ATACseq_Tutorial3_Downstream

September 10, 2023

1 ATAC-seq Module3: Downstream Analysis

1.1 Overview & Purpose

In the previous sections of this module we performed preprocessing quality control, mapping, deduplication, visualization, profiling aroud TSSs, and peak identification. In this section we will focus on differential peak identification, motif footprinting, and annotation of nearby genomic features.

1.1.1 Required Files

In this stage of the module you will use several of the files that we prepared in the previous sections. Don't worry if you are just jumping in now, we have examples of these files saved and will include a step that copies them for your use. You can also use this module on your own data or any published ATAC-seq dataset, but you should complete the mapping and deduplication steps first.

STEP1: Setup Environment

Initial items to configure your google cloud environment. In this step we will use conda to install the following packages:

Differential Peak Idnetification: manorm

Genome Annotation: homer

Motif Analysis: tobias

```
[1]: #!python -m ipykernel install --user --name ATACtraining
    numthreads=!lscpu | grep '^CPU(s)'| awk '{print $2-1}'
    numthreadsint = int(numthreads[0])
    !conda config --prepend channels bioconda
    !conda install -y -c bioconda manorm tobias homer
    !pip install jupyterquiz
    from jupyterquiz import display_quiz
    from IPython.display import IFrame
    from IPython.display import display
    import pandas as pd
```

```
Warning: 'bioconda' already in 'channels' list, moving to the top
Retrieving notices: ...working... done
Collecting package metadata (current_repodata.json): done
Solving environment: unsuccessful initial attempt using frozen solve. Retrying with flexible solve.
```

```
Solving environment: unsuccessful attempt using repodata from current_repodata.json, retrying with next repodata source.

Collecting package metadata (repodata.json): done

Solving environment: / ^C

unsuccessful initial attempt using frozen solve. Retrying with flexible solve.
```

CondaError: KeyboardInterrupt

Requirement already satisfied: jupyterquiz in /opt/conda/lib/python3.10/site-packages (2.6.3)

```
[6]: # !conda install -y -c bioconda manorm #installed
# !conda install -y -c bioconda tobias ### this is problematic --- build from
source
# !conda install -y -c bioconda homer #installed
```

```
[2]: # !conda install -y -c bioconda manorm tobias homer
```

```
Collecting package metadata (current_repodata.json): | ^C
/
```

1.2 Setup FileSystem

Now lets create some folders to stay organized and copy over our prepared fastq files. We're going to create a directory called "Tutorial1" which we'll use for this module. We'll then create subfolders for our InputFiles and for the files that we'll be creating during this module. We'll also copy over the fasta file for chromosome 4 as well as some bowtie2 index files (don't worry we'll teach you how to create these index files).

```
[7]: #These commands create our directory structure.
     #!cd $HOMEDIR
     #!mkdir -p Tutorial3
     #!mkdir -p Tutorial3/InputFiles
     !mkdir -p Tutorial3/GenomeAnnotation
     !mkdir -p Tutorial3/DiffPeaks
     !mkdir -p Tutorial3/MotifFootprinting
     #!mkdir -p Tutorial3/LessonImages
     !mkdir -p Tutorial3/Plots
     #!cd ./Tutorial3
     #!echo $PWD
     # #These commands help identify the google cloud storage bucket where the
      ⇔example files are held.
     # project id = "nosi-unmc-seq"
     # original_bucket = "qs://unmc_atac_data_examples/Tutorial3"
     # #!gsutil -m cp $original_bucket/images/* Tutorial3/LessonImages
     # #!gsutil -m cp $original_bucket/Annotations/* Tutorial3/GenomeAnnotations
```

```
##This command copies our example files to the Tutorial1/Inputfiles folder_

that we created above.

#! gsutil -m cp $original_bucket/InputFiles/* Tutorial3/InputFiles
```

1.2.1 OK

Let's make sure that the files copied correctly. You should see 2 .bam files, 2 .bai files, and 2 .narrowPeak files after running the following command:

```
[8]: !ls Tutorial3/InputFiles/*
```

```
Tutorial3/InputFiles/CTL_dedup.bam
Tutorial3/InputFiles/CTL_dedup.bam.bai
Tutorial3/InputFiles/CTL_peaks.narrowPeak
Tutorial3/InputFiles/Mutant_dedup.bam
Tutorial3/InputFiles/Mutant_dedup.bam.bai
Tutorial3/InputFiles/Mutant_peaks.narrowPeak
Tutorial3/InputFiles/chr4.fa
Tutorial3/InputFiles/chr4.fa
```

Differential Peak Identification

If you have two or more samples and desire to discover differential peaks, we recommend using manorm. Novices may be tempted to simply intersect the two peak lists to find the overlap, however this is highly inadvisable.

Interactive Quiz Question 1: Click on the correct answer in following cell.

```
[9]: display_quiz("Tutorial3/LessonImages/DiffPeaks.json")

<IPython.core.display.HTML object>
```

<IPython.core.display.Javascript object>

1.2.2 Consider the below peak which was identified in both the control and mutant sample. A simple intersect would result in this peak being reported as unchanged between the two samples. To represent the differences we will use manorm.

```
[10]: #We specify several non-default parameters to better reflect ATAC-seq data
!manorm --p1 Tutorial3/InputFiles/CTL_peaks.narrowPeak --p2 Tutorial3/

InputFiles/Mutant_peaks.narrowPeak --r1 Tutorial3/InputFiles/CTL_dedup.bam_

--r2 Tutorial3/InputFiles/Mutant_dedup.bam --rf bam --n1 CTL --n2 Mutant_

--pe -w 1000 -o Tutorial3/DiffPeaks --wa 2> Tutorial3/DiffPeaks/log_manorm.

-txt

print("done")
```

done

The above command will write out several files including the differential peaks for each sample as well as the unchanged peaks.

