

RNA-seq and Differential Expression

Texas A&M HPRC

27 February 2026



High Performance
Research Computing
DIVISION OF RESEARCH

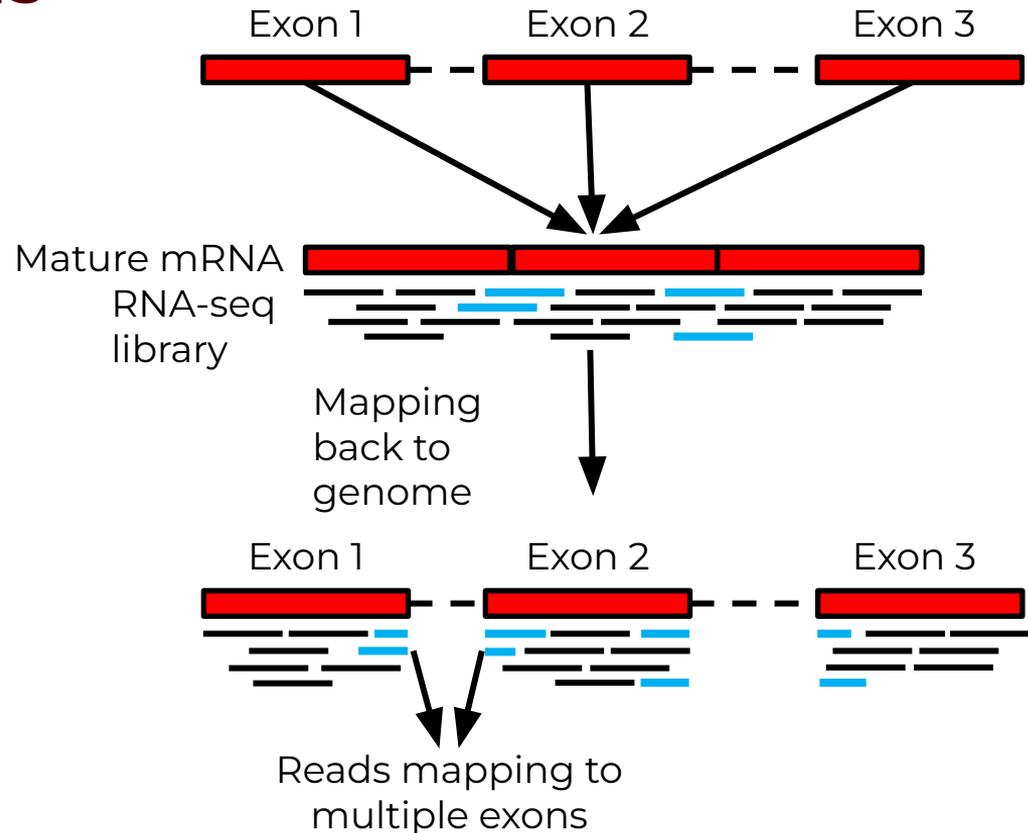
What does RNA-seq data provide?

- Measure gene expression
- Detect differences in expression between groups
- Annotate genomes
- Transcriptome assembly
- Nucleotide variant discovery
- Genome assembly scaffolding



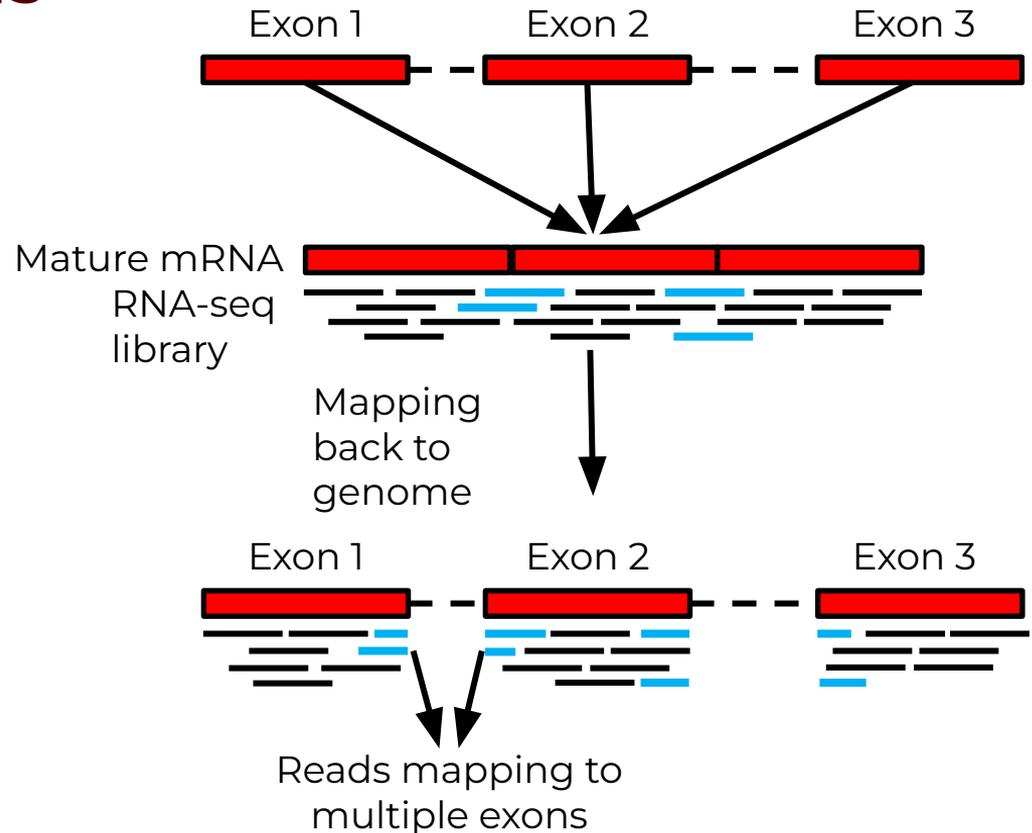
RNA-seq Applications

- Transcriptome Assembly
 - *de novo*: Trinity, Oases, SOAPdenovo-Trans
 - Reference-based: Trinity, StringTie, Cufflinks
- Splice-aware alignment
 - HISAT2
 - STAR
 - Clara Parabricks (GPU-accelerated STAR)



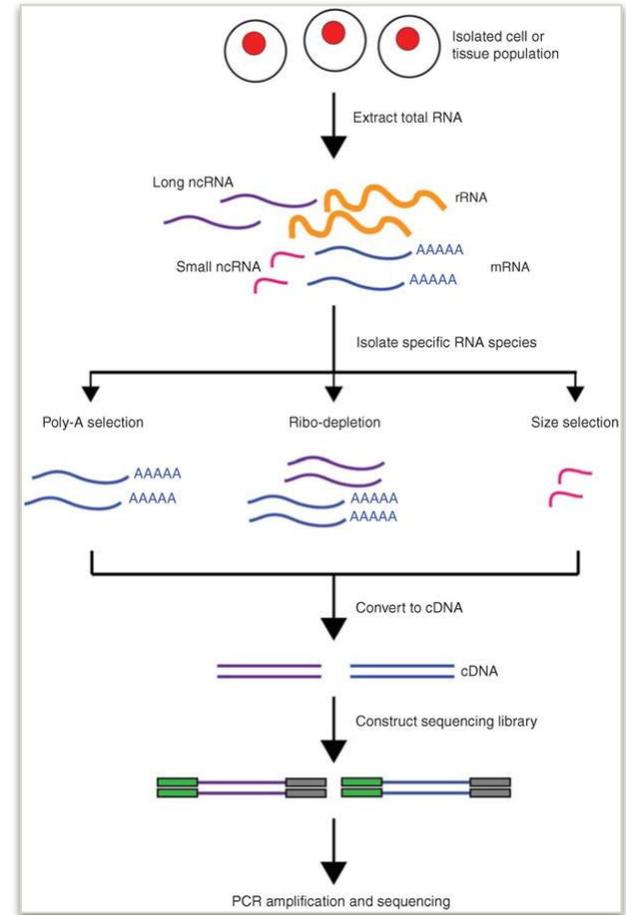
RNA-seq Applications

- File conversion and formatting
 - SAMtools
 - Picard tools
- Variant Calling
 - GATK (HaplotypeCaller in RNA-seq mode)
- Scaffolding Assemblies
 - L_RNA_scaffolder
 - Rascaf



Types of RNA-seq Libraries

- Poly-A selection - enriches for mRNA
- Ribosomal depletion - removes rRNA, leaving mRNA, lncRNA, and pre-mRNA
- Size selection (smRNA)



