Differential Analysis: Alzheimer's Disease in Female Prefrontal Cortex

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Contents

Packages

```
library(data.table)
library(DESeq2)
library(stringr)
library(limma)
library(ggplot2)
library(EnhancedVolcano)
library(svglite)
library(RUVSeq)
```

Constants/Significance Thresholds

- A peak region will be considered differentially accessible between the disease groups if:
 - 1. Final DESeq2 FDR-adjusted satisfies $p_{adj} < .05\,$
 - 2. The (absolute) fold change between patient groups $|\log_2{\rm (FC)}| > 0.25$

```
INIT_COLDATA_FILE = "dnase_ad_metadata.tsv"
INIT_COUNT_MATRIX_FILE = "rocco_consenrich_dnase_ad_signal_v1.6.1.counts.tsv"
PADJ_THRESH = 0.05
LFC_THRESH = 0.25
```

Read and Parse Metadata and Peak-by-Sample Count Matrix

```
coldata <- read.table(INIT_COLDATA_FILE, sep = "\t",header = TRUE)</pre>
cts = read.table(INIT COUNT MATRIX FILE, sep = "\t", header = TRUE,
                  check.names = FALSE)
rownames(coldata) <- coldata$sample</pre>
rownames(cts) <- cts$peak_name</pre>
cts = cts[,-1]
if(!all(rownames(coldata) == colnames(cts))) {
  stop('rownames of `coldata` must equal colnames of `cts`')
coldata$status <- as.factor(coldata$status)</pre>
coldata$status <- relevel(coldata$status, ref = "No_AD")</pre>
coldata$age <- as.numeric(coldata$age)</pre>
```

Determine Negative/Empirical Control Regions for RUVg

Per guidance in RNA-seq workflow: gene-level exploratory analysis and differential expression - Section 8.2

• First, run DEseq2 and obtain 'raw' p-values

```
dds <- DESeqDataSetFromMatrix(countData = cts, colData = coldata,</pre>
                                 design= ~ age + status)
dds$status <- relevel(dds$status, ref = "No AD")</pre>
dds <- estimateSizeFactors(dds)</pre>
dds <- estimateDispersions(dds)</pre>
dds <- nbinomLRT(dds, maxit = 1000, reduced = ~1)</pre>
uncorrected results <- results(dds)</pre>
uncorrected_results <- na.exclude(uncorrected_results)</pre>
regions = rownames(uncorrected_results)
```

• Define a criteria for the negative/empirical control regions

```
start_end <- strsplit(gsub("chr", "", regions), "_")</pre>
start <- as.numeric(sapply(start_end, function(x) as.numeric(x[2])))</pre>
end <- as.numeric(sapply(start_end, function(x) as.numeric(x[3])))</pre>
# We restrict negative/empirical control regions to those
# greater than 100bp and less than 5000bp
small_regions <- regions[end - start < 100 & grepl("^chr[[:alnum:][:punct:]]+_",</pre>
                                                     regions)]
large_regions <- regions[end - start > 5000 & grepl("^chr[[:alnum:][:punct:]]+_",
                                                      regions)]
# We restrict the negative/empirical control regions to autosomal chromosomes
XY_regions <- regions[grepl("chrX|chrY", regions)]</pre>
# Per (Love, Anders, Kim, Huber, 2019), we restrict negative/empirical control
# regions to those 'initial' pvalues aboth a threshold (0.50)
nonnull regions <- rownames(uncorrected results[uncorrected results$pvalue < 0.50, ])
ctrlregion=uncorrected_results
ctrlregion = ctrlregion[! match(rownames(ctrlregion), XY_regions, nomatch=0),]
```

```
ctrlregion = ctrlregion[! match(rownames(ctrlregion), small_regions, nomatch=0),]
ctrlregion = ctrlregion[! match(rownames(ctrlregion), large_regions, nomatch=0),]
# remove nonnull_regions
ctrlregion = ctrlregion[! match(rownames(ctrlregion), nonnull_regions, nomatch=0),]
ctrl_length = length(rownames(ctrlregion))
ctrlregion_names <- rownames(ctrlregion)</pre>
```

• Restrict number of negative/empirical control regions to at most 5000.

- Apply DESeq2's variance-stabilizing transformation to mitigate heteroskedasticity
 - Note: vst data converges in scale to log2 which Limma's removeBatchEffect expects in later steps

```
vsd <- vst(dds, blind=TRUE)
mm <- model.matrix(~1, colData(vsd))</pre>
```

- Remove known, easy-to-model effects with a linear mixed model
- We apply Limma's removeBatchEffect
- Note: removeBatchEffect expects log-scaled counts as input and returns log-scaled data

```
assay(vsd) <- removeBatchEffect(assay(vsd), covariates = coldata$age)
```

Determine Number of RUV Factors to Represent Negative Control Regions

- RUV factors are the left-singular vectors of the count matrix defined over negative/empirical control regions.
- Here, we plot the corresponding singular values of each left-singular vector.
 - Using too few RUV factors \rightarrow Poor representation of unwanted variation in negative control regions
 - Using too many RUV factors \rightarrow Increased model complexity (sample size considerations) without a meaningfully enhanced representation of unwanted variation.