[11]: !ls Tutorial3/DiffPeaks/output_filters CTL_vs_Mutant_M_above_1.0_biased_peaks.bed CTL_vs_Mutant_unbiased_peaks.bed CTL vs Mutant M below -1.0 biased peaks.bed [12]: #Let's also check the format of these files !head Tutorial3/DiffPeaks/output_filters/CTL_vs_Mutant_M_above_1.0_biased_peaks. chr4 52059325 52059732 CTL_unique 2.20155 $\mathtt{CTL_unique}$ chr4 52298589 52298799 1.09775 chr4 52550105 52550494 CTL_unique 1.29536 chr4 52698223 CTL_unique 1.84416 52698464 chr4 52834103 52834470 CTL_unique 1.26119 CTL_unique chr4 52884232 52884622 1.09835 chr4 52968329 52968671 CTL_unique 1.41519 CTL_unique chr4 52993914 52994157 1.22576 CTL unique chr4 53595301 53595477 1.20393 CTL_unique chr4 53702525 53703113 1.07373 [13]: #We can also count how many are in each. !wc -l Tutorial3/DiffPeaks/output_filters/*bed 124 Tutorial3/DiffPeaks/output_filters/CTL vs_Mutant_M_above_1.0_biased_peaks.bed Tutorial3/DiffPeaks/output_filters/CTL_vs_Mutant_M_below_-1.0_biased_peaks.bed 590 Tutorial3/DiffPeaks/output_filters/CTL_vs_Mutant_unbiased_peaks.bed 788 total [14]: #Our log file tells us this information as well !tail Tutorial3/DiffPeaks/log_manorm.txt ==== Stats ==== Total read pairs of sample 1: 167,920 Total read pairs of sample 2: 219,380 Total peaks of sample 1: 650 (unique: 277 common: 373) Total peaks of sample 2: 560 (unique: 190 common: 370) Number of merged common peaks: 369 $M-A \mod 1: M = -0.04460 * A + 0.18904$ 590 peaks are filtered as unbiased peaks 124 peaks are filtered as sample1-biased peaks 74 peaks are filtered as sample2-biased peaks Annotating Peaks

Let's take the differential peaks and annotate them with nearby genes and perform gene ontology using homer.

First we need to reformat the differential peaks file to the format required by homer.

In an earlier command, we examined the format of manorm's ouput using head and saw that it outputs a five column format. We will change this to a 6 column bed format including a unique name for each peak.

```
[15]: #This command will reformat the peaks file including the line number in naming_

the peaks (NR) as well as a place-holder strand in the 6th column (note that_

peaks don't necessarily have a strand, but the format requires this column).

The -F \ t tells awk that the file is tab delimited.

!awk '{print $1"\t"$2"\t"$3"\t"$4"_"NR"\t"$5"\t+"}' Tutorial3/DiffPeaks/

output_filters/CTL_vs_Mutant_M_above_1.0_biased_peaks.bed > Tutorial3/
GenomeAnnotation/CTL_specific_peaks.bed

#Let's head this to compare
!head Tutorial3/GenomeAnnotation/CTL_specific_peaks.bed
```

chr4	52059325	52059732	CTL_unique_1	2.20155 +
chr4	52298589	52298799	CTL_unique_2	1.09775 +
chr4	52550105	52550494	CTL_unique_3	1.29536 +
chr4	52698223	52698464	$\mathtt{CTL_unique_4}$	1.84416 +
chr4	52834103	52834470	CTL_unique_5	1.26119 +
chr4	52884232	52884622	CTL_unique_6	1.09835 +
chr4	52968329	52968671	CTL_unique_7	1.41519 +
chr4	52993914	52994157	CTL_unique_8	1.22576 +
chr4	53595301	53595477	CTL_unique_9	1.20393 +
chr4	53702525	53703113	CTL_unique_10	1.07373 +

Now let's configure homer to recognize our genome build. We aligned our reads to hg38, so we'll have homer use that.

done

Let's use that reformatted peak file to get nearby genes and perform gene onotology analysis.

```
Peak file = Tutorial3/GenomeAnnotation/CTL_specific_peaks.bed
Genome = hg38
Organism = human
Will perform Gene Ontology analysis - output to directory =
Tutorial3/GenomeAnnotation/CTL_GO
Peak/BED file conversion summary:
BED/Header formatted lines: 124
peakfile formatted lines: 0
Duplicated Peak IDs: 0
```

Peak File Statistics:

Total Peaks: 124 Redundant Peak IDs: 0

Peaks lacking information: 0 (need at least 5 columns per peak)

Peaks with misformatted coordinates: 0 (should be integer)

Peaks with misformatted strand: 0 (should be either \pm - or 0/1)

Peak file looks good!

Reading Positions...

Finding Closest TSS...

Annotating:.

	Annotat	ion	Number	of peaks	Total s	ize (bp)	Log2 Ratio
(obs/exp)	LogP enric	hment (+	values d	epleted)			
	3UTR	0.0	1226327	-0.852	0.802		
	miRNA	0.0	3258	-0.003	0.002		
	ncRNA	0.0	315963	-0.271	0.206		
	TTS	1.0	1306500	0.231	-0.554		
	pseudo	0.0	40049	-0.037	0.026		
	Exon	0.0	1490268	-0.985	0.975		
	Intron	33.0	7316608	3	-0.532	5.597	
	Interge	nic	84.0	11112173	36	0.213	-3.865
	Promote	r	5.0	1403974	2.450	-6.038	
	5UTR	1.0	114432	3.745	-2.632		

NOTE: If this part takes more than 2 minutes, there is a good chance your machine ran out of memory: consider hitting ctrl+C and

rerunning

the command with "-noann"

Annotating:.