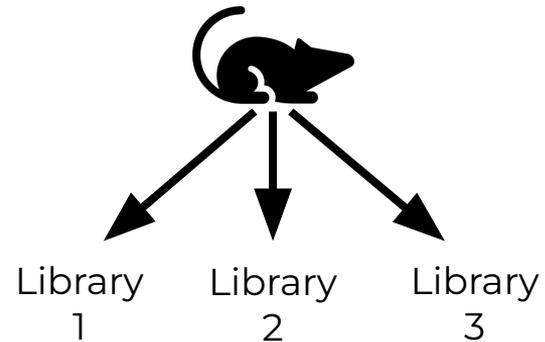
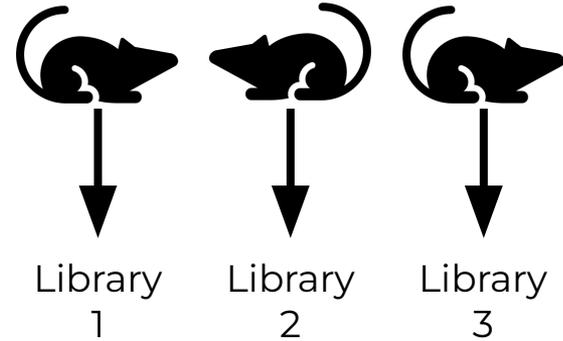
Kukurba and
Montgomery,
2016

Experimental Design (for Differential Expression)

- Sequencing Depth
 - Minimum 30 million aligned reads per replicate (ENCODE)
 - 30-60 million reads per replicate (Illumina)
- Replicate Number
 - 3 replicates per condition minimum (will likely recover 20-40% of true DEGs)
 - Schurch et al. (2016) suggest 6 replicates per condition minimum, 12 replicates per condition optimal

Experimental Design (for Differential Expression)

- Biological Replicates
 - Independent samples from different populations or individuals
- Technical Replicates
 - Multiple libraries from the same individual



Experimental Design (for Differential Expression)

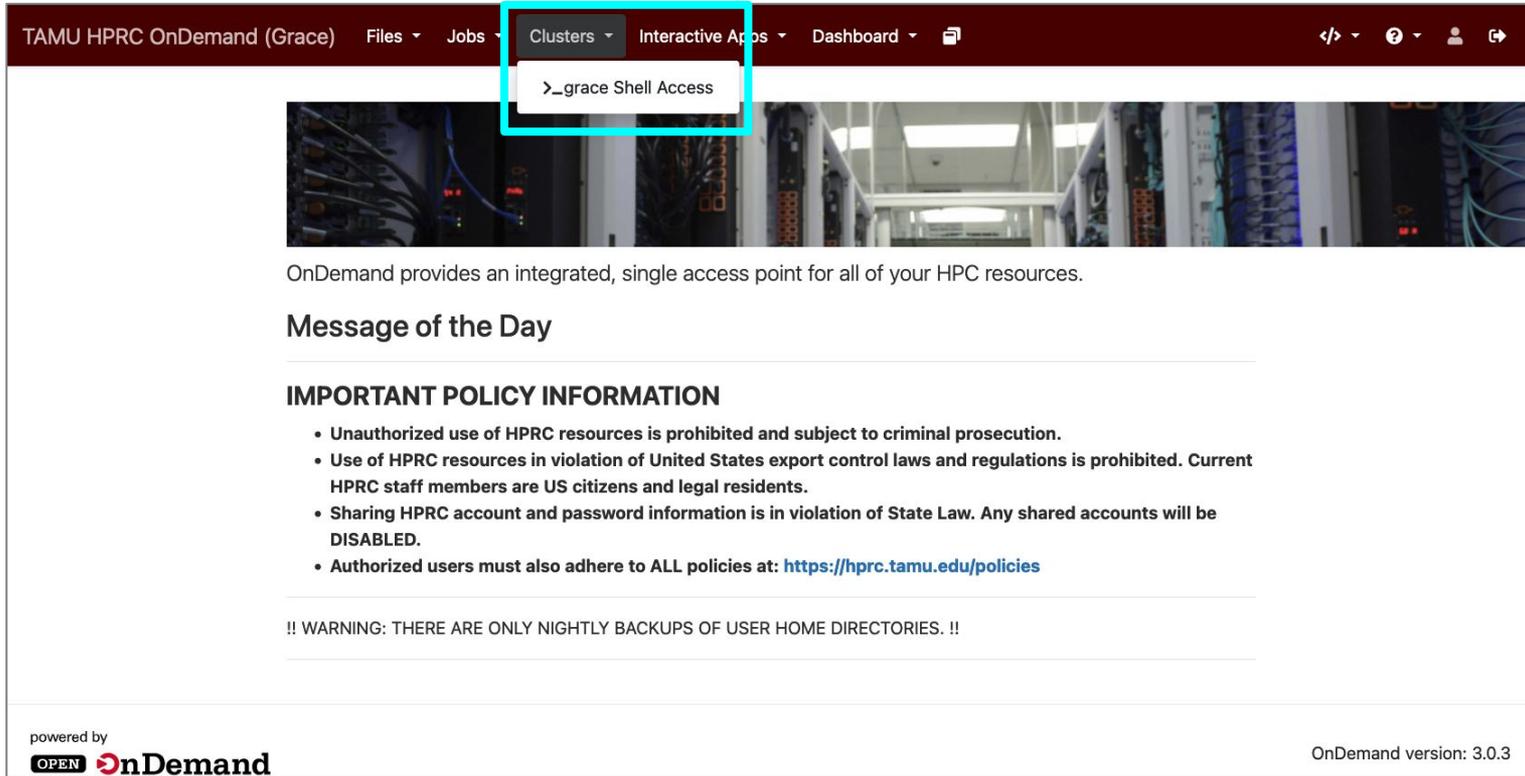
Replicates - Which to use?

- Biological replicates generally increase statistical power more than technical replicates
- Biological variability > Technical variability
- Biological replicates contain both biological and technical variability

Accessing the HPRC Grace Portal

The screenshot shows the HPRC website interface. At the top left is the Texas A&M logo. The main header reads "TEXAS A&M HIGH PERFORMANCE RESEARCH COMPUTING". On the right side of the header are social media icons for X, YouTube, and a search icon. Below the header is a dark red navigation bar with the following menu items: Home, User Services, Resources, Research, Policies, Events, Training, About, and Portal. The "Portal" item is highlighted with a red box. A dropdown menu is open under "Portal", listing: Grace Portal (highlighted with a red box), FASTER Portal, ACES Portal (ACCESS), and Launch Portal (ACCESS). Below the navigation bar is a banner image of server racks. On the left side of the page is a "Quick Links" section with a list of links: New User Information, Accounts (with sub-links: Apply for Accounts, Manage Accounts), User Consulting, Training, Knowledge Base, Software, and FAQ. Below that is a "User Guides" section with a list: Launch, ACES, FASTER, Grace, Portal, and Galaxy. The main content area features a 3D simulation of a blue tractor-trailer impacting a yellow barrier system. The simulation title is "LS-DYNA keyword deck by LS-PrePost" with a time of 1.28. A text box in the simulation reads "MASH 5-12 - Tractor-Trailer Impacting Barrier System with 50 mi/h at 15 degrees". In the top right corner of the simulation area is the Texas A&M Transportation Institute logo.

Accessing Grace Shell in OOD Portal



TAMU HPRC OnDemand (Grace) Files Jobs Clusters Interactive Apps Dashboard

>_grace Shell Access

OnDemand provides an integrated, single access point for all of your HPC resources.

