------------------	--

---

**Description**

This was a function written by Kwame Okrah and perhaps also Laura Dillon to remove low-count genes. It drops genes based on a threshold and number of samples.

**Usage**

```
simple_filter_counts(count_table, threshold = 2)
```

**Arguments**

count_table	Data frame of (pseudo)counts by sample.
threshold	Lower threshold of counts for each gene.

**Value**

Dataframe of counts without the low-count genes.

**See Also****edgeR****Examples**

```
## Not run:
  filtered_table <- simple_filter_counts(count_table)

## End(Not run)
```

---

simple_gadem	<i>run the rGADEM suite</i>
--------------	-----------------------------

---

**Description**

This should provide a set of rGADEM results given an input file of sequences and a genome.

**Usage**

```
simple_gadem(inputfile, genome = "BSgenome.Hsapiens.UCSC.hs19", ...)
```

**Arguments**

inputfile	Fasta or bed file containing sequences to search.
genome	BSgenome to read.
...	Parameters for plotting the gadem result.

**Value**

A list containing slots for plots, the stdout output from gadem, the gadem result, set of occurrences of motif, and the returned set of motifs.

---

simple_goseq	<i>Perform a simplified goseq analysis.</i>
--------------	---

---

**Description**

goseq can be pretty difficult to get set up for non-supported organisms. This attempts to make that process a bit simpler as well as give some standard outputs which should be similar to those returned by clusterprofiler/topgo/gostats/gprofiler.

goseq can be pretty difficult to get set up for non-supported organisms. This attempts to make that process a bit simpler as well as give some standard outputs which should be similar to those returned by clusterprofiler/topgo/gostats/gprofiler.



**Usage**

```
simple_goseq(sig_genes, go_db = NULL, length_db = NULL, doplot = TRUE,
  adjust = 0.1, pvalue = 0.1, qvalue = 0.1,
  length_keytype = "transcripts", go_keytype = "ENTREZID",
  goseq_method = "Wallenius", padjust_method = "BH",
  bioc_length_db = "ensGene", ...)
```

```
simple_goseq(sig_genes, go_db = NULL, length_db = NULL, doplot = TRUE,
  adjust = 0.1, pvalue = 0.1, qvalue = 0.1,
  length_keytype = "transcripts", go_keytype = "ENTREZID",
  goseq_method = "Wallenius", padjust_method = "BH",
  bioc_length_db = "ensGene", ...)
```

**Arguments**

sig_genes	Data frame of differentially expressed genes, containing IDs etc.
go_db	Database of go to gene mappings (OrgDb/OrganismDb)
length_db	Source of gene lengths?
doplot	Include pwf plots?
adjust	Minimum adjusted pvalue for 'significant.'
pvalue	Minimum pvalue for 'significant.'
qvalue	Minimum qvalue for 'significant.'
length_keytype	Keytype to provide to extract lengths
go_keytype	Keytype to provide to extract go IDs
goseq_method	Statistical test for goseq to use.
padjust_method	Which method to use to adjust the pvalues.
bioc_length_db	Source of gene lengths?
...	Extra parameters which I do not recall
de_genes	Data frame of differentially expressed genes, containing IDs etc.
all_genes	Universe of possible genes.
lengths	Length of each gene with an ID in de_genes.
goids_df	List of ontology accessions to gene accessions.
species	Optionally choose a species from supportedOrganisms().
gff	gff file source of gene lengths.
length_db	Database of gene lengths (gff/TxDb)
doplot	Include pwf plots?
adjust	Minimum adjusted pvalue for 'significant.'
pvalue	Minimum pvalue for 'significant.'
qvalue	Minimum qvalue for 'significant.'
goseq_method	Statistical test for goseq to use.
padjust_method	Which method to use to adjust the pvalues.
...	Extra parameters which I do not recall

**Value**

Big list including: the `pwd:pwf` function, `alldata`:the `godata` dataframe, `pvalue_histogram`:p-value histograms, `godata_interesting`:the ontology information of the enhanced groups, `term_table`:the `goterms` with some information about them, `mf_subset`:a plot of the MF enhanced groups, `mfp_plot`:the pvalues of the MF group, `bp_subset`:a plot of the BP enhanced groups, `bpp_plot`, `cc_subset`, and `ccp_plot`