reacing						
Annotat	ion	Number	of peaks	Total s	size (bp)	Log2 Ratio
LogP enric	hment (+	values d	epleted)			
3UTR	0.0	1226327	-0.852	0.802		
Retropo	son	0.0	200838	-0.178	0.131	
RC?	0.0	2850	-0.003	0.002		
RNA	0.0	6910	-0.006	0.005		
miRNA	0.0	3258	-0.003	0.002		
ncRNA	0.0	315963	-0.271	0.206		
TTS	1.0	1306500	0.232	-0.554		
LINE	18.0	4501438	2	-0.705	4.777	
${\tt srpRNA}$	0.0	13945	-0.013	0.009		
SINE	6.0	1893628)	-1.041	3.470	
RC	0.0	20949	-0.020	0.014		
tRNA	0.0	2852	-0.003	0.002		
DNA?	0.0	27318	-0.025	0.018		
pseudo	0.0	40049	-0.037	0.026		
DNA	1.0	6724040	-2.132	2.750		
	Annotati LogP enrici 3UTR Retropol RC? RNA miRNA ncRNA TTS LINE srpRNA SINE RC tRNA DNA? pseudo	Annotation LogP enrichment (+ 3UTR 0.0 Retroposon RC? 0.0 RNA 0.0 miRNA 0.0 ncRNA 0.0 TTS 1.0 LINE 18.0 srpRNA 0.0 SINE 6.0 RC 0.0 tRNA 0.0 DNA? 0.0 pseudo 0.0	Annotation Number of LogP enrichment (+values de 3UTR 0.0 1226327 Retroposon 0.0 RC? 0.0 2850 RNA 0.0 6910 miRNA 0.0 3258 ncRNA 0.0 315963 TTS 1.0 1306500 LINE 18.0 45014383 srpRNA 0.0 13945 SINE 6.0 18936286 RC 0.0 20949 tRNA 0.0 2852 DNA? 0.0 27318 pseudo 0.0 40049	Annotation Number of peaks LogP enrichment (+values depleted) 3UTR 0.0 1226327 -0.852 Retroposon 0.0 200838 RC? 0.0 2850 -0.003 RNA 0.0 6910 -0.006 miRNA 0.0 3258 -0.003 ncRNA 0.0 315963 -0.271 TTS 1.0 1306500 0.232 LINE 18.0 45014382 srpRNA 0.0 13945 -0.013 SINE 6.0 18936280 RC 0.0 20949 -0.020 tRNA 0.0 2852 -0.003 DNA? 0.0 27318 -0.025 pseudo 0.0 40049 -0.037	Annotation Number of peaks Total and Sutra 0.0 1226327 -0.852 0.802 Retroposon 0.0 200838 -0.178 RC? 0.0 2850 -0.003 0.002 RNA 0.0 6910 -0.006 0.005 miRNA 0.0 3258 -0.003 0.002 ncRNA 0.0 315963 -0.271 0.206 TTS 1.0 1306500 0.232 -0.554 LINE 18.0 45014382 -0.705 srpRNA 0.0 13945 -0.013 0.009 SINE 6.0 18936280 -1.041 RC 0.0 20949 -0.020 0.014 tRNA 0.0 2852 -0.003 0.002 DNA? 0.0 27318 -0.025 0.018 pseudo 0.0 40049 -0.037 0.026	Annotation Number of peaks Total size (bp) LogP enrichment (+values depleted) 3UTR 0.0 1226327 -0.852 0.802 Retroposon 0.0 200838 -0.178 0.131 RC? 0.0 2850 -0.003 0.002 RNA 0.0 6910 -0.006 0.005 miRNA 0.0 3258 -0.003 0.002 ncRNA 0.0 315963 -0.271 0.206 TTS 1.0 1306500 0.232 -0.554 LINE 18.0 45014382 -0.705 4.777 srpRNA 0.0 13945 -0.013 0.009 SINE 6.0 18936280 -1.041 3.470 RC 0.0 20949 -0.020 0.014 tRNA 0.0 2852 -0.003 0.002 DNA? 0.0 27318 -0.025 0.018 pseudo 0.0 40049 -0.037 0.026

```
Exon
       0.0
                1490268 -0.985 0.975
Intron 25.0
                38474934
                                -0.005 0.605
Intergenic
                39.0
                       48657251
                                       0.298
                                               -2.484
Promoter
               5.0
                       1403974 2.450
                                       -6.038
5UTR
                               -2.632
       1.0
               114432 3.745
LTR?
       0.0
               92183
                       -0.084 0.060
scRNA
       0.0
                6881
                       -0.006 0.004
                0.0
CpG-Island
                       373419 -0.315 0.244
Low complexity 0.0
                       365373 -0.309 0.238
               20757981
LTR
        27.0
                               0.997
                                       -7.957
Simple_repeat
                       2265635 -0.563 0.572
                1.0
\mathtt{snRNA}
       0.0
               18664
                       -0.017 0.012
Unknown 0.0
               49238
                       -0.046 0.032
SINE?
       0.0
               130
                       -0.000 0.000
               0.0
                        2306654 -1.335 1.513
Satellite
rRNA
       0.0
               7760
                       -0.007 0.005
```

Performing Gene Ontology Analysis...

rm: cannot remove '0.353503496709408.bg.tmp': No such file or directory

Counting Tags in Peaks from each directory...

Organism: human

Loading Gene Information...

Outputing Annotation File...

Done annotating peaks file

Let's look at the output files. First, let's look at the first 2 lines of at our annotation stats.

```
[20]: #Clean up duplicate entries
!sort -u Tutorial3/GenomeAnnotation/CTL annState
```

```
#Load results into a pandas table
```

¬names=['annotation','peakcount','size','foldenrichment','log10significance'])

#View entries sorted by enrichment

annstats_sorted = annstats.sort_values(by=["foldenrichment"], ascending=False)
display(annstats_sorted)

	annotation	peakcount	size	foldenrichment	log10significance
1	5UTR	1.0	114432	3.745	-2.632
14	Promoter	5.0	1403974	2.450	-6.038
11	LTR	27.0	20757981	0.997	-7.957
6	Intergenic	39.0	48657251	0.298	-2.484
24	TTS	1.0	1306500	0.232	-0.554
23	TTS	1.0	1306500	0.231	-0.554
7	Intergenic	84.0	111121736	0.213	-3.865