Message of the Day

IMPORTANT POLICY INFORMATION

- Unauthorized use of HPRC resources is prohibited and subject to criminal prosecution.
- Use of HPRC resources in violation of United States export control laws and regulations is prohibited. Current HPRC staff members are US citizens and legal residents.
- Sharing HPRC account and password information is in violation of State Law. Any shared accounts will be DISABLED.
- Authorized users must also adhere to ALL policies at: <https://hprc.tamu.edu/policies>

!! WARNING: THERE ARE ONLY NIGHTLY BACKUPS OF USER HOME DIRECTORIES. !!

powered by
OPEN OnDemand

OnDemand version: 3.0.3

Accessing Grace Shell in OOD Portal

```
Success. Logging you in...
Last login: Wed Oct 16 13:39:28 2024 from 128.194.35.38
=====
|           Texas A&M University High Performance Research Computing           |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| Consulting:      help@hprc.tamu.edu (preferred) or (979) 845-0219          |
| Website:         https://hprc.tamu.edu                                    |
| Knowledgebase:   https://hprc.tamu.edu/kb/                                |
| YouTube Channel: https://www.youtube.com/texasamhprc                       |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
*****
*           === IMPORTANT POLICY INFORMATION ===                             *
* - Unauthorized use of HPRC resources is prohibited and subject to          *
*   criminal prosecution.                                                    *
* - Use of HPRC resources in violation of United States export control      *
*   laws and regulations is prohibited.                                       *
* - Sharing HPRC account and password information is in violation of        *
*   Texas State Law. Any shared accounts will be DISABLED.                 *
* - Authorized users must also adhere to ALL policies at:                   *
*   https://hprc.tamu.edu/policies/                                          *
*****

!! WARNING: THERE ARE ONLY NIGHTLY BACKUPS OF USER HOME DIRECTORIES. !!

Please restrict usage to 8_CORES across ALL login nodes.
Users found in violation of this policy will be SUSPENDED.

To see these messages again, run the motd command.

Your current disk quotas are:
Disk          Disk Usage   Limit   File Usage   Limit
/home/wbrashear      8.5G      10.0G      6303      10000
/scratch/user/wbrashear 2.6T      15.0T     214600    250000
* Quota increase for /scratch/user/wbrashear will expire on Dec 17, 2021
/scratch/group/hprc    5.5T      10.0T     768659    1000000
* Quota increase for /scratch/group/hprc will expire on Dec 31, 2026
Type 'showquota' to view these quotas again.
[wbrashear@grace2 ~]$
```

Example Data

- Create a new directory in your scratch space

```
$ mkdir $SCRATCH/RNA_class
```

- Change your working directory to the one you just created

```
$ cd $SCRATCH/RNA_class
```

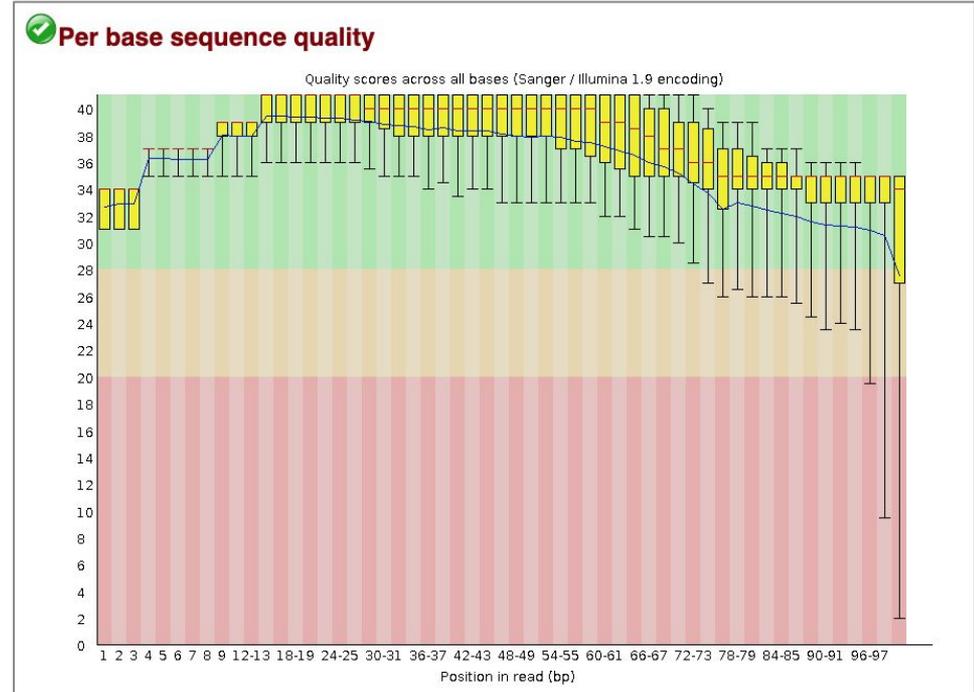
- Copy the example data to your directory

```
$ cp -r /scratch/training/bio/rna-seq/* .
```

The screenshot shows the Science journal website. At the top, the Science logo is on the left, and navigation links for 'Current issue', 'First release papers', 'Archive', 'About', and 'Submit manuscript' are on the right. Below the navigation, a breadcrumb trail reads 'HOME > SCIENCE > VOL. 355, NO. 6326 > VITAMIN B₃ MODULATES MITOCHONDRIAL VULNERABILITY AND PREVENTS GLAUCOMA IN AGED MICE'. The main article title is 'Vitamin B₃ modulates mitochondrial vulnerability and prevents glaucoma in aged mice'. Below the title, the authors are listed: PETE A. WILLIAMS, JEFFREY M. HARDES, NICOLE E. FOXWORTH, KELLY E. COCHRAN, VIVEK M. PHILIP, VITTORIO FORCIATTI, OLIVER SMITHIES, and SIMON W. M. JOHN. There is a link for 'Authors Info & Affiliations'. The article is dated '17 Feb 2017' and is from 'Vol 355, Issue 6326', pages 756-760, with DOI 10.1126/science.1240992. The article abstract is titled 'Vitamin B₃ protects mice from glaucoma' and discusses how vitamin B₃ (niacin) prevents eye degeneration in glaucoma-prone mice. A citation note at the bottom states 'Science, this issue p. 756; see also p. 688'.

Quality Control

- NGS libraries should be assessed for adapter content and low-quality reads before downstream analysis
- Low-quality bases and adapters can introduce errors and reduce map rates
- Avoid overly aggressive trimming practices



Quality Control

- Will use FastQC to examine the quality of our example data
- Look for the appropriate module on Grace:

```
$ module spider fastqc
```

```
$ module spider FastQC/0.12.1-Java-11
```

- Clear any previously loaded modules and load FastQC:

```
$ module purge
```

```
$ module load FastQC/0.12.1-Java-11
```

Running jobs on Grace

- Small jobs can be run on the login nodes (< 60 minutes, up to 8 cores)
- Larger jobs should be submitted to the compute nodes:
 - Slurm job scheduler
 - Can specify computing requirements:
 - Amount of memory required
 - Number of cores
 - Which modules to load
- Template job scripts are available:

<https://hprc.tamu.edu/kb/Software/useful-tools/GCATemplates/>

Quality Control

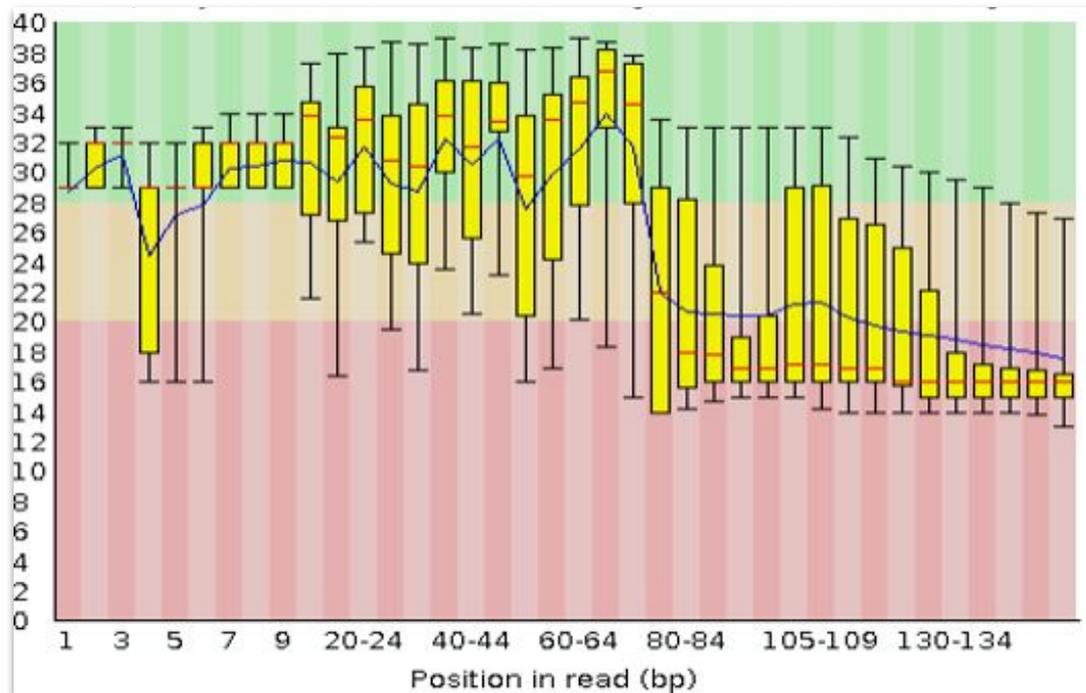
- Run FastQC on our example fastqs:

```
$ fastqc -t 2 -o . Control1_R1.fastq.gz Control1_R2.fastq.gz
```

- Go to “Files” tab in Grace portal and navigate to the RNA_class directory
- FastQC results saved as html files