Big list including: the `pwd:pwf` function, `alldata`:the `godata` dataframe, `pvalue_histogram`:p-value histograms, `godata_interesting`:the ontology information of the enhanced groups, `term_table`:the `goterms` with some information about them, `mf_subset`:a plot of the MF enhanced groups, `mfp_plot`:the pvalues of the MF group, `bp_subset`:a plot of the BP enhanced groups, `bpp_plot`, `cc_subset`, and `ccp_plot`

**See Also**

[goseq](#) [goseq nullp](#)

[goseq GO.db](#)

**Examples**

```
## Not run:
lotsotables <- simple_goseq(gene_list, godb, lengthdb)

## End(Not run)
```

---

`simple_gostats`

*Simplification function for `gostats`, in the same vein as those written for `clusterProfiler`, `goseq`, and `topGO`.*

---

**Description**

`GOSTats` has a couple interesting peculiarities: Chief among them: the gene IDs must be integers. As a result, I am going to have this function take a `gff` file in order to get the `go` ids and gene ids on the same page.

**Usage**

```
simple_gostats(sig_genes, gff, goids_df, universe_merge = "id",
  second_merge_try = "locus_tag", species = "fun", pcutoff = 0.1,
  direction = "over", conditional = FALSE, categorysize = NULL,
  gff_type = "cds", ...)
```

**Arguments**

<code>sig_genes</code>	Input list of differentially expressed genes.
<code>gff</code>	Annotation information for this genome.
<code>goids_df</code>	Set of GOids, as before in the format ID/GO.

universe_merge	Column from which to create the universe of genes.
second_merge_try	If the first universe merge fails, try this.
species	Genbank organism to use.
pcutoff	Pvalue cutoff for deciding significant.
direction	Under or over represented categories.
conditional	Perform a conditional search?
categorysize	Category size below which to not include groups.
gff_type	Gff column to use for creating the universe.
...	More parameters!

**Value**

List of returns from GSEABase, Category, etc.

**See Also**

**GSEABase Category**

**Examples**

```
## Not run:
knickerbockers <- simple_gostats(sig_genes, gff_file, goids)

## End(Not run)
```

---

simple_gprofiler	<i>Run searches against the web service g:Profiler.</i>
------------------	---

---

**Description**

Thank you Ginger for showing me your thesis, gProfiler is pretty cool!

**Usage**

```
simple_gprofiler(sig_genes, species = "hsapiens", first_col = "logFC",
  second_col = "limma_logfc", do_go = TRUE, do_kegg = TRUE,
  do_reactome = TRUE, do_mi = TRUE, do_tf = TRUE, do_corum = TRUE,
  do_hp = TRUE, significant = TRUE, pseudo_gsea = TRUE,
  id_col = "row.names")
```

**Arguments**

sig_genes	Guess! The set of differentially expressed/interesting genes.
species	Organism supported by gprofiler.
first_col	First place used to define the order of 'significant'.
second_col	If that fails, try a second column.
do_go	Perform GO search?
do_kegg	Perform KEGG search?
do_reactome	Perform reactome search?
do_mi	Do miRNA search?
do_tf	Search for transcription factors?
do_corum	Do corum search?
do_hp	Do the hp search?
significant	Only return the statistically significant hits?
pseudo_gsea	Is the data in a ranked order by significance?
id_col	Which column in the table should be used for gene ID crossreferencing? gProfiler uses Ensembl ids. So if you have a table of entrez or whatever, translate it!

**Value**

a list of results for go, kegg, reactome, and a few more.

**See Also**

**gProfiler**

**Examples**

```
## Not run:
gprofiler_is_nice_and_easy <- simple_gprofiler(genes, species='mmusculus')

## End(Not run)
```

---

simple\_pathview

*Print some data onto KEGG pathways.*

---

**Description**

KEGGREST and pathview provide neat functions for coloring molecular pathways with arbitrary data. Unfortunately they are somewhat evil to use. This attempts to alleviate that.