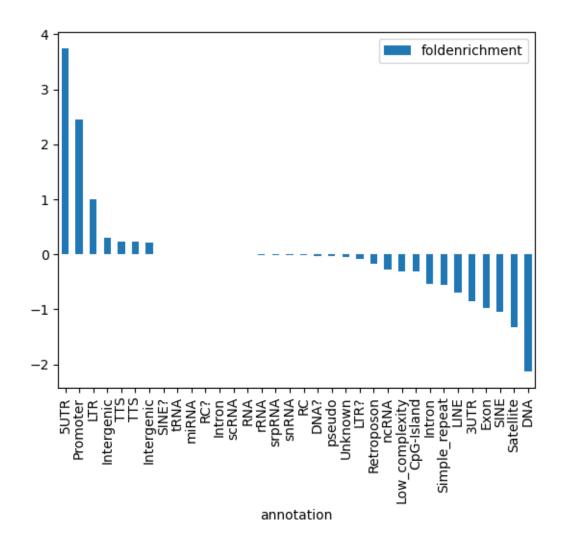
20	SINE?	0.0	130	-0.000	0.000
33	tRNA	0.0	2852	-0.003	0.002
26	miRNA	0.0	3258	-0.003	0.002
16	RC?	0.0	2850	-0.003	0.002
8	Intron	25.0	38474934	-0.005	0.605
30	scRNA	0.0	6881	-0.006	0.004
17	RNA	0.0	6910	-0.006	0.005
29	rRNA	0.0	7760	-0.007	0.005
32	${\tt srpRNA}$	0.0	13945	-0.013	0.009
31	${\tt snRNA}$	0.0	18664	-0.017	0.012
15	RC	0.0	20949	-0.020	0.014
4	DNA?	0.0	27318	-0.025	0.018
28	pseudo	0.0	40049	-0.037	0.026
25	Unknown	0.0	49238	-0.046	0.032
12	LTR?	0.0	92183	-0.084	0.060
18	Retroposon	0.0	200838	-0.178	0.131
27	ncRNA	0.0	315963	-0.271	0.206
13	Low_complexity	0.0	365373	-0.309	0.238
2	${\tt CpG-Island}$	0.0	373419	-0.315	0.244
9	Intron	33.0	73166083	-0.532	5.597
22	Simple_repeat	1.0	2265635	-0.563	0.572
10	LINE	18.0	45014382	-0.705	4.777
0	3UTR	0.0	1226327	-0.852	0.802
5	Exon	0.0	1490268	-0.985	0.975
19	SINE	6.0	18936280	-1.041	3.470
21	Satellite	0.0	2306654	-1.335	1.513
3	DNA	1.0	6724040	-2.132	2.750

From this we can see highest enrichment in 5' UTRs and promoters.

Let's plot the results as a barplot.

```
[21]: annstats_sorted.plot.bar(x="annotation", y="foldenrichment")
```

[21]: <Axes: xlabel='annotation'>



Homer also outputs the nearest annotation for each peak. Let's look at the first few lines of our annotation file.

[22]: | head -4 Tutorial3/GenomeAnnotation/CTL_specific_Annotated.txt

PeakID (cmd=annotatePeaks.pl Tutorial3/GenomeAnnotation/CTL_specific_peaks.bed hg38 -go Tutorial3/GenomeAnnotation/CTL_GO -annStats Tutorial3/GenomeAnnotation/CTL_annStats.txt) Chr Start End Strand Peak Score Focus Ratio/Region Size Annotation Detailed Distance to TSS Nearest PromoterID Annotation Entrez ID Nearest Unigene Nearest Refseq Nearest Ensembl Gene Name Gene Alias Gene Description Gene Type 64144792 64145494 3.01611 NA CTL_unique_56 chr4 Intergenic HERVK11-int|LTR|ERVK 264307 NM_001010874 253017 Hs.227752 ENSG00000205678 TECRL NM 001010874 CPVT3 | GPSN2L | SRD5A2L2 | TERL trans-2,3-enoyl-CoA reductase like proteincoding

```
54545647
                                                       54546360
                                                                                2.38644
     merged_common_90
                              chr4
                                                       NR_134657
                                                                       339978
     NA
             Intergenic
                              Intergenic
                                              61128
     NR_134657
                      ENSG00000250456 LINC02260
                                                               long intergenic non-
     protein coding RNA 2260
                                  ncRNA
     CTL unique 51
                      chr4
                              62835674
                                              62836120
                                                                       2.34453 NA
     Intergenic
                                      -674132 NR 110595
                                                               101927186
                      Intergenic
     Hs.723269
                      NR 110595
                                              ADGRL3-AS1
                                                               LPHN3-AS1
                                                                               adhesion
     G protein-coupled receptor L3 antisense RNA 1 ncRNA
     Lastly, let's take a look at the gene ontology results
[23]: #list the files in our GO directory
      !ls Tutorial3/GenomeAnnotation/CTL_GO/
     biocyc.txt
                              interactions.txt
                                                         prints.txt
     biological_process.txt
                              interpro.txt
                                                         prosite.txt
     cellular_component.txt
                              kegg.txt
                                                         reactome.txt
     chromosome.txt
                              lipidmaps.txt
                                                         smart.txt
                              molecular function.txt
     cosmic.txt
                                                         smpdb.txt
     gene3d.txt
                              msigdb.txt
                                                         wikipathways.txt
     geneOntology.html
                              pathwayInteractionDB.txt
     gwas.txt
                              pfam.txt
     Let's view the top terms in the biological process category.
[24]: bp GO = pd.read csv("Tutorial3/GenomeAnnotation/CTL GO/biological process.txt",
       ⇔sep='\t')
      #keep most significant
      bp_GO_top10 = bp_GO.nsmallest(10, "logP")
      display(bp_GO_top10)
            TermID
                                                                   Term \
       GD:0052695
                                              cellular glucuronidation
     1 GD:0019585
                                         glucuronate metabolic process
                                         uronic acid metabolic process
     2 GD:0006063
     3 GO:0010817
                                          regulation of hormone levels
     4 GD:0006068
                                              ethanol catabolic process
     5 GO:0034310
                                     primary alcohol catabolic process
     6 GD:0051923
                                                              sulfation
     7 GD:0006067
                                             ethanol metabolic process
     8 GD:0050427
                    3'-phosphoadenosine 5'-phosphosulfate metaboli...
     9 GO:0034035 purine ribonucleoside bisphosphate metabolic p...
          Enrichment
                                  Genes in Term
                                                 Target Genes in Term
                            logP
     0 8.476896e-07 -13.980751
                                              18
                                                                     3
     1 1.833506e-06 -13.209280
                                              23
                                                                     3
                                                                     3
     2 1.833506e-06 -13.209280
                                             23
     3 1.370570e-05 -11.197699
                                            528
                                                                     6
     4 7.141780e-05 -9.546963
                                             12
                                                                     2
```