Failed QC Examples

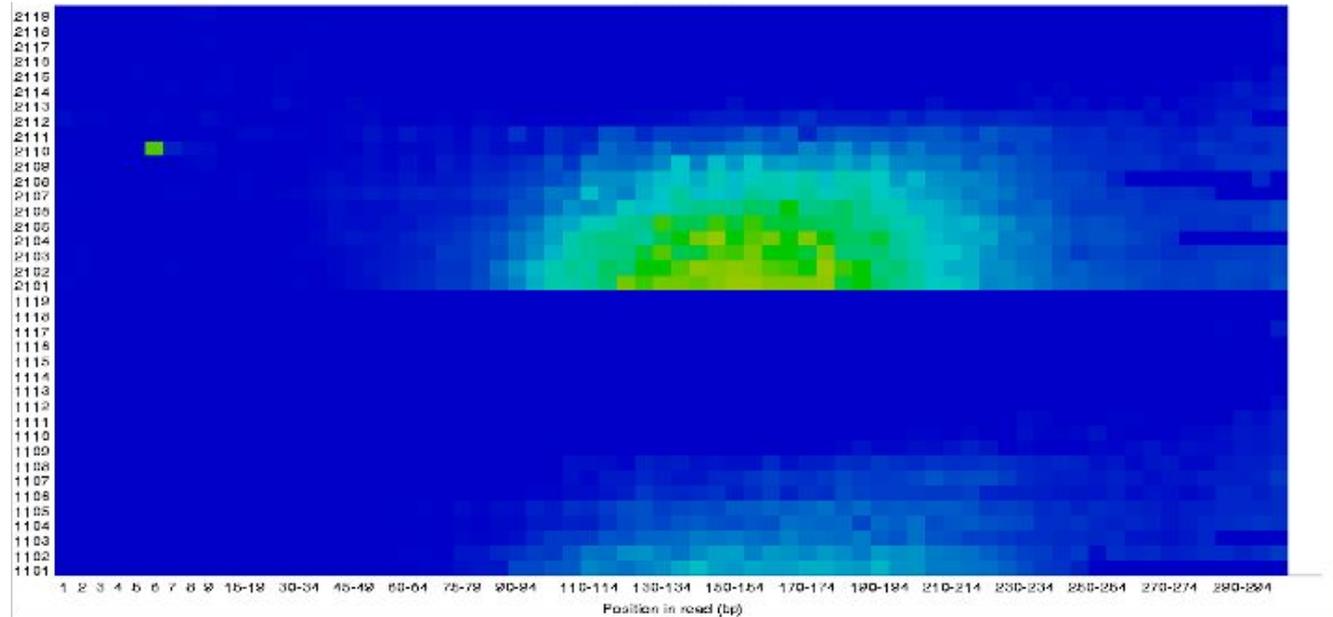
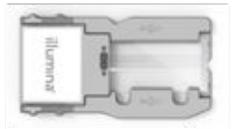
Example 1. Failed per base sequence quality - expired MiSeq kit



Failed QC Examples

Example 2. Faulty flowcell

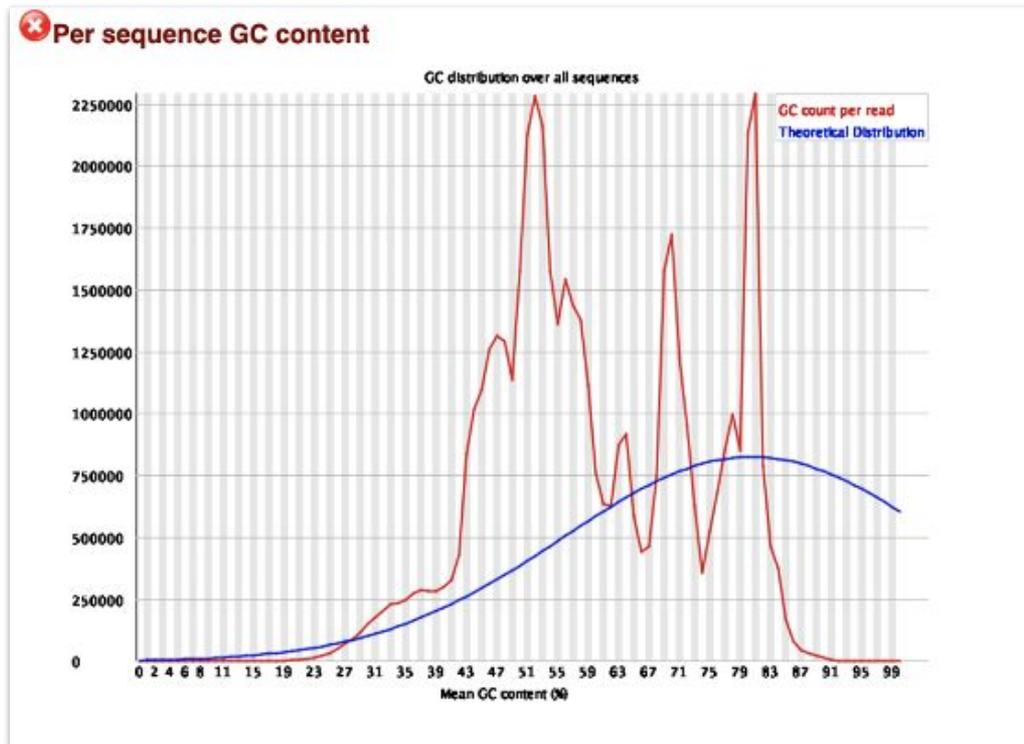
MiSeq flowcell



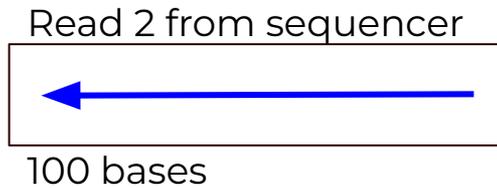
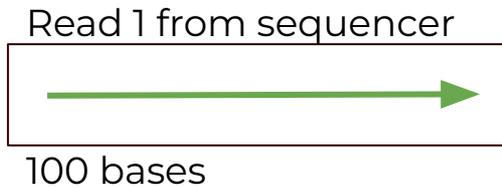
good quality  poor quality

Failed QC Examples

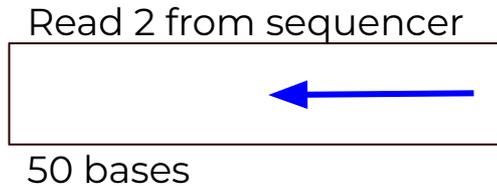
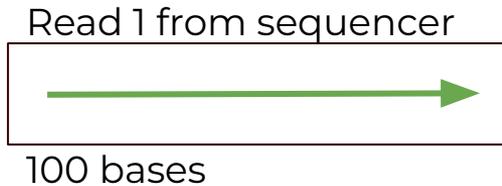
Example 3. Contamination



Library Trimming



Trimming with TrimGalore!



- Specify minimum read length (default = 20)
- Return only paired or retain unpaired

Library Trimming

- Remove loaded modules:

```
$ module purge
```

- Find and load the appropriate modules:

```
$ module spider trim_galore
```

```
$ module load GCCcore/11.2.0 Trim_Galore/0.6.10
```

- Run Trim_Galore!

```
$ trim_galore --paired --fastqc \  
    Control1_R1.fastq.gz Control1_R2.fastq.gz
```

Aligning Reads to a Reference Genome

- Popular splice-aware aligners
 - STAR (now available for GPUs!)
 - HISAT2
- Alignment software needs to have an indexed genome (software specific)
 - Only needs to be done once
 - HPRC maintains indexed genomes for popular aligners
 - Email help@hprc.tamu.edu if you would like us to add another indexed genome

Aligning Reads to a Reference Genome

- Clear any previously loaded modules:

```
$ module purge
```

- Search for and load the appropriate modules:

```
$ module spider hisat
```

```
$ module spider HISAT2/2.2.1
```

```
$ module load GCC/11.3.0 OpenMPI/4.1.4 HISAT2/2.2.1
```

- Get information on how to run the program:

```
$ hisat2 -h
```

Aligning Reads to a Reference Genome

- Align our trimmed reads to the mouse genome:
 - Path to previously indexed genome:

```
/scratch/data/bio/genome_indexes/ncbi/mm39/hisat2/GCF_000001635.27_GRCm39_genomic
```

- Set the path to the indexed genome as a new variable:

```
$ idx_genome=/path/to/genome
```

- Run the HISAT2 command

```
$ hisat2 -x $idx_genome -p 2 \  
  -1 Control1_R1_val_1.fq.gz \  
  -2 Control1_R2_val_2.fq.gz \  
  -S Control1.sam
```

