

# ChIPseeker: an R package for ChIP peak Annotation, Comparison and Visualization

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# 1 Introduction

---

Chromatin immunoprecipitation followed by high-throughput sequencing (ChIP-seq) has become standard technologies for genome wide identification of DNA-binding protein target sites. After read mappings and peak callings, the peak should be annotated to answer the biological questions. Annotation also create the possibility of integrate expression profile data to predict gene expression regulation. *ChIPseeker* was developed for annotating nearest genes and genomic features to peaks.

ChIP peak data set comparison is also very important. We can use it as an index to estimate how well biological replications are. Even more important is applying to infer cooperative regulation. If two ChIP seq data, obtained by two different binding proteins, overlap significantly, these two proteins may form a complex or have interaction in regulation chromosome remodelling or gene expression. *ChIPseeker* support statistical testing of significant overlap among ChIP seq data sets, and incorporate open access database GEO for users to compare their own dataset to those deposited in database. Protein interaction hypothesis can be generated by mining data deposited in database. Converting genome coordinations from one genome version to another is also supported, making this comparison available for different genome version and different species.

Several visualization functions are implemented to visualize the coverage of the ChIP seq data, peak annotation, average profile and heatmap of peaks binding to TSS region.

Functional enrichment analysis of the peaks can be performed by my Bioconductor packages *DOSE* , *ReactomePA*, *clusterProfiler* [1] .

```
## loading packages
require(ChIPseeker)
require(TxDb.Hsapiens.UCSC.hg19.knownGene)
txdb <- TxDb.Hsapiens.UCSC.hg19.knownGene
require(clusterProfiler)
```

## 2 ChIP profiling

---

The datasets CBX6 and CBX7 in this vignettes were downloaded from GEO (GSE40740) [2] while ARmo\_0M, ARmo\_1nM and ARmo\_100nM were downloaded from GEO (GSE48308) [3] . *ChIPseeker* provides `readPeakFile` to load the peak and store in `GRanges` object.

```
files <- getSampleFiles()
print(files)
```

```
## $ARmo_OM
## [1] "/private/tmp/Rtmp6efFkn/Rinstad681f146493/ChIPseeker/extdata/GEO_sample_dat
##
## $ARmo_1nM
## [1] "/private/tmp/Rtmp6efFkn/Rinstad681f146493/ChIPseeker/extdata/GEO_sample_dat
##
## $ARmo_100nM
## [1] "/private/tmp/Rtmp6efFkn/Rinstad681f146493/ChIPseeker/extdata/GEO_sample_dat
##
## $CBX6_BF
## [1] "/private/tmp/Rtmp6efFkn/Rinstad681f146493/ChIPseeker/extdata/GEO_sample_dat
##
## $CBX7_BF
## [1] "/private/tmp/Rtmp6efFkn/Rinstad681f146493/ChIPseeker/extdata/GEO_sample_dat

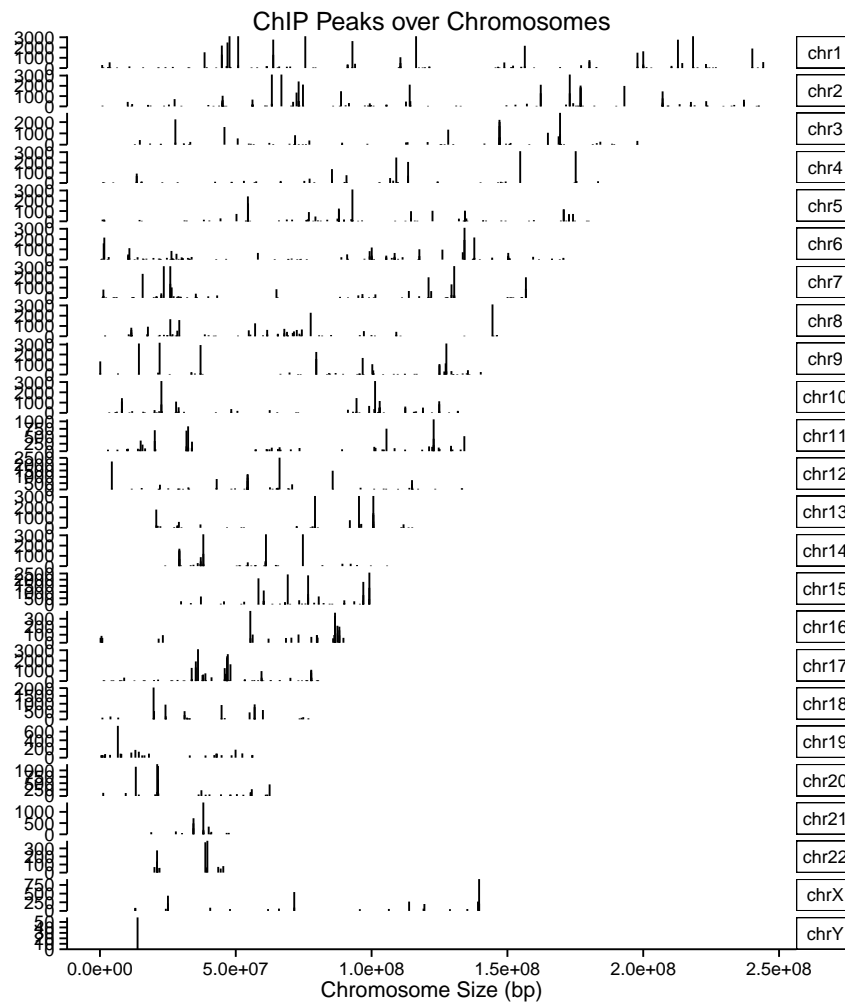
peak <- readPeakFile(files[[4]])
peak

## GRanges object with 1331 ranges and 2 metadata columns:
##           seqnames           ranges strand |           V4           V5
##           <Rle>             <IRanges> <Rle> |           <factor> <numeric>
##      [1]      chr1      [ 815092,   817883]   * |      MACS_peak_1      295.8
##      [2]      chr1      [1243287, 1244338]   * |      MACS_peak_2       63.2
##      [3]      chr1      [2979976, 2981228]   * |      MACS_peak_3     100.2
##      [4]      chr1      [3566181, 3567876]   * |      MACS_peak_4     558.9
##      [5]      chr1      [3816545, 3818111]   * |      MACS_peak_5       57.6
##      ...      ...      ...      ...      ...      ...
##    [1327]     chrX [135244782, 135245821]   * |      MACS_peak_1327     55.5
##    [1328]     chrX [139171963, 139173506]   * |      MACS_peak_1328    270.2
##    [1329]     chrX [139583953, 139586126]   * |      MACS_peak_1329    918.7
##    [1330]     chrX [139592001, 139593238]   * |      MACS_peak_1330    210.9
##    [1331]     chrY [ 13845133,  13845777]   * |      MACS_peak_1331     58.4
##    -----
##    seqinfo: 24 sequences from an unspecified genome; no seqlengths
```