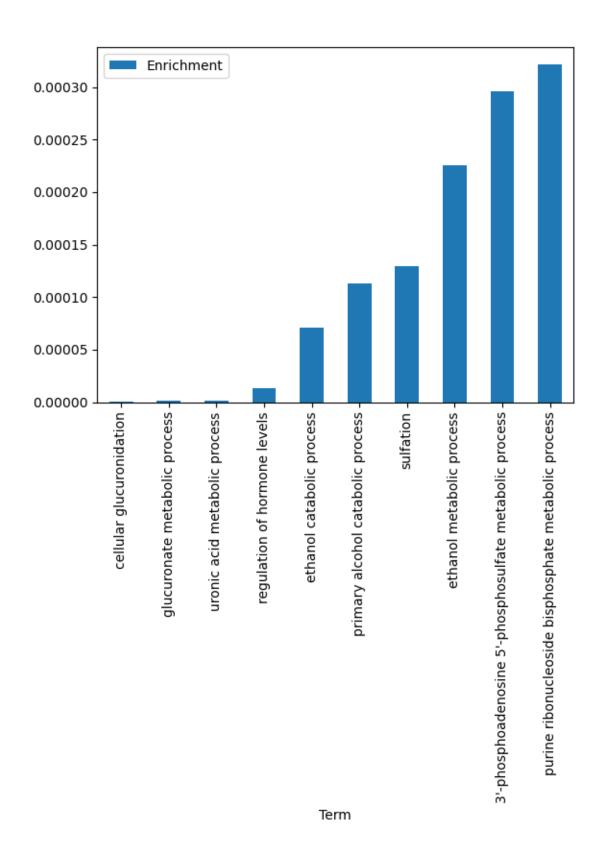
```
1.134005e-04
                  -9.084585
                                          15
                                                                   2
  1.295173e-04
                 -8.951696
                                          16
                                                                   2
6
  2.259286e-04
                                                                   2
7
                  -8.395291
                                          21
  2.963633e-04
                 -8.123925
                                          24
                                                                   2
8
                                                                   2
9
   3.219272e-04
                 -8.041185
                                          25
   Fraction of Targets in Term
                                  Total Target Genes
                                                        Total Genes
                            0.15
0
                                                    20
                                                               18680
1
                            0.15
                                                    20
                                                               18680
2
                            0.15
                                                    20
                                                               18680
3
                            0.30
                                                    20
                                                               18680
4
                            0.10
                                                    20
                                                               18680
5
                            0.10
                                                    20
                                                               18680
6
                            0.10
                                                    20
                                                               18680
7
                            0.10
                                                    20
                                                               18680
8
                            0.10
                                                    20
                                                               18680
9
                            0.10
                                                    20
                                                               18680
                   Entrez Gene IDs
                                                                   Gene Symbols
                                                          UGT2A3, UGT2B7, UGT2A1
0
                  79799,7364,10941
                  10941,79799,7364
                                                          UGT2A1, UGT2A3, UGT2B7
1
2
                  79799,7364,10941
                                                          UGT2A3, UGT2B7, UGT2A1
3
   5978,7364,2044,6783,9575,27284
                                      REST, UGT2B7, EPHA5, SULT1E1, CLOCK, SULT1B1
4
                         27284,6783
                                                                SULT1B1, SULT1E1
5
                         27284,6783
                                                                SULT1B1, SULT1E1
6
                         6783,27284
                                                                SULT1E1, SULT1B1
7
                         27284,6783
                                                                SULT1B1, SULT1E1
8
                         27284,6783
                                                                SULT1B1, SULT1E1
9
                                                                SULT1B1, SULT1E1
                         27284,6783
```

We can also plot the enrichment scores

Note that our results may look a little odd because we have severely downsampled the data to run quickly and focus on a single region of chr4.

```
[25]: bp_GO_top10.plot.bar(x="Term", y="Enrichment")
```

[25]: <Axes: xlabel='Term'>



Homer also saves an html file where you can navigate through the various categories.

```
[26]: #View the html results

IFrame(src='Tutorial3/GenomeAnnotation/CTL_GO/geneOntology.html', width=900, ⊔

⇔height=600)
```

[26]: <IPython.lib.display.IFrame at 0x7fc16e906ad0>

In the above html you can click throught the different ontology categories to view enriched terms and scores for genes near our differential peaks. Note that there are links to motifs, but these lead to "pages not found" because we have yet to do this analysis. We will run motif analysis in the next section using TOBIAS.