Aligning Reads to a Reference Genome

```
236499 reads; of these:
  236499 (100.00%) were paired; of these:
    30736 (13.00%) aligned concordantly 0 times
    197200 (83.38%) aligned concordantly exactly 1 time
    8563 (3.62%) aligned concordantly >1 times
    ----
    30736 pairs aligned concordantly 0 times; of these:
    3583 (11.66%) aligned discordantly 1 time
    ----
    27153 pairs aligned 0 times concordantly or discordantly; of these:
    54306 mates make up the pairs; of these:
    30660 (56.46%) aligned 0 times
    21188 (39.02%) aligned exactly 1 time
    2458 (4.53%) aligned >1 times
93.52% overall alignment rate
```

Processing Alignment Files

- Alignment files may need to be modified and/or converted before any downstream analyses:
 - Sorting (name or position/coord)
 - Adding read groups
 - Converting to binary format
- We will use SAMtools to process our alignment file:

```
$ module purge
```

```
$ module spider SAMtools
```

```
$ module spider SAMtools/1.17
```

```
$ module load GCC/12.2.0 SAMtools/1.17
```

Processing Alignment Files

- Run SAMtools sort to convert and sort the alignment file in one step:

```
$ samtools sort --threads 2 \  
-o Control1_sorted.bam Control1.sam
```

- Index the new bam file:

```
$ samtools index Control1_sorted.bam
```

Generating Count Files

- There are many packages available to generate read counts:
 - featureCounts
 - GenomicRanges (R package)
 - HTSeq
- Load the required modules and produce the count table:

```
$ module purge
```

```
$ module load GCC/11.2.0 OpenMPI/4.1.1 HTSeq/2.0.1
```

```
$ htseq-count -r pos -i gene Control1_sorted.bam \  
GCF_000001635.27_GRCm39_genomic.gff > Control1_counts.txt
```

Differential Expression Analysis with DESeq2

Analyzing RNA-seq data with DESeq2

Michael I. Love, Simon Anders, and Wolfgang Huber

10/27/2021

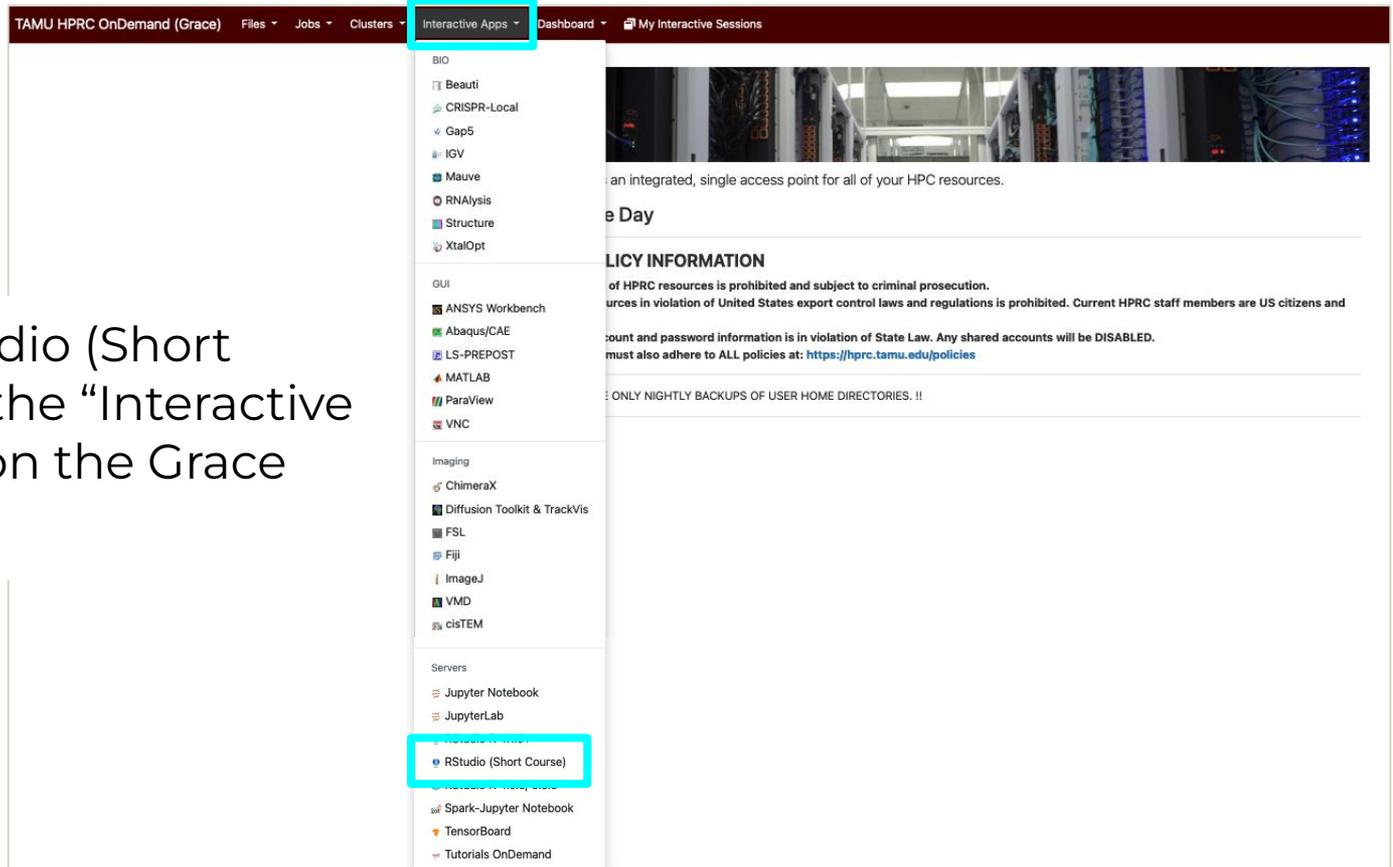
Abstract

A basic task in the analysis of count data from RNA-seq is the detection of differentially expressed genes. The count data are presented as a table which reports, for each sample, the number of sequence fragments that have been assigned to each gene. Analogous data also arise for other assay types, including comparative ChIP-Seq, HiC, shRNA screening, and mass spectrometry. An important analysis question is the quantification and statistical inference of systematic changes between conditions, as compared to within-condition variability. The package DESeq2 provides methods to test for differential expression by use of negative binomial generalized linear models; the estimates of dispersion and logarithmic fold changes incorporate data-driven prior distributions. This vignette explains the use of the package and demonstrates typical workflows. [An RNA-seq workflow](#) on the Bioconductor website covers similar material to this vignette but at a slower pace, including the generation of count matrices from FASTQ files. DESeq2 package version: 1.35.0

- Standard workflow
 - Quick start
 - How to get help for DESeq2
 - Acknowledgments
 - Funding
 - Input data
 - Why un-normalized counts?
 - The DESeqDataSet
 - Transcript abundance files and *tximport* / *tximeta*
 - Tximeta for import with automatic metadata
 - Count matrix input
 - *htseq-count* input
 - *SummarizedExperiment* input
 - Pre-filtering
 - Note on factor levels
 - Collapsing technical replicates
 - About the pasilla dataset
 - Differential expression analysis

<http://bioconductor.org/packages/devel/bioc/vignettes/DESeq2/inst/doc/DESeq2.html>

RStudio on Grace



- Open RStudio (Short Course) in the “Interactive Apps” tab on the Grace portal

RStudio on Grace

Home / My Interactive Sessions / RStudio R 4.1.0+

Interactive Apps

- BIO
- Beauti
- CRISPR-Local
- Gap5
- IGV
- Mauve
- RNAlysis
- Structure
- XtalOpt
- GUI
- ANSYS Workbench
- Abaqus/CAE
- LS-PREPOST
- MATLAB
- ParaView
- VNC
- Imaging
- ChimeraX
- Diffusion Toolkit & TrackVis

RStudio R 4.1.0+ version: 2023.09.1-494

This app will launch RStudio Server with Singularity and the R_tamu software module on a compute node.

You can install your own R packages directly within RStudio.

R version: R/4.3.1

Number of hours (max 168): 2

Number of CPU cores (max 48): 1

Total Memory in GB (max 360): 8

Number of A100 GPUs to use: 0

Select a value larger than 0 to use the GPU nodes

I would like to receive an email when the session starts

Slurm account (optional):

This field is needed ONLY IF you want to use a different account other than your default account. Leave it blank if you don't know what to provide.

Launch

* The RStudio R 4.1.0+ session data for this session can be accessed under the [data root directory](#).