**Usage**

```
simple_pathview(path_data, indir = "pathview_in", outdir = "pathview",
  pathway = "all", species = "lma", from_list = NULL, to_list = NULL,
  suffix = "_colored", filenames = "id", fc_column = "limma_logfc",
  format = "png", verbose = TRUE)
```

**Arguments**

path_data	Some differentially expressed genes.
indir	Directory into which the unmodified kegg images will be downloaded (or already exist).
outdir	Directory which will contain the colored images.
pathway	Perform the coloring for a specific pathway?
species	Kegg identifier for the species of interest.
from_list	Regex to help in renaming KEGG categories/gene names from one format to another.
to_list	Regex to help in renaming KEGG categories/gene names from one format to another.
suffix	Add a suffix to the completed, colored files.
filenames	Name the final files by id or name?
fc_column	What is the name of the fold-change column to extract?
format	Format of the resulting images, I think only png really works well.
verbose	When on, this function is quite chatty.

**Value**

A list of some information for every KEGG pathway downloaded/examined. This information includes: a. The filename of the final image for each pathway. b. The number of genes which were found in each pathway image. c. The number of genes in the 'up' category d. The number of genes in the 'down' category

**See Also**

**Ramigo pathview**

**Examples**

```
## Not run:
thy_el_comp2_path = hpgl_pathview(thy_el_comp2_kegg, species="spz", indir="pathview_in",
  outdir="kegg_thy_el_comp2", string_from="_Spy",
  string_to="_Spy_", filenames="pathname")

## End(Not run)
```

---

simple\_topgo

---

*Perform a simplified topgo analysis.*


---

## Description

This will attempt to make it easier to run topgo on a set of genes.

## Usage

```
simple_topgo(sig_genes, goid_map = "id2go.map", goids_df = NULL,
  pvals = NULL, limitby = "fisher", limit = 0.1, signodes = 100,
  sigforall = TRUE, numchar = 300, selector = "topDiffGenes",
  pval_column = "adj.P.Val", overwrite = FALSE, densities = FALSE,
  pval_plots = TRUE, parallel = FALSE, ...)
```

## Arguments

sig_genes	Data frame of differentially expressed genes, containing IDs any other columns.
goid_map	File containing mappings of genes to goids in the format expected by topgo.
goids_df	Data frame of the goids which may be used to make the goid_map.
pvals	Set of pvalues in the DE data which may be used to improve the topgo results.
limitby	Test to index the results by.
limit	Ontology pvalue to use as the lower limit.
signodes	I don't remember right now.
sigforall	Provide the significance for all nodes?
numchar	Character limit for the table of results.
selector	Function name for choosing genes to include.
pval_column	Column from which to acquire scores.
overwrite	Yeah I do not remember this one either.
densities	Densities, yeah, the densities...
pval_plots	Include pvalue plots of the results a la clusterprofiler?
parallel	Perform some operations in parallel to speed this up?
...	Other options which I do not remember right now!

## Value

Big list including the various outputs from topgo

## See Also

**topGO**

---

sm	<i>Silence, m...</i>
----	----------------------

---

### Description

Some libraries/functions just won't shut up. Ergo, silence, peasant! This is a simpler silence peasant.

### Usage

```
sm(...)
```

### Arguments

...                      Some code to shut up.

### Value

Whatever the code would have returned.

---

snp_add_file	<i>Add a new snp table to a set of comparisons for clustering.</i>
--------------	--

---

### Description

This is used by expt\_snp to read input files and relatively quickly merge them.

### Usage

```
snp_add_file(sample, input_dir = "preprocessing/outputs",
             file_suffix = "_parsed_ratio.txt")
```

### Arguments

sample                      A text snp summary for 1 sample.  
input\_dir                    Location of the data.  
file\_suffix                  Suffix to use when finding the file(s).

---

subset_expt	<i>An alias to expt_subset, because it is stupid to have something start with verbs and others start with nouns.</i>
-------------	--

---

### Description

This just calls expt\_subset.

### Usage

```
subset_expt(...)
```

### Arguments

... All arguments are passed to expt\_subset.

---

subset_ontology_search	<i>Perform ontology searches on up/down subsets of differential expression data.</i>
------------------------	--

---

### Description

In the same way all\_pairwise() attempts to simplify using multiple DE tools, this function seeks to make it easier to extract subsets of differentially expressed data and pass them to goseq, clusterProfiler, topGO, GOSTats, and gProfiler.