Motif Footprinting

1.2.3 ATAC-seq can be used to identify accessibility at transcription factor (TF) binding sites. We'll use tobias.

From: Bentsen et al., Nat. Comm. 2020

Th5 insertion during ATAC-seq has a sequence bias. In our first step, let's correct for that bias.

```
[27]: #Index the bam
      !samtools index Tutorial3/InputFiles/CTL dedup.bam
      !samtools index Tutorial3/InputFiles/Mutant_dedup.bam
      #Tn5 has an insertion sequence bias, which Tobias can correct for. Let's use
       the master list of peaks provided by manorm, but we need to first remove the
       ⇔header and extra columns.
      cat Tutorial3/DiffPeaks/CTL_vs_Mutant_all_MAvalues.xls | cut -f 1-3 | grep -v_
       ⇒start > Tutorial3/MotifFootprinting/MasterPeakList.bed
      #Now let's do the signal correction
      !TOBIAS ATACorrect --bam Tutorial3/InputFiles/CTL_dedup.bam --genome Tutorial3/
       →InputFiles/chr4.fa --peaks Tutorial3/MotifFootprinting/MasterPeakList.bed
       →--outdir Tutorial3/MotifFootprinting --prefix CTL --cores $numthreadsint_
       ⊶--verbosity 1
      #Let's also do this for the mutant
      !TOBIAS ATACorrect --bam Tutorial3/InputFiles/Mutant dedup.bam --genome,
       →Tutorial3/InputFiles/chr4.fa --peaks Tutorial3/MotifFootprinting/
       →MasterPeakList.bed --outdir Tutorial3/MotifFootprinting --prefix Mutant
       \rightarrow--cores $numthreadsint --verbosity 1
      print("done")
```

```
# TOBIAS 0.16.0 ATACorrect (run started 2023-09-10 04:21:57.812793)
# Working directory: /home/jupyter
# Command line call: TOBIAS ATACorrect --bam Tutorial3/InputFiles/CTL_dedup.bam
--genome Tutorial3/InputFiles/chr4.fa --peaks
Tutorial3/MotifFootprinting/MasterPeakList.bed --outdir
Tutorial3/MotifFootprinting --prefix CTL --cores 7 --verbosity 1
```

```
# ---- Input parameters ----
# bam: Tutorial3/InputFiles/CTL_dedup.bam
               Tutorial3/InputFiles/chr4.fa
# genome:
                Tutorial3/MotifFootprinting/MasterPeakList.bed
# peaks:
# regions_in:
                None
# regions out: None
# blacklist:
               None
# extend:
                100
                        False
# split_strands:
# norm_off:
               False
# track_off:
                # drop_chroms:
               ['chrM', 'chrMT', 'M', 'MT', 'Mito']
# k_flank:
                12
                [4, -5]
# read_shift:
# bg_shift:
                100
# window:
                100
# score_mat:
               DWM
# bias_pkl:
               None
# prefix:
                CTL
                /home/jupyter/Tutorial3/MotifFootprinting
# outdir:
# cores:
# split:
                100
# verbosity:
                1
# ---- Output files ----
# /home/jupyter/Tutorial3/MotifFootprinting/CTL_uncorrected.bw
# /home/jupyter/Tutorial3/MotifFootprinting/CTL_bias.bw
# /home/jupyter/Tutorial3/MotifFootprinting/CTL_expected.bw
# /home/jupyter/Tutorial3/MotifFootprinting/CTL_corrected.bw
# /home/jupyter/Tutorial3/MotifFootprinting/CTL_atacorrect.pdf
2023-09-10 04:21:57 (2986006) [WARNING] No additional chromosomes were removed.
Consider using '--drop-chroms' to remove mitochondrial and/or other unwanted
contigs.
# TOBIAS 0.16.0 ATACorrect (run started 2023-09-10 04:22:37.508418)
# Working directory: /home/jupyter
# Command line call: TOBIAS ATACorrect --bam
Tutorial3/InputFiles/Mutant_dedup.bam --genome Tutorial3/InputFiles/chr4.fa
--peaks Tutorial3/MotifFootprinting/MasterPeakList.bed --outdir
```

```
Tutorial3/MotifFootprinting --prefix Mutant --cores 7 --verbosity 1
# ---- Input parameters ----
# bam: Tutorial3/InputFiles/Mutant_dedup.bam
               Tutorial3/InputFiles/chr4.fa
# genome:
# peaks:
                Tutorial3/MotifFootprinting/MasterPeakList.bed
# regions_in:
# regions_out:
               None
# blacklist:
                None
# extend:
                100
# split_strands:
                        False
# norm_off:
               False
# track_off:
# drop_chroms:
                ['chrM', 'chrMT', 'M', 'MT', 'Mito']
# k_flank:
# read_shift:
                [4, -5]
# bg_shift:
                100
# window:
                100
# score_mat:
                DWM
# bias_pkl:
                None
# prefix:
               Mutant
# outdir:
                /home/jupyter/Tutorial3/MotifFootprinting
# cores:
# split:
                100
# verbosity:
                1
# ---- Output files ----
# /home/jupyter/Tutorial3/MotifFootprinting/Mutant_uncorrected.bw
# /home/jupyter/Tutorial3/MotifFootprinting/Mutant_bias.bw
# /home/jupyter/Tutorial3/MotifFootprinting/Mutant_expected.bw
# /home/jupyter/Tutorial3/MotifFootprinting/Mutant_corrected.bw
# /home/jupyter/Tutorial3/MotifFootprinting/Mutant_atacorrect.pdf
```

2023-09-10 04:22:37 (2988574) [WARNING] No additional chromosomes were removed. Consider using '--drop-chroms' to remove mitochondrial and/or other unwanted contigs.

done

Now let's use the bias-corrected bigwig files to calculate footprint scores around peaks

```
[28]: | !TOBIAS ScoreBigwig -s Tutorial3/MotifFootprinting/CTL_corrected.bw -ru
       →Tutorial3/MotifFootprinting/MasterPeakList.bed -o Tutorial3/
       →MotifFootprinting/CTL_footprintscores.bw --cores $numthreadsint --verbosity 1
      #Let's do the same for our mutant sample
      !TOBIAS ScoreBigwig -s Tutorial3/MotifFootprinting/Mutant_corrected.bw -ru
       →Tutorial3/MotifFootprinting/MasterPeakList.bed -o Tutorial3/
       {\scriptstyle \hookrightarrow} \texttt{MotifFootprinting/Mutant\_footprintscores.bw} \ -\text{-cores} \ \$ \texttt{numthreadsint}_{\sqcup}
       ⊶--verbosity 1
     # TOBIAS 0.16.0 ScoreBigwig (run started 2023-09-10 04:24:36.386281)
     # Working directory: /home/jupyter
     # Command line call: TOBIAS ScoreBigwig -s
     Tutorial3/MotifFootprinting/CTL_corrected.bw -r
     Tutorial3/MotifFootprinting/MasterPeakList.bed -o
     Tutorial3/MotifFootprinting/CTL_footprintscores.bw --cores 7 --verbosity 1
     # ---- Input parameters ----
     # signal:
                      Tutorial3/MotifFootprinting/CTL_corrected.bw
     # output:
                      Tutorial3/MotifFootprinting/CTL_footprintscores.bw
     # regions:
                      Tutorial3/MotifFootprinting/MasterPeakList.bed
     # score:
                      footprint
     # absolute:
                      False
     # extend:
                      100
     # smooth:
                      1
     # min_limit:
                      None
     # max_limit:
                      None
     # fp_min:
                      20
     # fp max:
                      50
     # flank_min:
                      10
     # flank max:
                      30
     # window:
                      100
     # cores:
     # split:
                      100
     # verbosity:
     # ---- Output files -----
     # Tutorial3/MotifFootprinting/CTL_footprintscores.bw
     # TOBIAS 0.16.0 ScoreBigwig (run started 2023-09-10 04:24:50.704446)
     # Working directory: /home/jupyter
     # Command line call: TOBIAS ScoreBigwig -s
     Tutorial3/MotifFootprinting/Mutant corrected.bw -r
     Tutorial3/MotifFootprinting/MasterPeakList.bed -o
     Tutorial3/MotifFootprinting/Mutant_footprintscores.bw --cores 7 --verbosity 1
```

```
# ---- Input parameters ----
# signal:
                Tutorial3/MotifFootprinting/Mutant_corrected.bw
# output:
                Tutorial3/MotifFootprinting/Mutant_footprintscores.bw
# regions:
                Tutorial3/MotifFootprinting/MasterPeakList.bed
# score:
                footprint
# absolute:
                False
# extend:
                100
# smooth:
# min_limit:
                None
# max_limit:
                None
# fp_min:
                20
# fp_max:
                50
# flank_min:
                10
# flank_max:
                30
# window:
                100
# cores:
                7
# split:
                100
# verbosity:
                1
# ---- Output files ----
# Tutorial3/MotifFootprinting/Mutant_footprintscores.bw
```

Now that we have our corrected signal and footprint scores, let's do TF binding site prediction as well as differential footprinting.