- Set the number of hours to 2
- Set the number of cores to 1
- Set the Total GB memory to 8
- Click Launch Button
- Wait for the session to start
- Click “Connect to RStudio Server”

Session was successfully created. x

Home / My Interactive Sessions

Interactive Apps

- GUI
- VNC
- Nextsilicon VNC
- Imaging
- CryoSPARC
- ImageJ
- TELE

RStudio (11145) 1 node | 1 core | Running

Host: ac006

Created at: 2023-10-25 15:03:09 CDT

Time Remaining: 1 hour and 56 minutes

Session ID: 2757dadb-693d-4954-ad3d-270aaaa0c804

Connect to RStudio Server

Delete

Differential Expression Analysis

Open a new R script and set your working directory

```
setwd("/scratch/user/username/RNA_class/counts")
```

- Let's look at the contents of the directory and the sample table (in the console):

```
> list.files()
```

```
> system("cat sampleTable.csv")
```

Differential Expression Analysis

- Load the required packages:

```
library(ggplot2)
library(pheatmap)
library(DESeq2)
library(EnhancedVolcano)
```

- Highlight this section of code in the script and click “Run”

Differential Expression Analysis

- Read in the sample table and reformat it:

```
sampleTable = read.csv("sampleTable.csv", header=TRUE)
sampleTable = as.data.frame(sampleTable)
sampleTable$condition = factor(sampleTable$condition)
sampleTable
```

- Output:

```
> sampleTable
  sampleName      fileName      condition
1 Control1 Control1_counts.txt      Control
2 Control2 Control2_counts.txt      Control
3 Control3 Control3_counts.txt      Control
4 Control4 Control4_counts.txt      Control
5 Control5 Control5_counts.txt      Control
6      NAD1  NAD1_counts.txt NAD_supplement
7      NAD2  NAD2_counts.txt NAD_supplement
8      NAD3  NAD3_counts.txt NAD_supplement
9      NAD4  NAD4_counts.txt NAD_supplement
10     NAD5  NAD5_counts.txt NAD_supplement
> |
```

Differential Expression Analysis

- Create the dds object

```
dds = DESeqDataSetFromHTSeqCount(sampleTable = sampleTable,  
                                  directory = ".",  
                                  design = ~ condition)  
dds
```

- Output:

```
> dds  
class: DESeqDataSet  
dim: 46316 10  
metadata(1): version  
assays(1): counts  
rownames(46316): 0610005C13Rik 0610006L08Rik ... n-TYgta9 n-Tcgca44  
rowData names(0):  
colnames(10): Control1 Control2 ... NAD4 NAD5  
colData names(1): condition  
> |
```

Differential Expression Analysis

- Filter out genes with low read counts:

```
keep <- rowSums(counts(dds)) >= 10  
dds <- dds[keep,]
```

- Run the differential expression analysis:

```
dds <- DESeq(dds)  
res <- results(dds)  
res
```

Differential Expression Analysis

DESeq Results Explained:

```
> res
log2 fold change (MLE): condition NAD supplement vs Control
Wald test p-value: condition NAD supplement vs Control
DataFrame with 46316 rows and 6 columns
```

	baseMean	log2FoldChange	lfcSE	stat	pvalue	padj
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
0610005C13Rik	5.99463012842517	0.847110388480526	1.0536757176372	0.803957398183298	0.4214215791485	0.626767086797856
0610006L08Rik	0.595406936513421	-1.33338402962542	2.80181545117752	-0.475900020133387	0.634145607845708	NA
0610009B22Rik	229.572854136365	-0.46059738889209	0.272726760296267	-1.688860265827	0.0912462113650002	0.227131423458176
0610009E02Rik	52.7148015454124	-1.18516447577791	0.483501805720158	-2.45121003015211	0.0142376849790884	0.058533268492583
0610009L18Rik	5.27096640148362	0.500548878654153	1.0060551707554	0.497536211933899	0.618810973397835	0.779869206330055

Differential Expression Analysis

DESeq Results Explained:

```
> res
```

```
log2 fold change (MLE): condition NAD supplement vs Control
```

```
Wald test p-value: condition NAD supplement vs Control
```

```
DataFrame with 46316 rows and 6 columns
```

	baseMean	log2FoldChange	lfcSE	stat	pvalue	padj
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
0610005C13Rik	5.99463012842517	0.847110388480526	1.0536757176372	0.803957398183298	0.4214215791485	0.626767086797856
0610006L08Rik	0.595406936513421	-1.33338402962542	2.80181545117752	-0.475900020133387	0.634145607845708	NA
0610009B22Rik	229.572854136365	-0.46059738889209	0.272726760296267	-1.688860265827	0.0912462113650002	0.227131423458176
0610009E02Rik	52.7148015454124	-1.18516447577791	0.483501805720158	-2.45121003015211	0.0142376849790884	0.058533268492583
0610009L18Rik	5.27096640148362	0.500548878654153	1.0060551707554	0.497536211933899	0.618810973397835	0.779869206330055



Mean of normalized
counts for all samples

Differential Expression Analysis

DESeq Results Explained:

```
> res
```

```
log2 fold change (MLE): condition NAD supplement vs Control
```

```
Wald test p-value: condition NAD supplement vs Control
```

```
DataFrame with 46316 rows and 6 columns
```

	baseMean	log2FoldChange	lfcSE	stat	pvalue	padj
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
0610005C13Rik	5.99463012842517	0.847110388480526	1.0536757176372	0.803957398183298	0.4214215791485	0.626767086797856
0610006L08Rik	0.595406936513421	-1.33338402962542	2.80181545117752	-0.475900020133387	0.634145607845708	NA
0610009B22Rik	229.572854136365	-0.46059738889209	0.272726760296267	-1.688860265827	0.0912462113650002	0.227131423458176
0610009E02Rik	52.7148015454124	-1.18516447577791	0.483501805720158	-2.45121003015211	0.0142376849790884	0.058533268492583
0610009L18Rik	5.27096640148362	0.500548878654153	1.0060551707554	0.497536211933899	0.618810973397835	0.779869206330055



Log2 fold change: NAD
supplement vs Control

Differential Expression Analysis

DESeq Results Explained:

```
> res
```

```
log2 fold change (MLE): condition NAD supplement vs Control
```

```
Wald test p-value: condition NAD supplement vs Control
```

```
DataFrame with 46316 rows and 6 columns
```

	baseMean	log2FoldChange	lfcSE	stat	pvalue	padj
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
0610005C13Rik	5.99463012842517	0.847110388480526	1.0536757176372	0.803957398183298	0.4214215791485	0.626767086797856
0610006L08Rik	0.595406936513421	-1.33338402962542	2.80181545117752	-0.475900020133387	0.634145607845708	NA
0610009B22Rik	229.572854136365	-0.46059738889209	0.272726760296267	-1.688860265827	0.0912462113650002	0.227131423458176
0610009E02Rik	52.7148015454124	-1.18516447577791	0.483501805720158	-2.45121003015211	0.0142376849790884	0.058533268492583
0610009L18Rik	5.27096640148362	0.500548878654153	1.0060551707554	0.497536211933899	0.618810973397835	0.779869206330055

Log fold change
standard error

Differential Expression Analysis

DESeq Results Explained:

```
> res
```

```
log2 fold change (MLE): condition NAD supplement vs Control
```

```
Wald test p-value: condition NAD supplement vs Control
```

```
DataFrame with 46316 rows and 6 columns
```

	baseMean	log2FoldChange	lfcSE	stat	pvalue	padj
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
0610005C13Rik	5.99463012842517	0.847110388480526	1.0536757176372	0.803957398183298	0.4214215791485	0.626767086797856
0610006L08Rik	0.595406936513421	-1.33338402962542	2.80181545117752	-0.475900020133387	0.634145607845708	NA
0610009B22Rik	229.572854136365	-0.46059738889209	0.272726760296267	-1.688860265827	0.0912462113650002	0.227131423458176
0610009E02Rik	52.7148015454124	-1.18516447577791	0.483501805720158	-2.45121003015211	0.0142376849790884	0.058533268492583
0610009L18Rik	5.27096640148362	0.500548878654153	1.0060551707554	0.497536211933899	0.618810973397835	0.779869206330055

Wald statistic: NAD
supplement vs Control

Differential Expression Analysis

DESeq Results Explained:

```
> res
log2 fold change (MLE): condition NAD supplement vs Control
Wald test p-value: condition NAD supplement vs Control
DataFrame with 46316 rows and 6 columns
```

	baseMean	log2FoldChange	lfcSE	stat	pvalue	padj
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
0610005C13Rik	5.99463012842517	0.847110388480526	1.0536757176372	0.803957398183298	0.4214215791485	0.626767086797856
0610006L08Rik	0.595406936513421	-1.33338402962542	2.80181545117752	-0.475900020133387	0.634145607845708	NA
0610009B22Rik	229.572854136365	-0.46059738889209	0.272726760296267	-1.688860265827	0.0912462113650002	0.227131423458176
0610009E02Rik	52.7148015454124	-1.18516447577791	0.483501805720158	-2.45121003015211	0.0142376849790884	0.058533268492583
0610009L18Rik	5.27096640148362	0.500548878654153	1.0060551707554	0.497536211933899	0.618810973397835	0.779869206330055