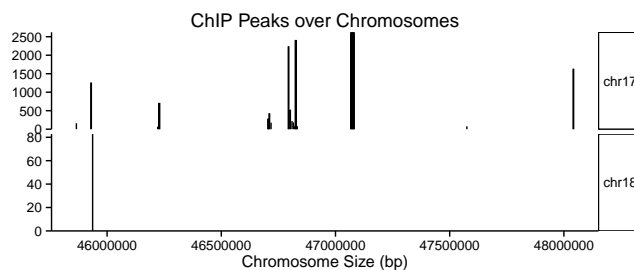
## 2.1 ChIP peaks coverage plot

After peak calling, we would like to know the peak locations over the whole genome, `covplot` function calculates the coverage of peak regions over chromosomes and generate a figure to visualize.

```
covplot(peak, weightCol="V5")
```



```
covplot(peak, weightCol="V5", chrs=c("chr17", "chr18"), xlim=c(4.5e7, 5e7))
```



## 2.2 Profile of ChIP peaks binding to TSS regions

First of all, for calculate the profile of ChIP peaks binding to TSS regions, we should prepare the TSS regions, which are defined as the flanking sequence of the TSS sites. Then align the peaks that are mapping to these regions, and generate the tagMatrix.

```
## promoter <- getPromoters(Txdb=txdb, upstream=3000, downstream=3000)
## tagMatrix <- getTagMatrix(peak, windows=promoter)
##
## to speed up the compilation of this vignettes, we use a precalculated tagMatrix
data("tagMatrixList")
tagMatrix <- tagMatrixList[[4]]
```

In the above code, you should notice that tagMatrix is not restricted to TSS regions. The regions can be other types that defined by the user.

### 2.2.1 Heatmap of ChIP binding to TSS regions

```
tagHeatmap(tagMatrix, xlim=c(-3000, 3000), color="red")
```

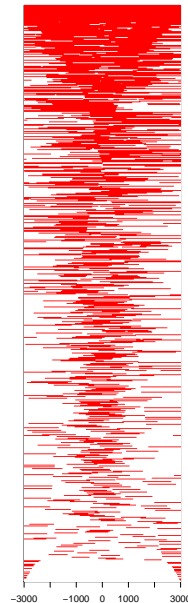


Figure 1: Heatmap of ChIP peaks binding to TSS regions

*ChIPseeker* provide a one step function to generate this figure from bed file. The following function will generate the same figure as above.

```
peakHeatmap(files[[4]], TxDb=txdb, upstream=3000, downstream=3000, color="red")
```

### 2.2.2 Average Profile of ChIP peaks binding to TSS region

```
plotAvgProf(tagMatrix, xlim=c(-3000, 3000), xlab="Genomic Region (5'→3')", ylab =
```

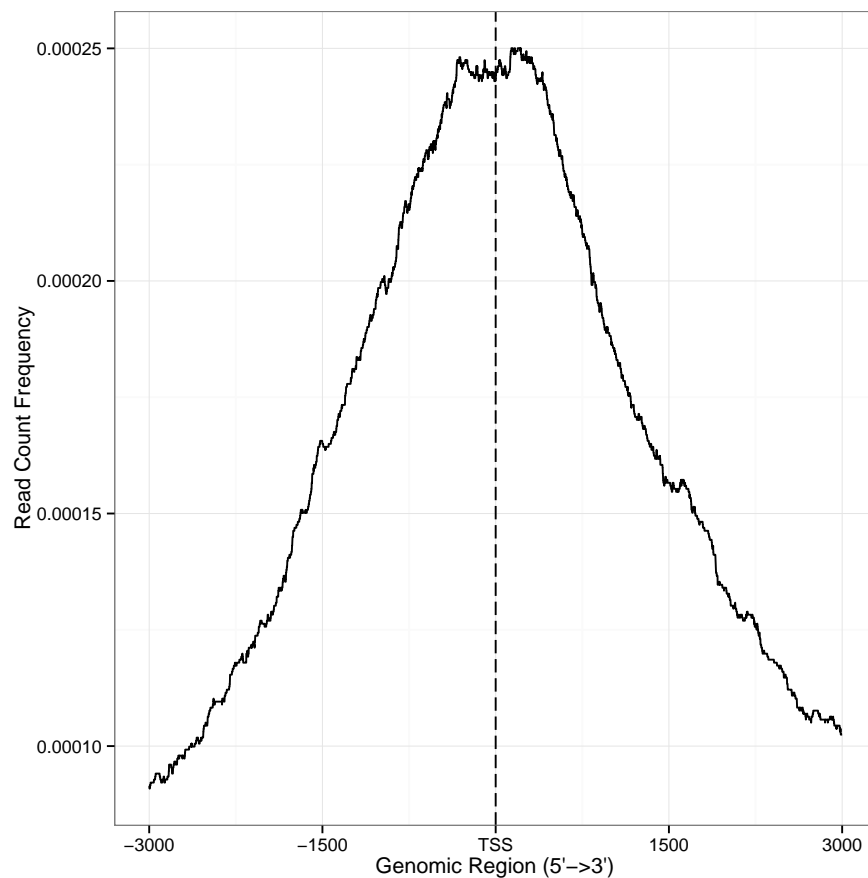


Figure 2: Average Profile of ChIP peaks binding to TSS region

The function `plotAvgProf2` provide a one step from bed file to average profile plot. The following command will generate the same figure as shown above.

```
plotAvgProf2(files[[4]], TxDb=txdb, upstream=3000, downstream=3000, xlab="Genomic R
```