### Usage

```
subset_ontology_search(changed_counts, doplot = TRUE, do_goseq = TRUE,
  do_cluster = TRUE, do_topgo = TRUE, do_gostats = TRUE,
  do_gprofiler = TRUE, according_to = "limma", ...)
```

### Arguments

changed_counts	List of changed counts as ups and downs.
doplot	Include plots in the results?
do_goseq	Perform goseq search?
do_cluster	Perform clusterprofiler search?
do_topgo	Perform topgo search?
do_gostats	Perform gostats search?
do_gprofiler	Do a gprofiler search?
according_to	If results from multiple DE tools were passed, which one defines 'significant'?
...	Extra arguments!



**Value**

List of ontology search results, up and down for each contrast.

**See Also**

**goseq clusterProfiler topGO goStats gProfiler**

---

sum_exons	<i>Given a data frame of exon counts and annotation information, sum the exons.</i>
-----------	---

---

**Description**

This function will merge a count table to an annotation table by the child column. It will then sum all rows of exons by parent gene and sum the widths of the exons. Finally it will return a list containing a df of gene lengths and summed counts.

**Usage**

```
sum_exons(data, gff = NULL, annotdf = NULL, parent = "Parent",  
          child = "row.names")
```

**Arguments**

data	Count tables of exons.
gff	Gff filename.
annotdf	Dataframe of annotations (probably from gff2df).
parent	Column from the annotations with the gene names.
child	Column from the annotations with the exon names.

**Value**

List of 2 data frames, counts and lengths by summed exons.

**See Also**

**rtracklayer** [gff2df](#)

**Examples**

```
## Not run:  
summed <- sum_exons(counts, gff='reference/xenopus_laevis.gff.xz')  
  
## End(Not run)
```

---

tseq_saturation	<i>Make a plot and some simple numbers about tseq saturation</i>
-----------------	--

---

### Description

This function takes as input a tab separated file from essentiality\_tas.pl This is a perl script written to read a bam alignment of tseq reads against a genome and count how many hits were observed on every TA in the given genome. It furthermore has some logic to tell the difference between reads which were observed on the forward vs. reverse strand as well as reads which appear to be on both strands (eg. they start and end with 'TA').

### Usage

```
tseq_saturation(file)
```

### Arguments

file	a file created using the perl script 'essentiality_tas.pl'
------	--

### Value

A plot and some numbers

### See Also

**ggplot2**

---

topDiffGenes	<i>A very simple selector of strong scoring genes (by p-value)</i>
--------------	--

---

### Description

This function was provided in the topGO documentation, but not defined. It was copied/pasted here. I have ideas for including up/down expression but have so far deemed them not needed because I am feeding topGO already explicit lists of genes which are up/down/whatever. But it still is likely to be useful to be able to further subset the data.

### Usage

```
topDiffGenes(allScore)
```

### Arguments

allScore	The scores of the genes
----------	-------------------------

---

topgo_tables	<i>Make pretty tables out of topGO data</i>
--------------	---

---

### Description

The topgo function GenTable is neat, but it needs some simplification to not be obnoxious.

### Usage

```
topgo_tables(result, limit = 0.1, limitby = "fisher", numchar = 300,
  orderby = "classic", ranksof = "classic")
```

### Arguments

result	Topgo result.
limit	Pvalue limit defining 'significant'.
limitby	Type of test to perform.
numchar	How many characters to allow in the description?
orderby	Which of the available columns to order the table by?
ranksof	Which of the available columns are used to rank the data?

### Value

prettier tables

### See Also

**topGO**

---

topgo_trees	<i>Print trees from topGO.</i>
-------------	--------------------------------

---

### Description

The tree printing functionality of topGO is pretty cool, but difficult to get set correctly.

### Usage

```
topgo_trees(tg, score_limit = 0.01, sigforall = TRUE,
  do_mf_fisher_tree = TRUE, do_bp_fisher_tree = TRUE,
  do_cc_fisher_tree = TRUE, do_mf_ks_tree = FALSE, do_bp_ks_tree = FALSE,
  do_cc_ks_tree = FALSE, do_mf_el_tree = FALSE, do_bp_el_tree = FALSE,
  do_cc_el_tree = FALSE, do_mf_weight_tree = FALSE,
  do_bp_weight_tree = FALSE, do_cc_weight_tree = FALSE, parallel = FALSE)
```

**Arguments**

tg	Data from simple_topgo().
score_limit	Score limit to decide whether to add to the tree.
sigforall	Add scores to the tree?
do_mf_fisher_tree	Add the fisher score molecular function tree?
do_bp_fisher_tree	Add the fisher biological process tree?
do_cc_fisher_tree	Add the fisher cellular component tree?
do_mf_ks_tree	Add the ks molecular function tree?
do_bp_ks_tree	Add the ks biological process tree?
do_cc_ks_tree	Add the ks cellular component tree?
do_mf_el_tree	Add the el molecular function tree?
do_bp_el_tree	Add the el biological process tree?
do_cc_el_tree	Add the el cellular component tree?
do_mf_weight_tree	Add the weight mf tree?
do_bp_weight_tree	Add the bp weighted tree?
do_cc_weight_tree	Add the guess
parallel	Perform operations in parallel to speed this up?

**Value**

Big list including the various outputs from topgo.

**See Also**

**topGO**

---

transform_counts	<i>Perform a simple transformation of a count table (log2)</i>
------------------	--

---

**Description**

the add argument is only important if the data was previously cpm'd because that does a +1, thus this will avoid a double+1 on the data.

**Usage**

```
transform_counts(count_table, design = NULL, transform = "raw",
  base = NULL, ...)
```

**Arguments**

count_table	A matrix of count data
design	Sometimes the experimental design is also required.
transform	A type of transformation to perform: log2/log10/log.
base	Other log scales?
...	Options I might pass from other functions are dropped into arglist.

**Value**

dataframe of transformed counts.

**See Also**

**limma**

**Examples**

```
## Not run:
  filtered_table = transform_counts(count_table, transform='log2', converted='cpm')

## End(Not run)
```

---

translate\_ids\_querymany

*Use mygene's queryMany to translate gene ID types*

---

**Description**

Juggling between entrez, ensembl, etc can be quite a hassel. This hopes to make it easier.

**Usage**

```
translate_ids_querymany(queries, email = "abelew@gmail.com", fields = "all",
  species = "all")
```

**Arguments**

queries	Gene IDs to translate.
fields	Set of fields to request, pass null for all.
species	Human readable species for translation (Eg. 'human' instead of 'hsapiens').)
from	Database to translate IDs from, pass null if you want it to choose.

**Details**

Tested in test\_40ann\_biomart.R This function really just sets a couple of hopefully helpful defaults. When I first attempted to use queryMany, it seemed to need much more intervention than it does now. But at the least this function should provide a reminder of this relatively fast and useful ID translation service.

**Value**

Df of translated IDs/accessions

**See Also**

**mygene** [queryMany](#)

**Examples**

```
## Not run:
data <- translate_ids_querymany(genes)

## End(Not run)
```

---

trityp_downloads	<i>Download the various data files from <a href="http://tritypdb.org/">http://tritypdb.org/</a></i>
------------------	---

---

**Description**

The tritypdb nicely makes their downloads standardized!

**Usage**

```
trityp_downloads(version = "27", species = "lmajor", strain = "friedlin",
  dl_dir = "organdb/trityp", quiet = TRUE)
```

**Arguments**

version	What version of the tritypdb to use?
species	Human readable species to use.
strain	Strain of the given species to download.
dl_dir	Directory into which to download the various files.
quiet	Print download progress?

**Value**

List of downloaded files.

Examples

```
## Not run:
  filenames <- tritryp_downloads(species="lmajor", strain="friedlin", version="28")

## End(Not run)
```

---

u_plot	<i>Plot the rank order svd\$u elements to get a view of how much the first genes contribute to the total variance by PC.</i>
--------	--

---

Description

Plot the rank order svd\$u elements to get a view of how much the first genes contribute to the total variance by PC.

Usage

```
u_plot(plotted_us)
```

Arguments

plotted\_us      a list of svd\$u elements

Value

a recordPlot() plot showing the first 3 PCs by rank-order svd\$u.

---

varpart	<i>Use variancePartition to try and understand where the variance lies in a data set.</i>
---------	---

---

Description

variancePartition is the newest toy introduced by Hector.

Usage

```
varpart(expt, predictor = "condition", factors = c("batch"), cpus = 6,
  genes = 40, parallel = TRUE)
```

Arguments

expt	Some data
predictor	Non-categorical predictor factor with which to begin the model.
factors	Character list of columns in the experiment design to query
cpus	Number cpus to use
genes	Number of genes to count.
parallel	use doParallel?

**Value**

partitions List of plots and variance data frames

**See Also**

**doParallel** **variancePartition**

---

varpart_summaries	<i>Attempt to use variancePartition's fitVarPartModel() function.</i>
-------------------	---

---

**Description**

Note the word 'attempt'. This function is so ungodly slow that it probably will never be used.

**Usage**

```
varpart_summaries(expt, factors = c("condition", "batch"), cpus = 6)
```

**Arguments**

expt	Input expressionset.
factors	Set of factors to query
cpus	Number of cpus to use in doParallel.

**Value**

Summaries of the new model, in theory this would be a nicely batch-corrected data set.

**See Also**

**variancePartition**

---

what_happened	<i>Print a string describing what happened to this data.</i>
---------------	--

---

**Description**

Sometimes it is nice to have a string like: log2(cpm(data)) describing what happened to the data.

**Usage**

```
what_happened(expt = NULL, transform = "raw", convert = "raw",
  norm = "raw", filter = "raw", batch = "raw")
```



**Arguments**

expt	The expressionset.
transform	How was it transformed?
convert	How was it converted?
norm	How was it normalized?
filter	How was it filtered?
batch	How was it batch-corrected?

**Value**

An expression describing what has been done to this data.

**See Also**

[create\\_expt](#)

---

write_basic	<i>Writes out the results of a basic search using write_de_table()</i>
-------------	--

---

**Description**

Looking to provide a single interface for writing tables from basic and friends.

**Usage**

```
write_basic(data, ...)
```

**Arguments**

data	Output from basic_pairwise()
...	Options for writing the xlsx file.

**Details**

Tested in test\_26basic.R

**See Also**

[write\\_de\\_table](#)

**Examples**

```
## Not run:
finished_comparison <- basic_pairwise(expressionset)
data_list <- write_basic(finished_comparison)

## End(Not run)
```

---

write_deseq	<i>Writes out the results of a deseq search using write_de_table()</i>
-------------	--

---

### Description

Looking to provide a single interface for writing tables from deseq and friends.

### Usage

```
write_deseq(data, ...)
```

### Arguments

data	Output from deseq_pairwise()
...	Options for writing the xlsx file.

### Details

Tested in test\_24deseq.R

### See Also

**DESeq2** [write\\_xls](#)

### Examples

```
## Not run:
finished_comparison = deseq_pairwise(expressionset)
data_list = write_deseq(finished_comparison)

## End(Not run)
```

---

write_de_table	<i>Writes out the results of a single pairwise comparison.</i>
----------------	--

---

### Description

However, this will do a couple of things to make one's life easier: 1. Make a list of the output, one element for each comparison of the contrast matrix. 2. Write out the results() output for them in separate sheets in excel. 3. Since I have been using qvalues a lot for other stuff, add a column for them.

### Usage

```
write_de_table(data, type = "limma", ...)
```

**Arguments**

data	Output from results().
type	Which DE tool to write.
...	Parameters passed downstream, dumped into arglist and passed, notably the number of genes (n), the coefficient column (coef)

**Details**

Tested in test\_24deseq.R Rewritten in 2016-12 looking to simplify combine\_de\_tables(). That function is far too big, This should become a template for that.

**Value**

List of data frames comprising the toptable output for each coefficient, I also added a qvalue entry to these toptable() outputs.

**See Also**

[write\\_xls](#)

**Examples**

```
## Not run:
finished_comparison = eBayes(deseq_output)
data_list = write_deseq(finished_comparison, workbook="excel/deseq_output.xls")

## End(Not run)
```

---

write\_edger

---

*Writes out the results of a edger search using write\_de\_table()*


---

**Description**

Looking to provide a single interface for writing tables from edger and friends.

**Usage**

```
write_edger(data, ...)
```

**Arguments**

data	Output from deseq_pairwise()
...	Options for writing the xlsx file.

**Details**

Tested in test\_26edger.R

See Also

**limma** [toptable](#) [write\\_xls](#)

Examples

```
## Not run:
finished_comparison <- edger_pairwise(expressionset)
data_list <- write_edger(finished_comparison)

## End(Not run)
```

---

write_expt	<i>Make pretty xlsx files of count data.</i>
------------	--

---

Description

Some folks love excel for looking at this data. ok.

Usage

```
write_expt(expt, excel = "excel/pretty_counts.xlsx", norm = "quant",
  violin = FALSE, convert = "cpm", transform = "log2", batch = "sva",
  filter = "cbcb")
```

Arguments

expt	An expressionset to print.
excel	Filename to write.
norm	Normalization to perform.
violin	Include violin plots?
convert	Conversion to perform.
transform	Transformation used.
batch	Batch correction applied.
filter	Filtering method used.

Details

Tested in test\_03graph\_metrics.R This performs the following: Writes the raw data, graphs the raw data, normalizes the data, writes it, graphs it, and does a median-by-condition and prints that. I replaced the openxlsx function which writes images into xlsx files with one which does not require an opening of a pre-existing plotter. Instead it (optionally)opens a pdf device, prints the plot to it, opens a png device, prints to that, and inserts the resulting png file. Thus it sacrifices some flexibility for a hopefully more consistent behavior. In addition, one may use the pdfs as a set of images importable into illustrator or whatever.

**Value**

A big honking excel file and a list including the dataframes and images created.

**See Also**

**openxlsx** **Biobase** [normalize\\_expt](#) [graph\\_metrics](#)

**Examples**

```
## Not run:
excel_sucks <- write_expt(expt)

## End(Not run)
```

---

write_goseq_data	<i>Make a pretty table of goseq data in excel.</i>
------------------	--

---

**Description**

It is my intention to make a function like this for each ontology tool in my repertoire

**Usage**

```
write_goseq_data(goseq, excel = "excel/goseq.xlsx", wb = NULL,
  add_trees = TRUE, pval = 0.1, add_plots = TRUE, height = 15,
  width = 10, ...)
```

**Arguments**

goseq	A set of results from <code>simple_goseq()</code> .
excel	An excel file to which to write some pretty results.
wb	Workbook object to write to.
add_trees	Include topgoish ontology trees?
pval	Choose a cutoff for reporting by p-value.
add_plots	Include some pvalue plots in the excel output?
height	Height of included plots.
width	and their width.
...	Extra arguments are passed to <code>arglist</code> .

**Value**

The result from `openxlsx` in a prettyified xlsx file.

**See Also**

**openxlsx** **goseq**

---

write_go_xls	<i>Write gene ontology tables for excel</i>
--------------	---

---

### Description

Combine the results from goseq, cluster profiler, topgo, and gostats and drop them into excel Hopefully with a relatively consistent look.

### Usage

```
write_go_xls(goseq, cluster, topgo, gostats, gprofiler,  
             file = "excel/merged_go", dated = TRUE, n = 30, overwritefile = TRUE)
```

### Arguments

goseq	The goseq result from simple_goseq()
cluster	The result from simple_clusterprofiler()
topgo	Guess
gostats	Yep, ditto
gprofiler	woo hoo!
file	the file to save the results.
dated	date the excel file
n	the number of ontology categories to include in each table.
overwritefile	overwrite an existing excel file

### Value

the list of ontology information

### See Also

**openxlsx goseq clusterProfiler goStats topGO gProfiler**

---

`write_gprofiler_data`    *Write some excel results from a gprofiler search.*

---

### Description

Gprofiler is pretty awesome. This function will attempt to write its results to an excel file.

### Usage

```
write_gprofiler_data(gprofiler_result, wb = NULL,
  excel = "excel/gprofiler_result.xlsx", add_plots = TRUE, height = 15,
  width = 10, ...)
```

### Arguments

<code>gprofiler_result</code>	The result from <code>simple_gprofiler()</code> .
<code>wb</code>	Optional workbook object, if you wish to append to an existing workbook.
<code>excel</code>	Excel file to which to write.
<code>add_plots</code>	Add some pvalue plots?
<code>height</code>	Height of included plots?
<code>width</code>	And their width.
<code>...</code>	More options, not currently used I think.

### Value

A prettyfied table in an xlsx document.

### See Also

**openxlsx gProfiler**

---

`write_limma`    *Writes out the results of a limma search using `write_de_table()`*

---

### Description

Looking to provide a single interface for writing tables from limma and friends.

### Usage

```
write_limma(data, ...)
```

**Arguments**

data	Output from limma_pairwise()
...	Options for writing the xlsx file.

**Details**

Tested in test\_21limma.R

**See Also**

[write\\_de\\_table](#)

**Examples**

```
## Not run:
finished_comparison = limma_pairwise(expressionset)
data_list = write_limma(finished_comparison)

## End(Not run)
```

---

write\_subset\_ontologies

*Write gene ontology tables for data subsets*

---

**Description**

Given a set of ontology results, this attempts to write them to an excel workbook in a consistent and relatively easy-to-read fashion.

**Usage**

```
write_subset_ontologies(kept_ontology, outfile = "excel/subset_go",
  dated = TRUE, n = NULL, overwritefile = TRUE, add_plots = TRUE,
  table_style = "TableStyleMedium9", ...)
```

**Arguments**

kept_ontology	A result from subset_ontology_search()
outfile	Workbook to which to write.
dated	Append the year-month-day-hour to the workbook.
n	How many ontology categories to write for each search
overwritefile	Overwrite an existing workbook?
add_plots	Add the various p-value plots to the end of each sheet?
table_style	The chosen table style for excel
...	some extra parameters



**Value**

a set of excel sheet/coordinates

**See Also**

**openxlsx**

**Examples**

```
## Not run:
all_contrasts <- all_pairwise(expt, model_batch=TRUE)
keepers <- list(bob = ('numerator','denominator'))
kept <- combine_de_tables(all_contrasts, keepers=keepers)
changed <- extract_significant_genes(kept)
kept_ontologies <- subset_ontology_search(changed, lengths=gene_lengths,
                                         goids=goids, gff=gff, gff_type='gene')
go_writer <- write_subset_ontologies(kept_ontologies)

## End(Not run)
```

---

write\_xls

---

Write a dataframe to an excel spreadsheet sheet.

---

**Description**

I like to give folks data in any format they prefer, even though I sort of hate excel. Most people I work with use it, so therefore I do too. This function has been through many iterations, first using XLConnect, then xlsx, and now openxlsx. Hopefully this will not change again.

**Usage**

```
write_xls(data = "undef", wb = NULL, sheet = "first", rownames = TRUE,
          start_row = 1, start_col = 1, ...)
```

**Arguments**

data	Data frame to print.
wb	Workbook to which to write.
sheet	Name of the sheet to write.
rownames	Include row names in the output?
start_row	First row of the sheet to write. Useful if writing multiple tables.
start_col	First column to write.
...	Set of extra arguments given to openxlsx.

Value

List containing the sheet and workbook written as well as the bottom-right coordinates of the last row/column written to the worksheet.

See Also

**openxlsx**

Examples

```
## Not run:
xls_coords <- write_xls(dataframe, sheet="hpgl_data")
xls_coords <- write_xls(another_df, sheet="hpgl_data", start_row=xls_coords$end_col)

## End(Not run)
```

---

xlsx_plot_png	<i>An attempt to improve the behavior of openxlsx's plot inserter.</i>
---------------	--

---

Description

The functions provided by openxlsx for adding plots to xlsx files are quite nice, but they can be a little annoying. This attempt to catch some corner cases and potentially save an extra svg-version of each plot inserted.

Usage

```
xlsx_plot_png(a_plot, wb = NULL, sheet = 1, width = 6, height = 6,
  res = 90, plotname = "plot", savedir = "saved_plots",
  fancy_type = "pdf", start_row = 1, start_col = 1, file_type = "png",
  units = "in", ...)
```

Arguments

a_plot	The plot provided
wb	Workbook to which to write.
sheet	Name or number of the sheet to which to add the plot.
width	Plot width in the sheet.
height	Plot height in the sheet.
res	Resolution of the png image inserted into the sheet.
plotname	Prefix of the pdf file created.
savedir	Directory to which to save pdf copies of the plots.
fancy_type	Plot publication quality images in this format.
start_row	Row on which to place the plot in the sheet.

start_col	Column on which to place the plot in the sheet.
file_type	Currently this only does pngs, but perhaps I will parameterize this.
units	Units for the png plotter.
...	Extra arguments are passed to arglist (Primarily for vennerable plots which are odd)

**Value**

A list containing the result of the tryCatch used to invoke the plot prints.

**See Also**

**openxlsx**

**Examples**

```
## Not run:
fun_plot <- plot_pca(stuff)$plot
try_results <- xlsx_plot_png(fun_plot)

## End(Not run)
```

---

ymxb\_print

---

*Print a model as  $y = mx + b$  just like in grade school!*


---

**Description**

Because, why not!?

**Usage**

```
ymxb_print(model)
```

**Arguments**

model                      Model to print from glm/lm/robustbase.

**Value**

a string representation of that model.

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