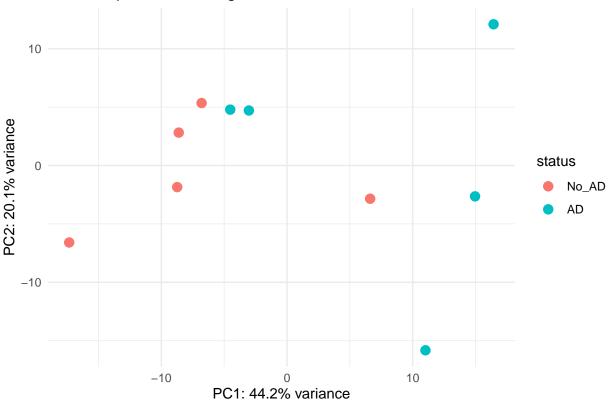
```
K=2
RUVg_results <- RUVg(assay(vsd), ctrlregion_names, k = K, isLog=TRUE)
ruvg_normalized_counts <- RUVg_results$normalizedCounts
ruv_factors <- RUVg_results$W</pre>
```

PCAs: RUVg-Normalized, Batch-Corrected, Variance-Stabilized Count Data

• Color by disease status

```
ylab(paste0("PC2: ", percentVar[2], "% variance")) +
theme_minimal() + ggtitle("PCA nTop=1000: *RUVg-Normalized, Batch-Corrected, Variance-Stabilized Count
```

PCA nTop=1000: *RUVg-Normalized, Batch-Corrected, Variance-Stabilize



ggsave(paste0("dnase_ad_k", K, "_pca_nTop1000.svg"))

Apply DESeq2 with RUVg-Augmented Design Formula on Raw Counts

- Note that the previous normalization/transformation steps were only to determine the RUV factors and generate a PCA plot.
- Now, DESeq2 is supplied the *raw* count data that it expects—but with an augmented design formula that ensures effects due to the unwanted variation encompassed in the RUV factors do not contribute to influence testing for differential accessibility.

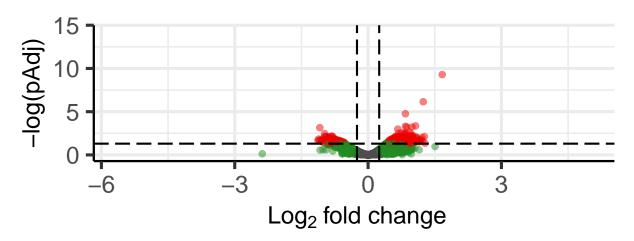
```
coldata$age <- as.numeric(coldata$age)</pre>
w_terms <- paste0("W_", 1:K)</pre>
coldata <- cbind(coldata, ruv_factors)</pre>
design_formula <- as.formula(paste0("~ age +", paste0(w_terms, collapse = "+"),</pre>
                                       "+ status"))
dds_final <- DESeqDataSetFromMatrix(countData = cts, colData = coldata,</pre>
                                       design = design formula)
dds_final <- DESeq(dds_final)</pre>
results <- results(dds_final)
design_formula <- as.formula(</pre>
  paste0("~ age +", paste0(w_terms, collapse = "+"),
         "+ status")
dds_final <- DESeqDataSetFromMatrix(</pre>
  countData = cts,
  colData = coldata,
  design = design_formula
dds_final <- DESeq(dds_final)</pre>
results <- results(dds_final)
significant_results <- results[</pre>
  complete.cases(results) &
    ((results$padj < PADJ_THRESH &
      all(abs(results$log2FoldChange))) > LFC_THRESH),
]
significant_regions <- rownames(significant_results)</pre>
```

Volcano Plot

Differentially Accessible Regions between AD a

EnhancedVolcano





total = 132860 variables

```
ggsave(paste0("dnase_ad_DESeq_results_k", K, "_volcano.svg"))
```

Save DAR results in BED format

• A bed file of regions satisfying the criteria above is saved for downstream analysis.

Per-Chromosome Differential Results

Chromosome	Total DARS	Positive LFC	Negative LFC
19	125	119	6
1	108	94	14
17	83	71	12
2	80	66	14
11	78	70	8
7	66	55	11
16	61	57	4
9	57	52	5
3	56	43	13
12	52	44	8
8	51	48	3
6	44	35	9
5	42	35	7
10	42	38	4
22	40	40	0
14	39	34	5
15	39	30	9
20	39	31	8
4	28	23	5
X	16	15	1
21	15	14	1
13	12	10	2
18	10	6	4

Distribution: Approximated Regulatory Roles of Differentially Accessible Regions

```
## >> identifying nearest features... 2025-03-19 15:42:10
## >> calculating distance from peak to TSS... 2025-03-19 15:42:11
## >> assigning genomic annotation... 2025-03-19 15:42:11
## >> adding gene annotation... 2025-03-19 15:42:22
## >> assigning chromosome lengths 2025-03-19 15:42:23
## >> done... 2025-03-19 15:42:23
knitr::kable(peakAnno@annoStat, format = "markdown", col.names = c("Feature Type", "Frequency"), row.names = FALSE)
```

п
Frequency
42.4344886
0.6762468
3.2967033
1.9442096
4.4801352
13.3558749
17.9205410
0.1690617
15.7227388

PCA over Differentially Accessible Regions