Caution: this step searches throug the signal at every signal location corresponding to motifs in your jaspar file. Here we use all the motifs in the jaspar database. This can take several minutes...

```
[29]: #First, we'll download the current jaspar motifs
!wget https://jaspar.genereg.net/download/data/2022/CORE/
    JASPAR2022_CORE_vertebrates_non-redundant_pfms_jaspar.txt -P Tutorial3/
    MotifFootprinting/

#Next we can calculate statistics for each motif represented in our jaspar_
    motif file. If we list both our CTL and Mutant sample, it will calculate the_
    differential footprint score for us as well.
!TOBIAS BINDetect --motifs Tutorial3/MotifFootprinting/
    JASPAR2022_CORE_vertebrates_non-redundant_pfms_jaspar.txt --signals_
    Tutorial3/MotifFootprinting/CTL_footprintscores.bw Tutorial3/
    MotifFootprinting/Mutant_footprintscores.bw --genome Tutorial3/InputFiles/
    chr4.fa --peaks Tutorial3/MotifFootprinting/MasterPeakList.bed --outdir_
    Tutorial3/MotifFootprinting/DiffMotifs --cond_names CTL Mutant --cores_
    snumthreadsint --verbosity 1
```

```
print("done")
--2023-09-10 04:28:13-- https://jaspar.genereg.net/download/data/2022/CORE/JASP
AR2022_CORE_vertebrates_non-redundant_pfms_jaspar.txt
Resolving jaspar.genereg.net (jaspar.genereg.net)... 193.60.222.202
Connecting to jaspar.genereg.net (jaspar.genereg.net)|193.60.222.202|:443...
connected.
HTTP request sent, awaiting response... 200 OK
Length: 327864 (320K) [text/plain]
Saving to: 'Tutorial3/MotifFootprinting/JASPAR2022 CORE vertebrates non-
redundant_pfms_jaspar.txt'
JASPAR2022 CORE ver 100%[==========] 320.18K 594KB/s
                                                                    in 0.5s
2023-09-10 04:28:14 (594 KB/s) -
'Tutorial3/MotifFootprinting/JASPAR2022_CORE_vertebrates_non-
redundant_pfms_jaspar.txt' saved [327864/327864]
/opt/conda/lib/python3.10/site-
packages/logomaker-0.8-py3.10.egg/logomaker/src/validate.py:98: SyntaxWarning:
"is" with a literal. Did you mean "=="?
  if matrix_type is 'information':
/opt/conda/lib/python3.10/site-
packages/logomaker-0.8-py3.10.egg/logomaker/src/validate.py:104: SyntaxWarning:
"is" with a literal. Did you mean "=="?
 elif matrix_type is 'probability':
# TOBIAS 0.16.0 BINDetect (run started 2023-09-10 04:28:24.496648)
# Working directory: /home/jupyter
# Command line call: TOBIAS BINDetect --motifs
Tutorial3/MotifFootprinting/JASPAR2022_CORE_vertebrates_non-
redundant_pfms_jaspar.txt --signals
Tutorial3/MotifFootprinting/CTL_footprintscores.bw
Tutorial3/MotifFootprinting/Mutant_footprintscores.bw --genome
Tutorial3/InputFiles/chr4.fa --peaks
Tutorial3/MotifFootprinting/MasterPeakList.bed --outdir
Tutorial3/MotifFootprinting/DiffMotifs --cond_names CTL Mutant --cores 7
--verbosity 1
# ---- Input parameters ----
# signals:
                ['Tutorial3/MotifFootprinting/CTL_footprintscores.bw',
'Tutorial3/MotifFootprinting/Mutant_footprintscores.bw']
                {\tt Tutorial 3/MotifFootprinting/MasterPeakList.bed}
# peaks:
# motifs:
                ['Tutorial3/MotifFootprinting/JASPAR2022_CORE_vertebrates_non-
redundant_pfms_jaspar.txt']
# genome:
                Tutorial3/InputFiles/chr4.fa
                ['CTL', 'Mutant']
# cond_names:
# peak_header: None
```

```
# naming:
               name_id
# motif_pvalue: 0.0001
# bound_pvalue: 0.001
# pseudo:
                None
# time series: False
# skip excel:
                False
# output peaks: None
# norm off:
                False
# prefix:
                bindetect
# outdir:
                /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs
# cores:
                7
# split:
                100
# debug:
                False
# verbosity:
# ---- Output files ----
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/*/beds/*_CTL_bound.bed
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/*/beds/*_CTL_unbound.bed
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/*/beds/*_Mutant_bound.bed
/home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/*/beds/* Mutant unbound.bed
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/*/beds/*_all.bed
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/*/plots/*_log2fcs.pdf
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/*/*_overview.txt
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/*/*_overview.xlsx
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/bindetect_distances.txt
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/bindetect_results.txt
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/bindetect_results.xlsx
# /home/jupyter/Tutorial3/MotifFootprinting/DiffMotifs/bindetect_figures.pdf
```

done

```
[30]: #View the html results

IFrame(src='Tutorial3/MotifFootprinting/DiffMotifs/bindetect_CTL_Mutant.html', 
→width=900, height=600)
```

[30]: <IPython.lib.display.IFrame at 0x7fc16e907790>

In the above html file you can hover over each point to see the motif name and the sequence. This

type of plot is a volcano plot showing the differntial signal on the x-axis and the significance values on the y-axis.

For example, the original paper focused on TP63, which is one of our differential dots in the html file.