↓
Wald test p value
(unadjusted)

Differential Expression Analysis

DESeq Results Explained:

```
> res
log2 fold change (MLE): condition NAD supplement vs Control
Wald test p-value: condition NAD supplement vs Control
DataFrame with 46316 rows and 6 columns
```

	baseMean	log2FoldChange	lfcSE	stat	pvalue	padj
	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>	<numeric>
0610005C13Rik	5.99463012842517	0.847110388480526	1.0536757176372	0.803957398183298	0.4214215791485	0.626767086797856
0610006L08Rik	0.595406936513421	-1.33338402962542	2.80181545117752	-0.475900020133387	0.634145607845708	NA
0610009B22Rik	229.572854136365	-0.46059738889209	0.272726760296267	-1.688860265827	0.0912462113650002	0.227131423458176
0610009E02Rik	52.7148015454124	-1.18516447577791	0.483501805720158	-2.45121003015211	0.0142376849790884	0.058533268492583
0610009L18Rik	5.27096640148362	0.500548878654153	1.0060551707554	0.497536211933899	0.618810973397835	0.779869206330055

BH corrected
p-values (corrected
for multiple testing)

Differential Expression Analysis

- How many genes are differentially expressed?

```
sum(res$padj <= 0.05, na.rm = TRUE)
```

- Collect all the DEGs and write them to file:

```
sigGenes <- res[ which(res$padj < 0.05), ]  
sigGenes  
write.csv(sigGenes,  
          "Differentially_Expressed.csv",  
          row.names = TRUE)
```

PCA (Principal Component Analysis)

- Log transform the results and calculate the row variance

```
logTran <- rlog(dds)
rv <- rowVars(assay(logTran))
```

- Create a list of genes with the greatest variance:

```
select <- order(rv, decreasing = TRUE)[1:100]
```

PCA plot

- Run the principal component analysis (PCA)

```
PCA <- prcomp(t(assay(logTran)[select, ]), scale = FALSE)
summary(PCA)
```

- Output:

```
> summary(PCA)
Importance of components:
      PC1      PC2      PC3      PC4      PC5      PC6      PC7      PC8      PC9      PC10
Standard deviation 13.1129 2.50384 1.94479 1.45805 1.42247 1.24092 1.08253 0.52065 0.38289 3.066e-15
Proportion of Variance 0.9084 0.03312 0.01998 0.01123 0.01069 0.00814 0.00619 0.00143 0.00077 0.000e+00
Cumulative Proportion 0.9084 0.94156 0.96154 0.97278 0.98347 0.99160 0.99779 0.99923 1.00000 1.000e+00
> |
```

PCA plot

- Set up the PCA for ggplot2

```
percentVar <- round(100*PCA$sdev^2/sum(PCA$sdev^2), 1)
ggPCA_out <- as.data.frame(PCA$x)
ggPCA_out <- cbind(ggPCA_out, sampleTable)
head(ggPCA_out)
```

- Output:

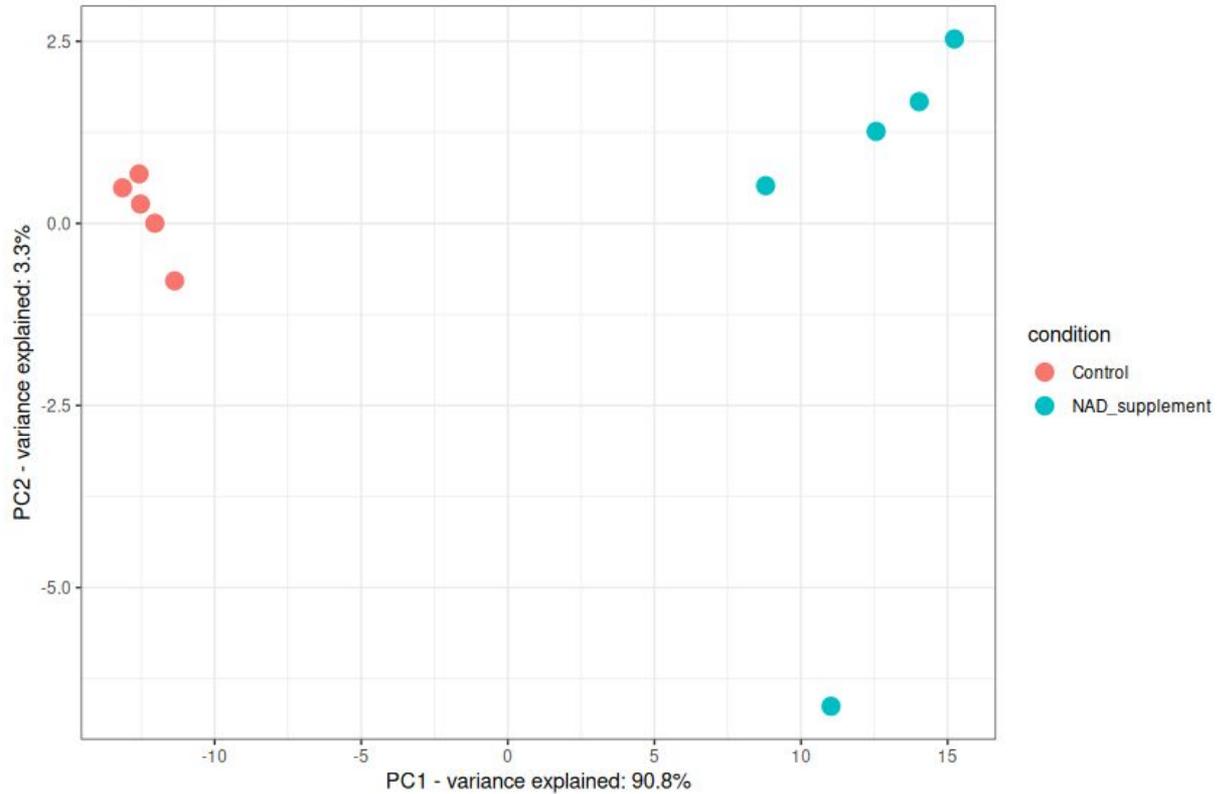
```
> head(ggPCA_out)
      PC1      PC2      PC3      PC4      PC5      PC6      PC7      PC8      PC9
Control1 -12.576882  0.679757091  1.4677571  1.4408177 -0.9772907 -2.58170153 -0.8901816  0.12856743  0.057730319
Control2 -11.362119 -0.789437801 -4.1149258  0.5846590 -1.6247299  0.15350772  1.1461662 -0.21539578  0.001565017
Control3 -12.038043  0.002152241  0.5811305 -3.0992919  1.4657618 -0.97863917  1.0515499 -0.04523746 -0.046467189
Control4 -13.139919  0.487982477  0.6723550  2.2531953  2.6066210  1.29314839  0.3152618 -0.07647994  0.001933003
Control5 -12.530993  0.265744874  1.7077315 -1.1646465 -1.8470308  2.10751112 -1.1715371  0.07993858 -0.013573324
NAD1      8.795471  0.517771986 -2.7475597 -0.6142266  1.1887028 -0.04330035 -1.5880439  0.71154077  0.323683075
      PC10 sampleName      fileName      condition
Control1 3.175046e-15 Control1 Control1_counts.txt Control
Control2 2.950899e-15 Control2 Control2_counts.txt Control
Control3 2.730071e-15 Control3 Control3_counts.txt Control
Control4 3.300727e-15 Control4 Control4_counts.txt Control
Control5 2.949020e-15 Control5 Control5_counts.txt Control
NAD1     2.826141e-15 NAD1     NAD1_counts.txt NAD_supplement
> |
```

PCA plot

- Plot the PCA

```
ggplot(ggPCA_out, aes(x=PC1,y=PC2,color=condition)) +  
  geom_point(size=4) +  
  labs(x = paste0("PC1 - variance explained: ", percentVar[1], "%"),  
       y = paste0("PC2 - variance explained: ", percentVar[2], "%")) +  
  theme_bw()
```

PCA plot

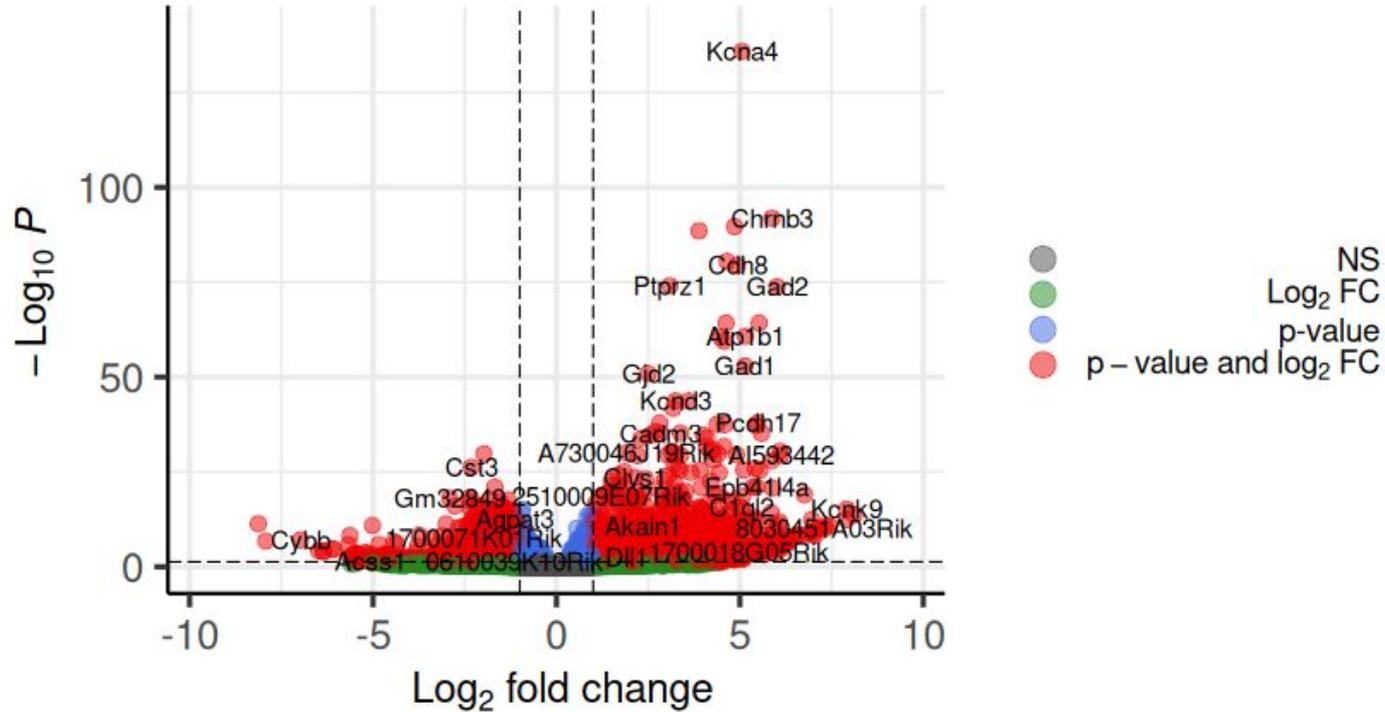


Volcano Plot

```
EnhancedVolcano(res,  
                lab = rownames(res),  
                x = 'log2FoldChange',  
                y = 'padj',  
                pCutoff = 0.05,  
                FCcutoff = 1.0,  
                pointSize = 3.0,  
                labSize = 4.0,  
                colAlpha = 1/2,  
                drawConnectors = FALSE,  
                legendPosition = "right")
```

Volcano plot

EnhancedVolcano



total = 23595 variables

Heatmap

- Reorder the results based on adjusted p-values
- Assign genes with adjusted p-values below 0.05 and absolute log2 fold changes ≥ 6.5 to the variable 'sig'

```
resorted_deresults <- res[order(res$padj),]  
sig <- resorted_deresults[!is.na(resorted_deresults$padj) &  
                           resorted_deresults$padj < 0.05 &  
                           abs(resorted_deresults$log2FoldChange) >=  
6.5,]
```

Heatmap

- Assign the gene names from 'sig' to a new variable named 'selected'
- We will use the list of gene names for the heatmap

```
selected <- rownames(sig)
selected
```

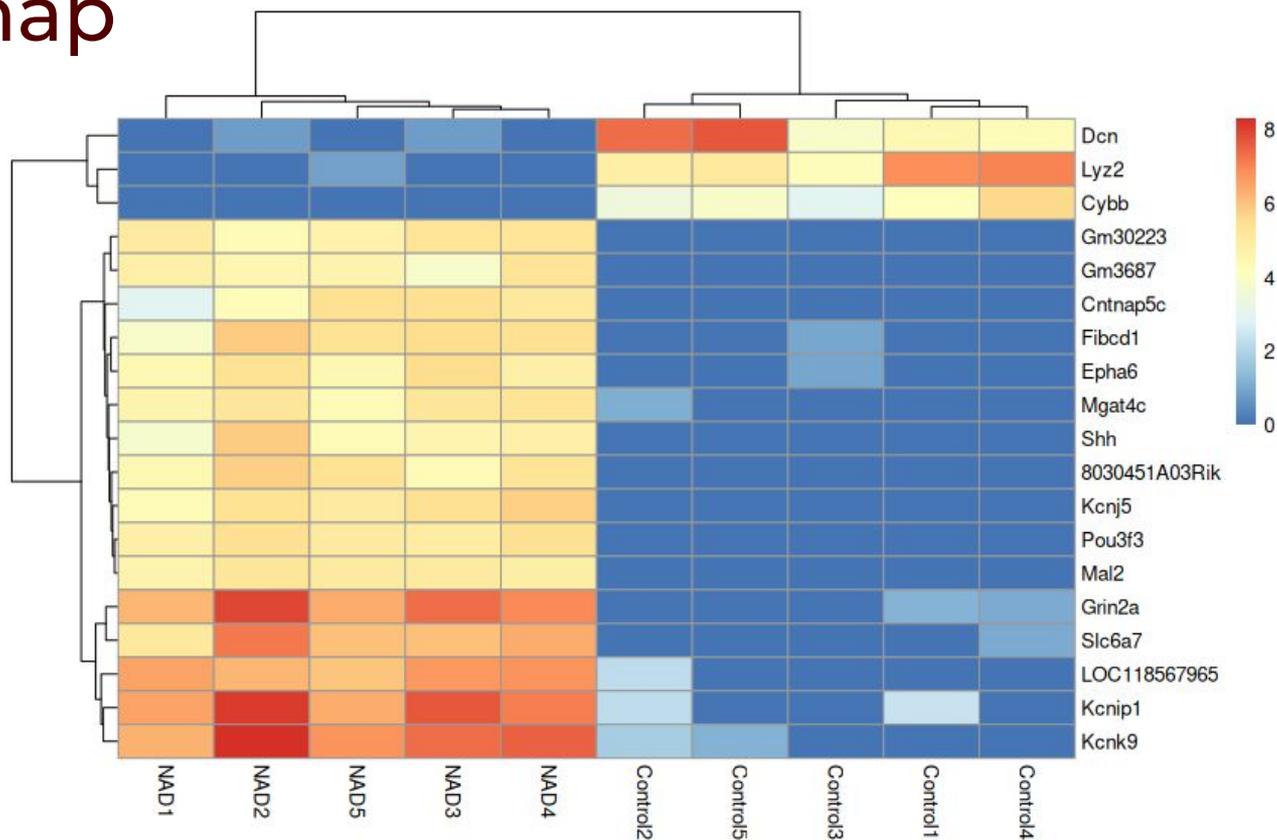
```
> selected
[1] "Kcnip1"      "Kcnk9"      "Grin2a"     "Slc6a7"     "LOC118567965" "Lyz2"
[7] "Pou3f3"     "Kcnj5"     "Ma12"      "8030451A03Rik" "Gm30223"     "Fibcd1"
[13] "Gm3687"     "Shh"       "Mgat4c"    "Cntnap5c"   "Epha6"      "Cybb"
[19] "Dcn"
> |
```

Heatmap

- We need to normalize the data
- Then we can create a heatmap using the pheatmap package

```
transformed_readcounts <- normTransform(dds)
pheatmap(assay(transformed_readcounts)[selected,],
         cluster_rows = TRUE, show_rownames = TRUE,
         cluster_cols = TRUE,
         labels_col = colData(dds)$sampleName)
```

Heatmap





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Help us help you. Please include details in your request for support, such as, Cluster (Faster, Grace, ACES, Launch), NetID (UserID), Job information (Job id(s), Location of your jobfile, input/output files, Application, Module(s) loaded, Error messages, etc), and Steps you have taken, so we can reproduce the problem.