### 3 Peak Annotation

---

```
peakAnno <- annotatePeak(files[[4]], tssRegion=c(-3000, 3000),
                        TxDb=txdb, annoDb="org.Hs.eg.db")

## >> loading peak file... 2015-03-18 21:23:22
## >> preparing features information... 2015-03-18 21:23:22
## >> identifying nearest features... 2015-03-18 21:23:23
## >> calculating distance from peak to TSS... 2015-03-18 21:23:24
## >> assigning genomic annotation... 2015-03-18 21:23:24
```

```
## >> adding gene annotation... 2015-03-18 21:24:04
## >> assigning chromosome lengths 2015-03-18 21:24:05
## >> done... 2015-03-18 21:24:05
```

```
peakAnno
```

```
## Annotated peaks generated by ChIPseeker
## 1331/1331 peaks were annotated
## Genomic Annotation Summary:
##           Feature Frequency
## 8 Promoter (<=1kb)      32.38
## 9 Promoter (1-2kb)       6.76
## 10 Promoter (2-3kb)      7.21
## 4           5' UTR       1.35
## 3           3' UTR       4.88
## 1           1st Exon      1.35
## 6           Other Exon    3.98
## 2           1st Intron    3.46
## 7           Other Intron  7.44
## 5 Distal Intergenic     31.18
```

Peak Annotation is performed by `annotatePeak`. User can define TSS (transcription start site) region, by default TSS is defined from -3kb to +3kb. The output of `annotatePeak` is `csAnno` instance. *ChIPseeker* provides `as.GRanges` to convert `csAnno` to `GRanges` instance, and `as.data.frame` to convert `csAnno` to `data.frame` which can be exported to file by `write.table`.

`TxDb` object contained transcript-related features of a particular genome. Bioconductor provides several package that containing `TxDb` object of model organisms with multiple commonly used genome version, for instance *TxDb.Hsapiens.UCSC.hg19.knownGene* and *TxDb.Hsapiens.UCSC.hg18.knownGene* for human genome hg19 and hg18, *TxDb.Mmusculus.UCSC.mm10.knownGene* and *TxDb.Mmusculus.UCSC.mm9.knownGene* for mouse genome mm10 and mm9, etc. User can also prepare their own `TxDb` object by retrieving information from UCSC Genome Bioinformatics and BioMart data resources by R function `makeTranscriptDbFromBiomart` and `makeTranscriptDbFromUCSC`. `TxDb` object should be passed for peak annotation.

All the peak information contained in peakfile will be retained in the output of `annotatePeak`. The position and strand information of nearest genes are reported. The distance from peak to the TSS of its nearest gene is also reported. The genomic region of the peak is reported in annotation column. Since some annotation may overlap, *ChIPseeker* adopted the following priority in genomic annotation.

- Promoter
- 5' UTR
- 3' UTR

- Exon
- Intron
- Downstream
- Intergenic

Downstream is defined as the downstream of gene end.

`annotatePeak` report detail information when the annotation is Exon or Intron, for instance "Exon (uc002sbe.3/9736, exon 69 of 80)", means that the peak is overlap with an Exon of transcript uc002sbe.3, and the corresponding Entrez gene ID is 9736 (Transcripts that belong to the same gene ID may differ in splice events), and this overlapped exon is the 69th exon of the 80 exons that this transcript uc002sbe.3 process.

Parameter `annoDb` is optional, if provided, extra columns including SYMBOL, GENENAME, ENSEMBL/ENTREZID will be added. The `geneID` column in annotation output will be consistent with the `geneID` in `TxDb`. If it is ENTREZID, ENSEMBL will be added if `annoDb` is provided, while if it is ENSEMBL ID, ENTREZID will be added.

### 3.1 Visualize Genomic Annotation

To annotate the location of a given peak in terms of genomic features, `annotatePeak` assigns peaks to genomic annotation in "annotation" column of the output, which includes whether a peak is in the TSS, Exon, 5' UTR, 3' UTR, Intronic or Intergenic. Many researchers are very interesting in these annotations. TSS region can be defined by user and `annotatePeak` output in details of which exon/intron of which genes as illustrated in previous section.

Pie and Bar plot are supported to visualize the genomic annotation.

```
plotAnnoPie(peakAnno)
```

```
plotAnnoBar(peakAnno)
```

Since some annotation overlap, user may interested to view the full annotation with their overlap, which can be partially resolved by `vennpie` function.

```
vennpie(peakAnno)
```





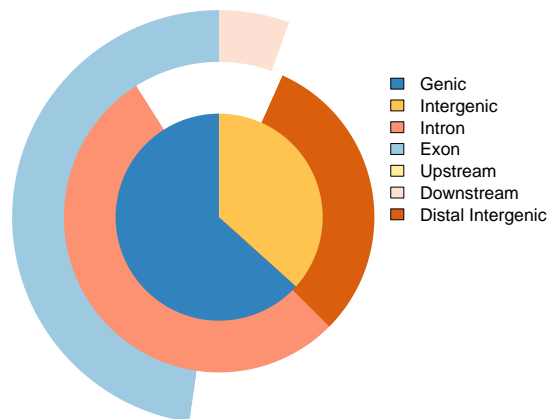


Figure 5: Genomic Annotation by vennpie

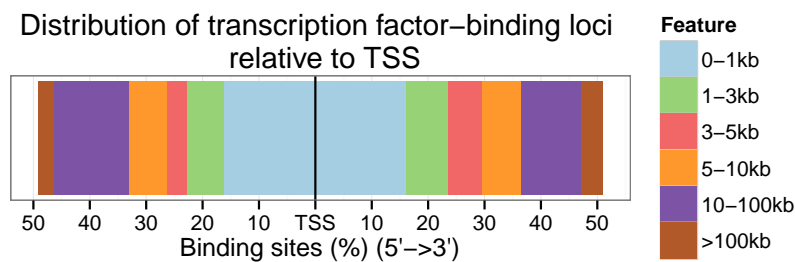


Figure 6: Distribution of Binding Sites

## 4 Functional enrichment analysis

Once we have obtained the annotated nearest genes, we can perform functional enrichment analysis to identify predominant biological themes among these genes by incorporating biological knowledge provided by biological ontologies. For instance, Gene Ontology (GO) [4] annotates genes to biological processes, molecular functions, and cellular components in a directed acyclic graph structure, Kyoto Encyclopedia of Genes and Genomes (KEGG) [5] annotates genes to pathways, Disease Ontology (DO) [6] annotates genes with human disease association, and Reactome [7] annotates gene to pathways and reactions.

Enrichment analysis is a widely used approach to identify biological themes. I have developed several Bioconductor packages for investigating whether the number of selected genes associated with a particular biological term is larger than expected, including *DOSE* for Disease Ontology, *ReactomePA* for reactome

pathway, *clusterProfiler* [1] for Gene Ontology and KEGG enrichment analysis.

```
require(clusterProfiler)
bp <- enrichGO(as.data.frame(peakAnno)$geneId, ont="BP", readable=TRUE)

## Loading required package: GO.db

head(summary(bp))
```

##	ID	Description	GeneRatio		
##	GO:0007275	GO:0007275 multicellular organismal development	405/774		
##	GO:0032502	GO:0032502 developmental process	439/774		
##	GO:0044767	GO:0044767 single-organism developmental process	435/774		
##	GO:0048731	GO:0048731 system development	367/774		
##	GO:0048513	GO:0048513 organ development	304/774		
##	GO:0030154	GO:0030154 cell differentiation	328/774		
##	BgRatio	pvalue	p.adjust	qvalue	
##	GO:0007275	4458/18229	2.67e-65	4.82e-62	2.24e-62
##	GO:0032502	5161/18229	3.75e-64	3.37e-61	1.57e-61
##	GO:0044767	5109/18229	2.19e-63	1.32e-60	6.13e-61
##	GO:0048731	3889/18229	2.89e-61	1.30e-58	6.04e-59
##	GO:0048513	2858/18229	1.56e-59	5.61e-57	2.61e-57
##	GO:0030154	3269/18229	3.46e-59	1.04e-56	4.83e-57
##	GO:0007275	SP9/DNM1L/EDIL3/OLIG2/SPRY1/CDKN2A/CCNO/WARS2/KLF2/MERTK/ZBTB18/HOXB1			
##	GO:0032502	SP9/DNM1L/EDIL3/OLIG2/SPRY1/CDKN2A/CCNO/WARS2/K			
##	GO:0044767				
##	GO:0048731				
##	GO:0048513				
##	GO:0030154				
##	Count				
##	GO:0007275	405			
##	GO:0032502	439			
##	GO:0044767	435			
##	GO:0048731	367			
##	GO:0048513	304			
##	GO:0030154	328			

More information can be found in the vignettes of Bioconductor packages *DOSE* , *ReactomePA*, *clusterProfiler* [1], which also provide several methods to visualize enrichment results. The *clusterProfiler* package is designed for comparing and visualizing functional profiles among gene clusters, and can directly applied to compare biological themes at GO, DO, KEGG, Reactome perspective.

## 5 ChIP peak data set comparison

### 5.1 Profile of several ChIP peak data binding to TSS region

Function `plotAvgProf` and `tagHeatmap` can accept a list of `tagMatrix` and visualize profile or heatmap among several ChIP experiments, while `plotAvgProf2` and `peakHeatmap` can accept a list of bed files and perform the same task in one step.

#### 5.1.1 Average profiles

```
## promoter <- getPromoters(Txdb=txdb, upstream=3000, downstream=3000)
## tagMatrixList <- lapply(files, getTagMatrix, windows=promoter)
##
## to speed up the compilation of this vignettes, we load a precalculated tagMatrix
data("tagMatrixList")
plotAvgProf(tagMatrixList, xlim=c(-3000, 3000))
```

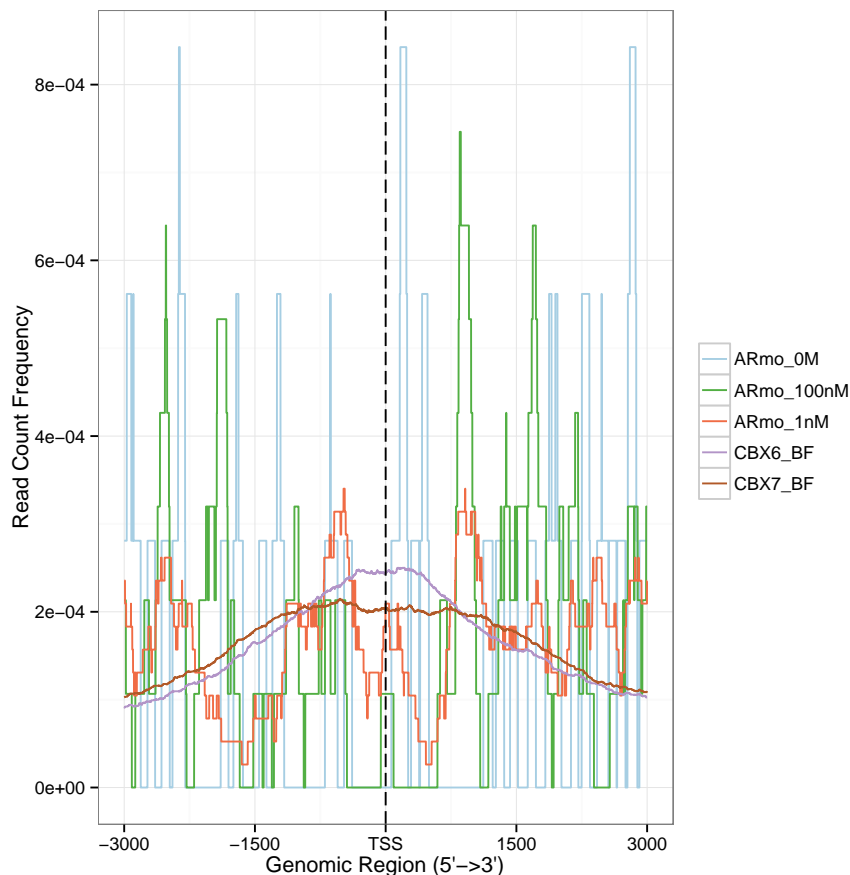


Figure 7: Average Profiles of ChIP peaks among different experiments

### 5.1.2 Peak heatmaps

```
tagHeatmap(tagMatrixList, xlim=c(-3000, 3000), color=NULL)
```

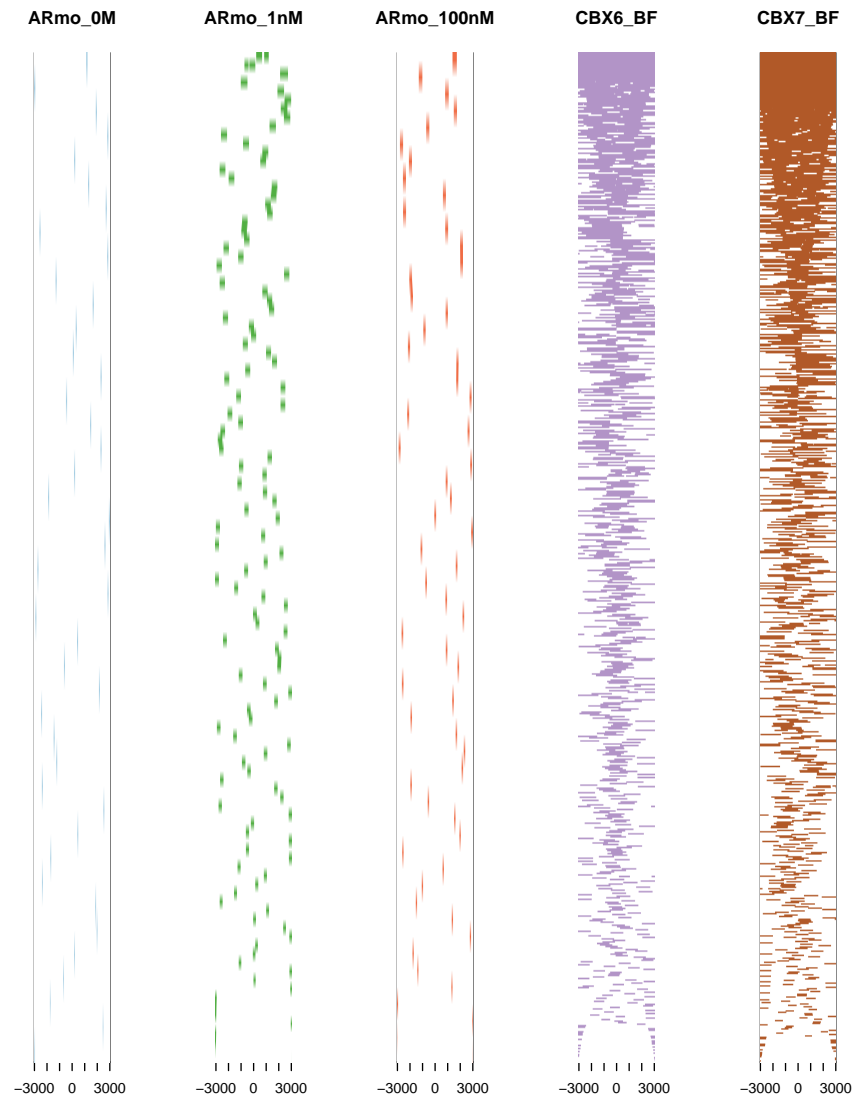


Figure 8: Heatmap of ChIP peaks among different experiments

## 5.2 ChIP peak annotation comparison

The `plotAnnoBar` and `plotDistToTSS` can also accept input of a named list of annotated peaks (output of `annotatePeak`).

```
peakAnnoList <- lapply(files, annotatePeak, TxDb=txdb, tssRegion=c(-3000, 3000), ve
```

We can use `plotAnnoBar` to comparing their genomic annotation.

```
plotAnnoBar(peakAnnoList)
```

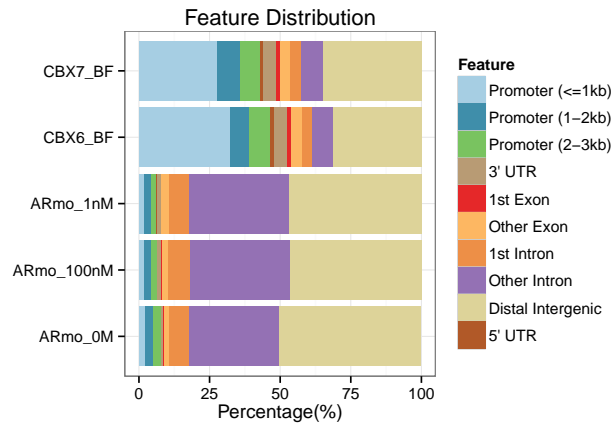


Figure 9: Genomic Annotation among different ChIPseq data

R function `plotDistToTSS` can use to comparing distance to TSS profiles among ChIPseq data.

```
plotDistToTSS(peakAnnoList)
```

```
## Warning: Stacking not well defined when ymin != 0
```

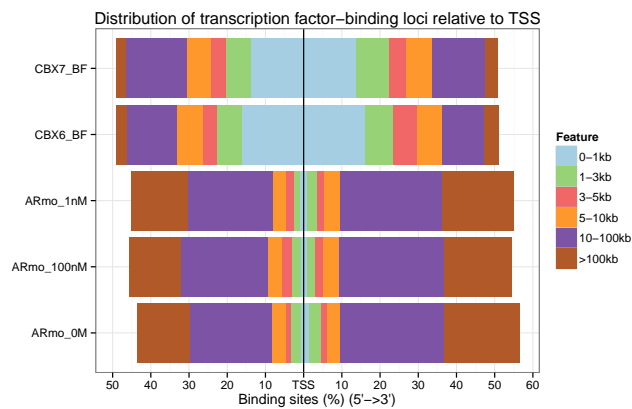


Figure 10: Distribution of Binding Sites among different ChIPseq data

### 5.3 Functional profiles comparison

As shown in section 4, the annotated genes can analyzed by *clusterProfiler*, *DOSE* and *ReactomePA* for Gene Ontology, KEGG, Disease Ontology and Reactome Pathway enrichment analysis.

The *clusterProfiler* package provide `compareCluster` function for comparing biological themes among gene clusters, and can be easily adopted to compare different ChIP peak experiments.

```
genes = lapply(peakAnnoList, function(i) as.data.frame(i)$geneId)
names(genes) = sub("_", "\\n", names(genes))
compGO <- compareCluster(geneCluster=genes, fun="enrichGO", ont="MF", organism="human",
plot(compGO, showCategory=20, title="Molecular Function Enrichment")
```

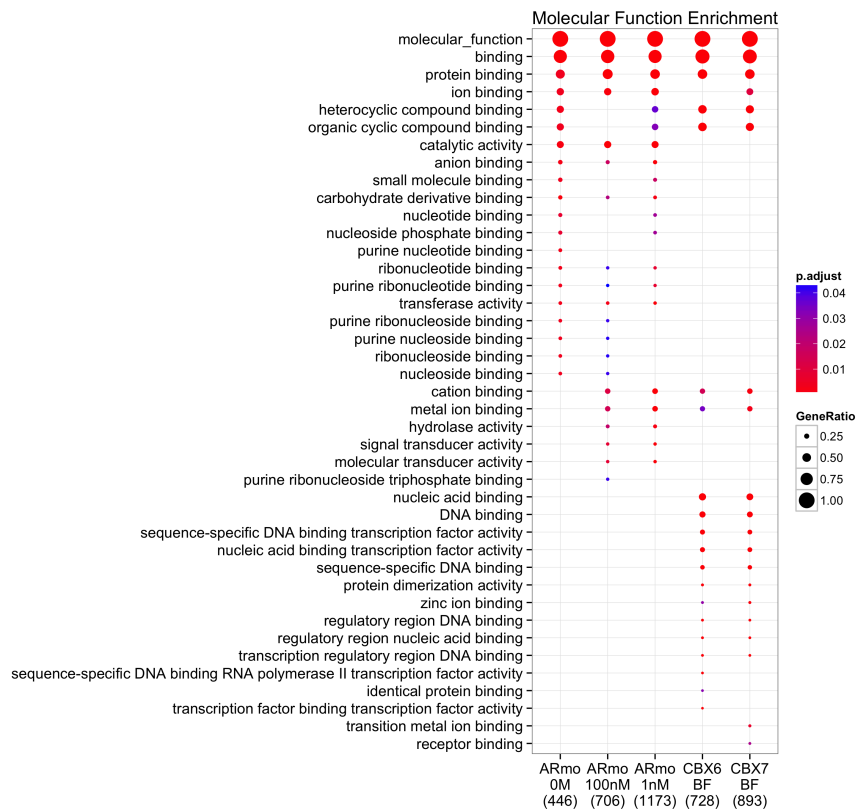


Figure 11: Compare Biological themes among different experiments

## 5.4 Overlap of peaks and annotated genes

User may want to compare the overlap peaks of replicate experiments or from different experiments. *ChIPseeker* provides `peak2GRanges` that can read peak file and stored in `GRanges` object. Several files can be read simultaneously using `lapply`, and then passed to `vennplot` to calculate their overlap and draw venn plot.

`vennplot` accept a list of object, can be a list of `GRanges` or a list of vector. Here, I will demonstrate using `vennplot` to visualize the overlap of the nearest genes stored in `peakAnnoList`.

```
genes= lapply(peakAnnoList, function(i) as.data.frame(i)$geneId)
vennplot(genes)
```

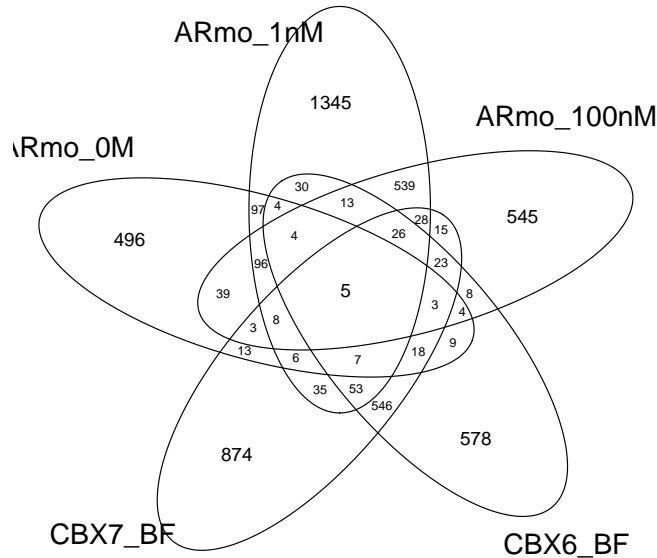


Figure 12: Overlap of annotated genes

## 6 Statistical testing of ChIP seq overlap

Overlap is very important, if two ChIP experiment by two different proteins overlap in a large fraction of their peaks, they may cooperative in regulation. Calculating the overlap is only touch the surface. *ChIPseeker* implemented statistical methods to measure the significance of the overlap.

### 6.1 Shuffle genome coordination

```
p <- GRanges(seqnames=c("chr1", "chr3"), ranges=IRanges(start=c(1, 100), end=c(50,
shuffle(p, TxDb=txdb)

## GRanges object with 2 ranges and 0 metadata columns:
##      seqnames      ranges strand
##      <Rle>         <IRanges>  <Rle>
## [1] chr1 [110173610, 110173660] *
```



```
##      [2]      chr3 [ 43467795,  43467826]      *
##      -----
##      seqinfo: 2 sequences from an unspecified genome; no seqlengths
```

We implement the `shuffle` function to randomly permute the genomic locations of ChIP peaks defined in a genome which stored in `TxDb` object.

## 6.2 Peak overlap enrichment analysis

With the ease of this `shuffle` method, we can generate thousands of random ChIP data and calculate the background null distribution of the overlap among ChIP data sets.

```
enrichPeakOverlap(queryPeak=files[[5]], targetPeak=unlist(files[1:4]), TxDb=txdb, p

##                                     qSample
## ARmo_OM      GSM1295077_CBX7_BF_ChipSeq_mergedReps_peaks.bed.gz
## ARmo_1nM      GSM1295077_CBX7_BF_ChipSeq_mergedReps_peaks.bed.gz
## ARmo_100nM    GSM1295077_CBX7_BF_ChipSeq_mergedReps_peaks.bed.gz
## CBX6_BF       GSM1295077_CBX7_BF_ChipSeq_mergedReps_peaks.bed.gz
##                                     tSample qLen tLen N_OL
## ARmo_OM      GSM1174480_ARmo_OM_peaks.bed.gz 1663  812    0
## ARmo_1nM      GSM1174481_ARmo_1nM_peaks.bed.gz 1663 2296    8
## ARmo_100nM    GSM1174482_ARmo_100nM_peaks.bed.gz 1663 1359    3
## CBX6_BF       GSM1295076_CBX6_BF_ChipSeq_mergedReps_peaks.bed.gz 1663 1331  968
##                                     pvalue p.adjust
## ARmo_OM      0.94    0.940
## ARmo_1nM      0.08    0.160
## ARmo_100nM    0.26    0.347
## CBX6_BF       0.00    0.000
```

Parameter `queryPeak` is the query ChIP data, while `targetPeak` is bed file name or a vector of bed file names from comparison; `nShuffle` is the number to shuffle the peaks in `targetPeak`. To speed up the compilation of this vignettes, we only set `nShuffle` to 50 as an example for only demonstration. User should set the number to 1000 or above for more robust result. Parameter `chainFile` are chain file name for mapping the `targetPeak` to the genome version consistent with `queryPeak` when their genome version are different. This create the possibility of comparison among different genome version and cross species.

In the output, `qSample` is the name of `queryPeak` and `qLen` is the the number of peaks in `queryPeak`. `N_OL` is the number of overlap between `queryPeak` and `targetPeak`.

## 7 Data Mining with ChIP seq data deposited in GEO

There are many ChIP seq data sets that have been published and deposited in GEO database. We can compare our own dataset to those deposited in GEO to search for significant overlap data. Significant overlap of ChIP seq data by different binding proteins may be used to infer cooperative regulation and thus can be used to generate hypotheses.

We collect about 15,000 bed files deposited in GEO, user can use `getGEOspecies` to get a summary based on species.

### 7.1 GEO data collection

```
getGEOspecies()
```

##	species	Freq
## 1	Aedes aegypti	11
## 2	Anabaena	6
## 3	Anolis carolinensis	2
## 4	Apis mellifera	5
## 5	Apis mellifera scutellata	1
## 6	Arabidopsis lyrata	4
## 7	Arabidopsis thaliana	65
## 8	Atelerix albiventris	2
## 9	Brassica rapa	8
## 10	Caenorhabditis elegans	164
## 11	Candida albicans	25
## 12	Candida dubliniensis	20
## 13	Canis lupus familiaris	7
## 14	Chlorocebus aethiops	2
## 15	Cleome hassleriana	1
## 16	Columba livia	6
## 17	Crassostrea gigas	1
## 18	Cryptococcus neoformans	39
## 19	Danio rerio	122
## 20	Drosophila melanogaster	551
## 21	Drosophila pseudoobscura	7
## 22	Drosophila simulans	9
## 23	Drosophila virilis	2
## 24	Drosophila yakuba	8
## 25	Equus caballus	1
## 26	Escherichia coli	1
## 27	Escherichia coli BW25113	4
## 28	Escherichia coli K-12	2
## 29	Escherichia coli str. K-12 substr. MG1655	8
## 30	Gallus gallus	43

## 31	Geobacter sulfurreducens PCA	3
## 32	Gorilla gorilla	2
## 33	Histophilus somni	1
## 34	Homo sapiens	7347
## 35	Human herpesvirus 6B	2
## 36	Human herpesvirus 8	6
## 37	Legionella pneumophila	5
## 38	Leishmania amazonensis	4
## 39	Leishmania major	2
## 40	Leishmania tarentolae	15
## 41	Macaca mulatta	28
## 42	Monodelphis domestica	4
## 43	Moraxella catarrhalis 035E	6
## 44	Mus musculus	5558
## 45	Mus musculus x Mus spretus	1
## 46	Mycobacterium tuberculosis	2
## 47	Myotis brandtii	15
## 48	Nematostella vectensis	23
## 49	Ornithorhynchus anatinus	5
## 50	Oryza sativa	23
## 51	Oryzias latipes	2
## 52	Pan troglodytes	3
## 53	Plasmodium falciparum 3D7	29
## 54	Pseudomonas putida KT2440	2
## 55	Pyrococcus furiosus	4
## 56	Rattus norvegicus	38
## 57	Rhodopseudomonas palustris	6
## 58	Rhodopseudomonas palustris CGA009	3
## 59	Saccharomyces cerevisiae	360
## 60	Saccharomyces paradoxus	8
## 61	Schizosaccharomyces japonicus	2
## 62	Schizosaccharomyces pombe	88
## 63	Schmidtea mediterranea	7
## 64	Streptomyces coelicolor A3(2)	6
## 65	Sus scrofa	17
## 66	Tupaia chinensis	7
## 67	Xenopus (Silurana) tropicalis	62
## 68	Zea mays	54

The summary can also be based on genome version as illustrated below:

```
getGEOgenomeVersion()
```

##	organism	genomeVersion	Freq
## 1	Anolis carolinensis	anoCar2	2
## 2	Caenorhabditis elegans	ce10	4
## 3	Caenorhabditis elegans	ce6	64

```
## 4          Danio rerio          danRer6      6
## 5          Danio rerio          danRer7     40
## 6      Drosophila melanogaster          dm3     340
## 7          Gallus gallus          galGal3     20
## 8          Gallus gallus          galGal4     15
## 9          Homo sapiens          hg18    1936
## 10         Homo sapiens          hg19    4948
## 11         Mus musculus          mm10      21
## 12         Mus musculus          mm8      465
## 13         Mus musculus          mm9    4543
## 14      Monodelphis domestica          monDom5      4
## 15         Macaca mulatta          rheMac2     24
## 16      Saccharomyces cerevisiae          sacCer2    141
## 17      Saccharomyces cerevisiae          sacCer3    100
## 18          Sus scrofa          susScr2      17
## 19 Xenopus (Silurana) tropicalis          xenTro3      3
```

User can access the detail information by `getGEOInfo`, for each genome version.

```
hg19 <- getGEOInfo(genome="hg19", simplify=TRUE)
head(hg19)
```

```
##      series_id      gsm      organism
## 111  GSE16256  GSM521889 Homo sapiens
## 112  GSE16256  GSM521887 Homo sapiens
## 113  GSE16256  GSM521883 Homo sapiens
## 114  GSE16256  GSM1010966 Homo sapiens
## 115  GSE16256  GSM896166 Homo sapiens
## 116  GSE16256  GSM910577 Homo sapiens
##
## 111      Reference Epigenome: ChIP-Seq Analysis of H3K27me3 in IMR90 Cells;
## 112      Reference Epigenome: ChIP-Seq Analysis of H3K27ac in IMR90 Cells;
## 113      Reference Epigenome: ChIP-Seq Analysis of H3K14ac in IMR90 Cells;
## 114      polyA RNA sequencing of STL003 Pancreas Cultured Cells;
## 115      Reference Epigenome: ChIP-Seq Analysis of H4K8ac in hESC H1 Cells;
## 116 Reference Epigenome: ChIP-Seq Analysis of H3K4me1 in Human Spleen Tissue; re
##
## 111      ftp://ftp.ncbi.nlm.nih.gov/geo/samples/GSM521nnn/GSM521889/suppl/GSM
## 112      ftp://ftp.ncbi.nlm.nih.gov/geo/samples/GSM521nnn/GSM521887/suppl/GS
## 113      ftp://ftp.ncbi.nlm.nih.gov/geo/samples/GSM521nnn/GSM521883/suppl/GS
## 114 ftp://ftp.ncbi.nlm.nih.gov/geo/samples/GSM1010nnn/GSM1010966/suppl/GSM101096
## 115      ftp://ftp.ncbi.nlm.nih.gov/geo/samples/GSM896nnn/GSM896166/suppl/GSM
## 116      ftp://ftp.ncbi.nlm.nih.gov/geo/samples/GSM910nnn/GSM910577/suppl/GSM91
##      genomeVersion pubmed_id
## 111      hg19      19829295
## 112      hg19      19829295
## 113      hg19      19829295
```

```
## 114      hg19 19829295
## 115      hg19 19829295
## 116      hg19 19829295
```

If `simplify` is set to `FALSE`, extra information including `source_name`, `extract_protocol`, `description`, `data_processing`, and `submission_date` will be incorporated.

## 7.2 Download GEO ChIP data sets

*ChIPseeker* provide function `downloadGEObedFiles` to download all the bed files of a particular genome.

```
downloadGEObedFiles(genome="hg19", destDir="hg19")
```

Or a vector of GSM accession number by `downloadGSMbedFiles`.

```
gsm <- hg19$gsm[sample(nrow(hg19), 10)]
downloadGSMbedFiles(gsm, destDir="hg19")
```

## 7.3 Overlap significant testing

After download the bed files from GEO, we can pass them to `enrichPeakOverlap` for testing the significant of overlap. Parameter `targetPeak` can be the folder, e.g. `hg19`, that containing bed files. `enrichPeakOverlap` will parse the folder and compare all the bed files. It is possible to test the overlap with bed files that are mapping to different genome or different genome versions, `enrichPeakOverlap` provide a parameter `chainFile` that can pass a chain file and `liftOver` the `targetPeak` to the genome version consistent with `queryPeak`. Significant overlap can be use to generate hypothesis of cooperative regulation. By mining the data deposited in GEO, we can identify some putative complex or interacted regulators in gene expression regulation or chromosome remodelling for further validation.

## 8 Session Information

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The version number of R and packages loaded for generating the vignette were:

- R version 3.1.3 (2015-03-09), x86\_64-apple-darwin10.8.0
- Locale:  
en\_US.UTF-8/en\_US.UTF-8/en\_US.UTF-8/C/en\_US.UTF-8/en\_US.UTF-8
- Base packages: base, datasets, graphics, grDevices, methods, parallel, stats, stats4, utils

- Other packages: AnnotationDbi 1.28.2, Biobase 2.26.0, BiocGenerics 0.12.1, ChIPseeker 1.2.6, clusterProfiler 2.0.1, DBI 0.3.1, GenomeInfoDb 1.2.4, GenomicFeatures 1.18.3, GenomicRanges 1.18.4, GO.db 3.0.0, IRanges 2.0.1, knitr 1.9, org.Hs.eg.db 3.0.0, RSQLite 1.0.0, S4Vectors 0.4.0, TxDb.Hsapiens.UCSC.hg19.knownGene 3.0.0
- Loaded via a namespace (and not attached): base64enc 0.1-2, BatchJobs 1.5, BBmisc 1.9, BiocParallel 1.0.3, biomaRt 2.22.0, Biostrings 2.34.1, bitops 1.0-6, brew 1.0-6, caTools 1.17.1, checkmate 1.5.1, chron 2.3-45, codetools 0.2-11, colorspace 1.2-6, data.table 1.9.4, digest 0.6.8, DO.db 2.8.0, DOSE 2.4.0, evaluate 0.5.5, fail 1.2, foreach 1.4.2, formatR 1.0, gdata 2.13.3, GenomicAlignments 1.2.2, ggplot2 1.0.1, GOSemSim 1.24.1, gplots 2.16.0, grid 3.1.3, gtable 0.1.2, gtools 3.4.1, highr 0.4, igraph 0.7.1, iterators 1.0.7, KEGG.db 3.0.0, KernSmooth 2.23-14, labeling 0.3, MASS 7.3-39, munsell 0.4.2, plotrix 3.5-11, plyr 1.8.1, proto 0.3-10, qvalue 1.43.0, RColorBrewer 1.1-2, Rcpp 0.11.5, RCurl 1.95-4.5, reshape2 1.4.1, Rsamtools 1.18.3, rtracklayer 1.26.2, scales 0.2.4, sendmailR 1.2-1, stringr 0.6.2, tools 3.1.3, XML 3.98-1.1, XVector 0.6.0, zlibbioc 1.12.0

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