Let's visualize the averge footprint at TP63 motifs.

```
[31]: | #IFrame(src='Tutorial2/MotifFootprinting/MYBL1_MA0776.1/plots/MYBL1_MA0776.
       \hookrightarrow 1_log2fcs.pdf', width=900, height=600)
      #note change to Tutorial3
      #!TOBIAS PlotAggregate --TFBS Tutorial3/MotifFootprinting/DiffMotifs/
       →TP63_MA0525.2/beds/TP63_MA0525.2_all.bed --signals Tutorial3/
       MotifFootprinting/CTL_corrected.bw Tutorial3/MotifFootprinting/
       →Mutant_corrected.bw --output Tutorial3/MotifFootprinting/
       \hookrightarrow TP63_footprint_compare.png --share_y both --verbosity 1 --plot_boundaries_\(\sigma\)
       →--flank 60 --smooth 2
      !TOBIAS PlotAggregate --TFBS Tutorial3/MotifFootprinting/DiffMotifs/TP63_MA0525.
       -2/beds/TP63_MA0525.2_all.bed --signals Tutorial3/MotifFootprinting/
       →CTL_corrected.bw Tutorial3/MotifFootprinting/Mutant_corrected.bw --output
       →Tutorial3/MotifFootprinting/TP63 footprint_compare.png --share_y both_
       →--verbosity 1 --plot_boundaries --flank 60 --smooth 2 --signal-on-x
     # TOBIAS 0.16.0 PlotAggregate (run started 2023-09-10 04:38:00.819069)
     # Working directory: /home/jupyter
     # Command line call: TOBIAS PlotAggregate --TFBS
     Tutorial3/MotifFootprinting/DiffMotifs/TP63_MA0525.2/beds/TP63_MA0525.2_all.bed
     --signals Tutorial3/MotifFootprinting/CTL_corrected.bw
     Tutorial3/MotifFootprinting/Mutant corrected.bw --output
     Tutorial3/MotifFootprinting/TP63_footprint_compare.png --share_y both
     --verbosity 1 --plot_boundaries --flank 60 --smooth 2 --signal-on-x
     # ---- Input parameters ----
     # TFBS: ['Tutorial3/MotifFootprinting/DiffMotifs/TP63_MA0525.2/beds/TP63_MA0525.
     2 all.bed']
                      ['Tutorial3/MotifFootprinting/CTL_corrected.bw',
     # signals:
     'Tutorial3/MotifFootprinting/Mutant_corrected.bw']
     # regions:
                      # whitelist:
                      Π
     # blacklist:
                     # output:
                     Tutorial3/MotifFootprinting/TP63_footprint_compare.png
     # output_txt:
                     None
     # title:
                     Aggregated signals
     # flank:
                     60
     # TFBS labels: None
     # signal_labels:
                              None
     # region_labels:
                              None
     # share_y:
                     both
```

```
# normalize: False
# negate: False
# smooth: 2
# log_transform: False
# plot_boundaries: True
# signal_on_x: True
# remove_outliers: 1
# verbosity: 1
# ---- Output files -----
# Tutorial3/MotifFootprinting/TP63_footprint_compare.png
```

```
[32]: IFrame(src='Tutorial3/MotifFootprinting/TP63_footprint_compare.png', width=600, width=600, wheight=400)
```

[32]: <IPython.lib.display.IFrame at 0x7fc16e906f20>

We can also get all the motifs that have differential footprints:

```
[33]: #!load the results as a pandas table Tutorial2/MotifFootprinting/

⇒bindetect_results.txt

dframe = pd.read_csv("Tutorial3/MotifFootprinting/DiffMotifs/bindetect_results.

⇒txt", sep='\t')

display(dframe)

DiffMotifs = dframe[dframe['CTL_Mutant_pvalue'] < .05]

#Write out to a tab separated file

DiffMotifs.to_csv('Tutorial3/MotifFootprinting/DiffMotifs_p05.txt')
```

```
output_prefix
                                  name
                                        motif_id
                                                          cluster total_tfbs
0
           Arnt_MA0004.1
                                  Arnt MA0004.1
                                                            C_MYC
                                                                            38
1
        AhrArnt_MA0006.1
                             Ahr::Arnt MA0006.1
                                                      C_Ahr::Arnt
                                                                            48
2
     Ddit3Cebpa_MA0019.1 Ddit3::Cebpa MA0019.1
                                                   C_Ddit3::Cebpa
                                                                            62
3
          Mecom_MA0029.1
                                 Mecom MA0029.1
                                                          C\_{Mecom}
                                                                           74
4
          FOXF2_MA0030.1
                                 FOXF2 MA0030.1
                                                          C FOXD1
                                                                           70
         ZNF281_MA1630.2
                                ZNF281 MA1630.2
                                                         C ZNF281
836
                                                                          442
837
          BACH1_MA1633.2
                                 BACH1 MA1633.2
                                                           C_JUNB
                                                                          292
          Prdm4 MA1647.2
                                                          C Prdm4
                                                                           90
838
                                 Prdm4 MA1647.2
839
          THAP1_MA0597.2
                                 THAP1 MA0597.2
                                                          C_THAP1
                                                                          236
          NR5A1_MA1540.2
840
                                 NR5A1 MA1540.2
                                                          C_NR5A1
                                                                           88
```

CTL_mean_score CTL_bound Mutant_mean_score Mutant_bound \

0	85.97575	16	10	8.49061	17
1	122.76075	24	11	5.50042	22
2	80.02321	24	8	0.35243	23
3	61.72563	20	5	8.21735	21
4	54.90034	16	5	7.53936	12
	•••	•••		•••	•••
836	87.47115	177	9	3.39986	192
837	107.33995	180	9	3.78144	132
838	65.86800	28	6	0.37410	24
839	90.57476	101	8	2.80139	92
840	60.86295	20	6	3.31876	24
	CTL_Mutant_change	CTL_Mutant	_pvalue	CTL_Mutant	_highlighted
0	-0.37973	7.880	020e-46		True
1	0.16950	1.263	900e-19		False
2	0.01402	3.506	450e-01		False
3	0.04204	6.714	740e-03		False
4	0.02603	1.081	680e-01		False
	•••				•••
836	-0.09869	3.777	940e-38		False
837	0.44457	1.482	660e-86		True
838	0.21494	1.058	610e-39		False
839	0.16366	5.913	700e-48		False
840	0.00371	2.191	130e-01		False

[841 rows x 12 columns]

Great job!

Thank you for completing these tutorials. Feel free to download these notebooks, customize, and use them to process your own data.

[]: