

# RNA-seq to study HIV Infection in cells

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- ✓ Consultation on Projects and Grants
- ✓ High Performance Compute Cluster
- ✓ Workshops

https://it.tufts.edu/research-technology

### Outline

Bulk and single cell RNA sequencing

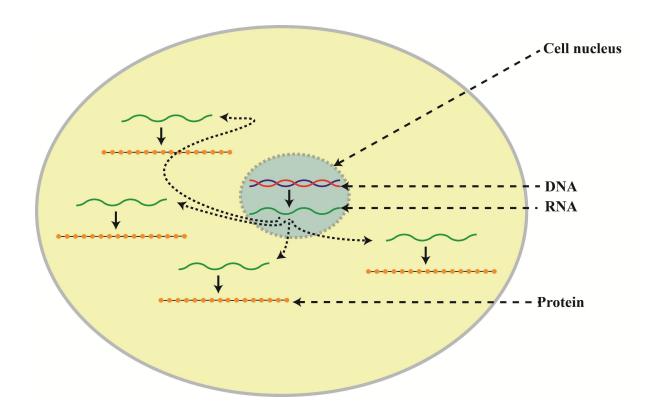
Intro to Galaxy Platform for Bioinformatics (Tufts network or VPN required)

https://galaxy.cluster.tufts.edu/

Work through RNAseq example together on Galaxy

https://rbatorsky.github.io/in tro-to-rnaseq-with-galaxy/ 2 days!

#### DNA and RNA in a cell

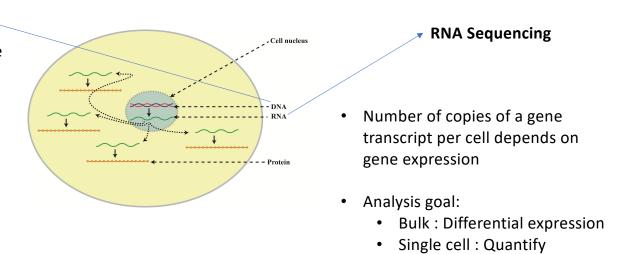


https://i0.wp.com/science-explained.com/wp-content/uploads/2013/08/Cell.jpg

#### Two common analyses

#### **DNA Sequencing**

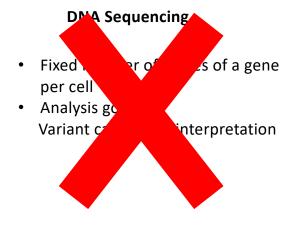
- Fixed number of copies of a gene per cell
- Analysis goal: Variant calling and interpretation

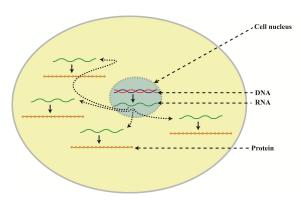


https://i0.wp.com/science-explained.com/wp-content/uploads/2013/08/Cell.jpg

different cell populations

#### Today we will cover RNA sequencing





#### **RNA Sequencing**

- Number of copies of a gene transcript per cell depends on gene expression
- Analysis goal:
  - Bulk: Differential expression
  - Single cell: Quantify different cell populations

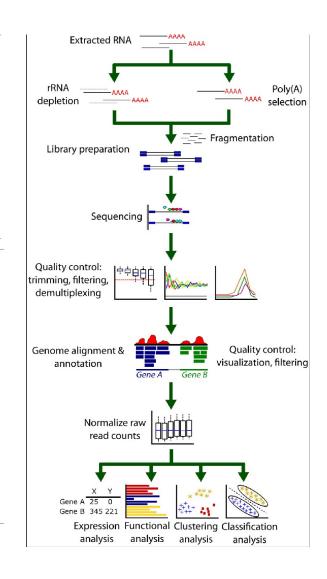
https://i0.wp.com/science-explained.com/wp-content/uploads/2013/08/Cell.jpg

### "Bulk" RNA seq workflow

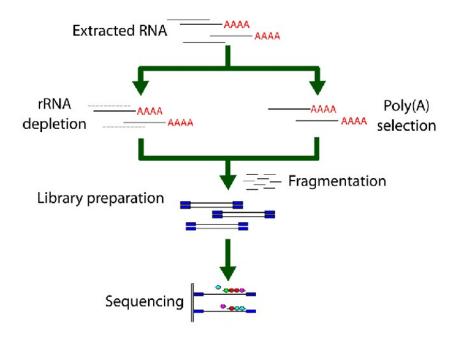
Library prep and sequencing

**Bioinformatics** 

Good resource: Griffiths et al Plos Comp Bio 2015



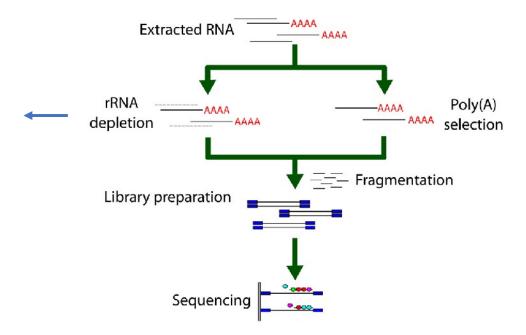
### RNA seq library prep and sequencing



Good resource: Griffiths et al Plos Comp Bio 2015

#### RNA seq library prep and sequencing

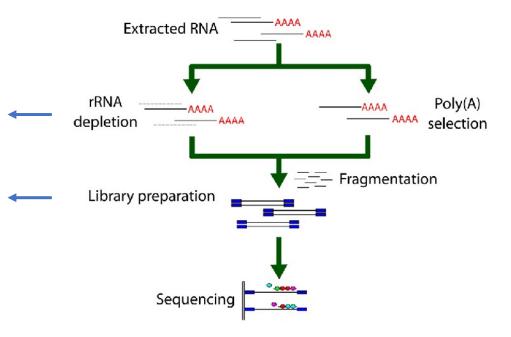
- Enrichment for mRNA, two options
- In humans, ~95%–98% of all RNA molecules are rRNAs



Good resource: Griffiths et al Plos Comp Bio 2015

#### RNA seq library prep and sequencing

- Enrichment for mRNA, two options
- In humans, ~95%–98% of all RNA molecules are rRNAs
- Random priming and reverse transcription
- Double stranded cDNA synthesis
- Sequencing adapter ligation



#### Resources:

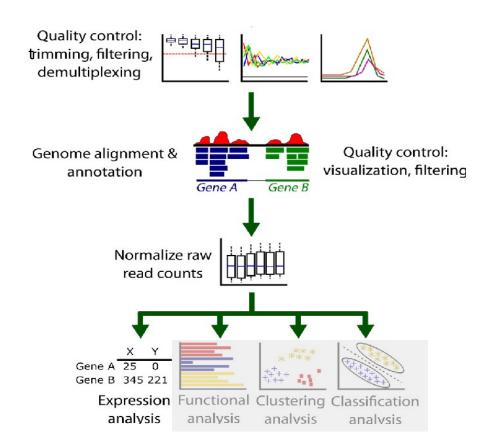
Illumina Sequencing by Synthesis Griffiths et al Plos Comp Bio 2015

#### RNA seq bioinformatics

**Goal of Differential Expression** 

"How can we detect genes for which the counts of reads change between conditions more systematically than as expected by chance"

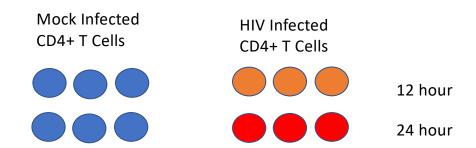
Oshlack et al. 2010. From RNA-seq reads to differential expression results. Genome Biology 2010, 11:220



#### Our dataset

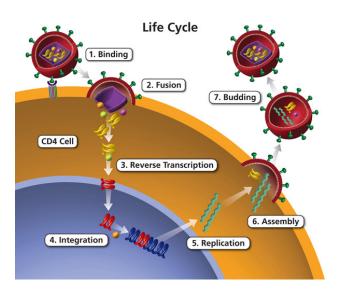
## Next-Generation Sequencing Reveals HIV-1-Mediated Suppression of T Cell Activation and RNA Processing and Regulation of Noncoding RNA Expression in a CD4<sup>+</sup> T Cell Line

Stewart T. Chang, Pavel Sova, Xinxia Peng, Jeffrey Weiss, G. Lynn Law, Robert E. Palermo, Michael G. Katze



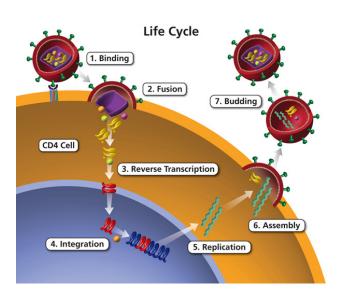
https://www.ncbi.nlm.nih.gov/pubmed/21933919

### HIV lifecycle

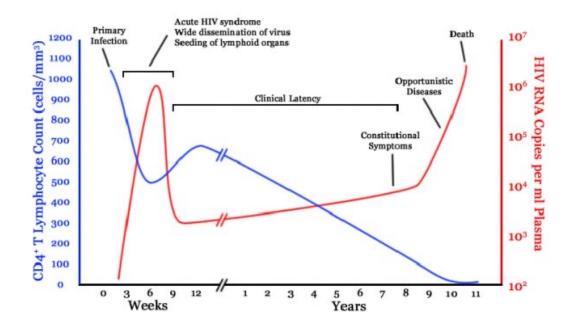


https://aidsinfo.nih.gov/understanding-hiv-aids/glossary/1596/life-cycle

### HIV lifecycle



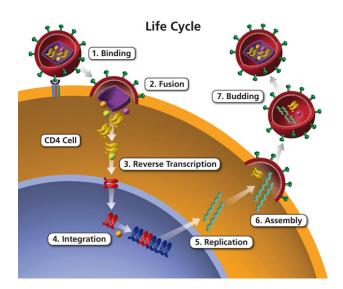
#### HIV infection in a human host

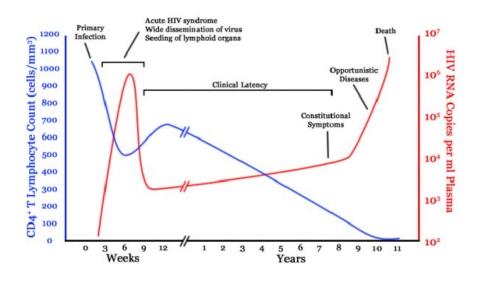


https://aidsinfo.nih.gov/understanding-hiv-aids/glossary/1596/life-cycle

#### The study question

What changes take place in the first 12-24 hours of HIV infection in terms of gene expression of host cell and viral replication levels?





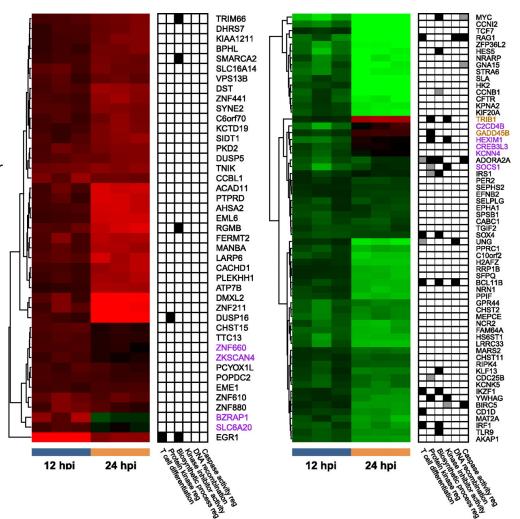
https://aidsinfo.nih.gov/understanding-hiv-aids/glossary/1596/life-cycle

### Study findings

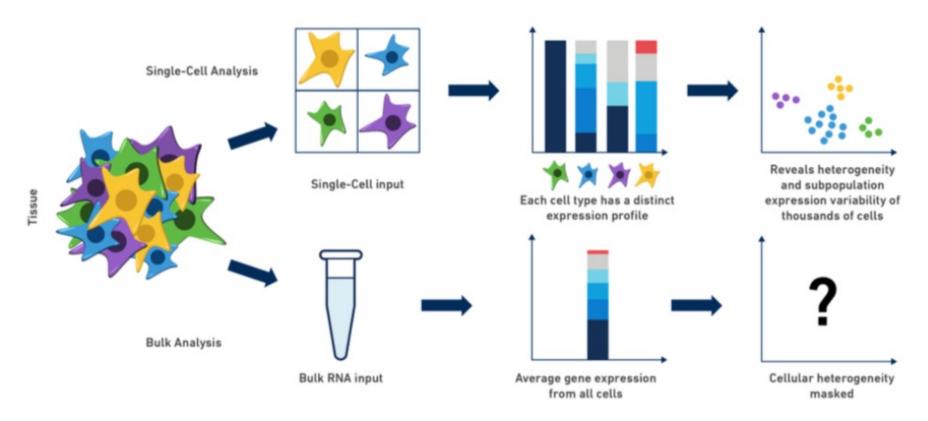
Using RNAseq, authors demonstrate:

- 20% of reads mapped to HIV at 12 hr, 40% at 24hr
- Downregulation of T cell differentiation genes at 12hr
- 'Large-scale disruptions to host transcription' at 24hr



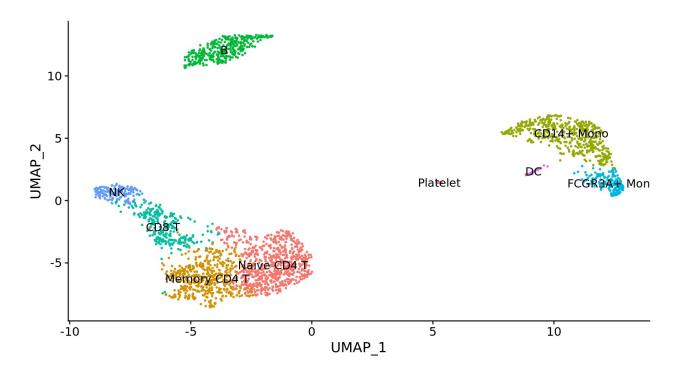


#### Bulk vs Single Cell RNA Sequencing



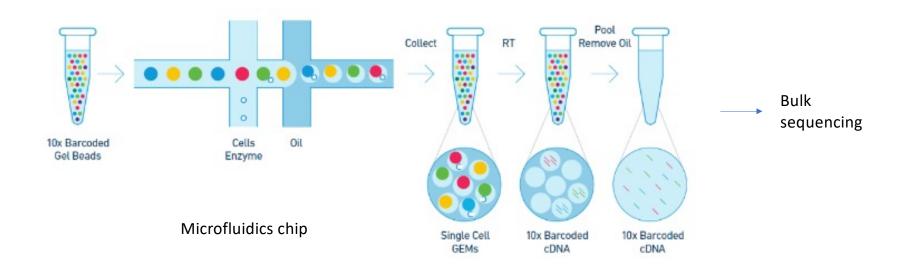
https://www.10xgenomics.com/blog/single-cell-rna-seq-an-introductory-overview-and-tools-for-getting-started

#### scRNA cell subsets in PBMC



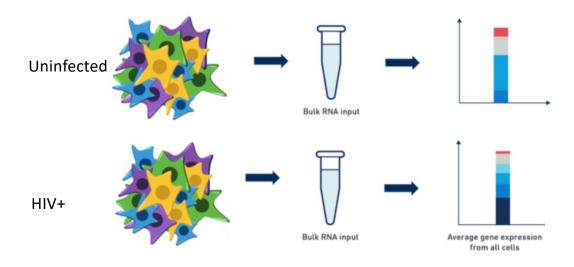
https://satijalab.org/seurat/v3.2/pbmc3k\_tutorial.html

### 10x single cell technology



https://github.com/hbctraining/scRNA-seq

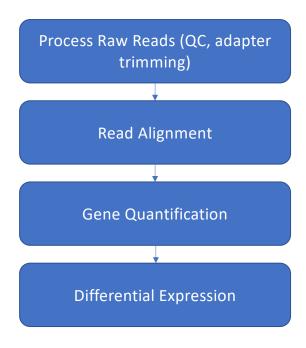
#### Bulk RNAseq for Differential Expression is OK!



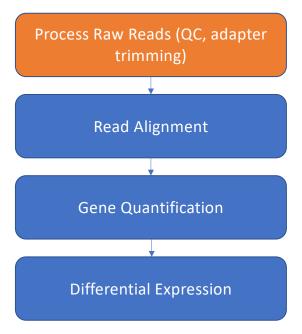
Compare relative gene expression between conditions

https://www.10 x genomics.com/blog/single-cell-rna-seq-an-introductory-overview-and-tools-for-getting-started

### Our (bulk) RNAseq Workflow



#### Quality control on Raw Reads



#### Raw reads in Fastq format

@SRR098401.109756285

GACTCACGTAACTTTAAACTCTAACAGAAATATACTA...

+

CAEFGDG?BCGGGEEDGGHGHGDFHEIEGGDDDD...

- 1. Sequence identifier
- 2. Sequence
- 3. + (optionally lists the sequence identifier again)
- 4. Quality string

#### **Base Quality Scores**

The symbols we see in the read quality string are an encoding of the quality score:

```
Quality encoding: !"#$%&'()*+,-./0123456789:;<=>?@ABCDEFGHI
```

A quality score is a prediction of the probability of an error in base calling:

Quality Score	Probability of Incorrect Base Call	Inferred Base Call Accuracy
10 (Q10)	1 in 10	90%
20 (Q20)	1 in 100	99%
30 (Q30)	1 in 1000	99.9%

#### Base Quality Scores

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10 (Q10)	1 in 10	90%
20 (Q20)	1 in 100	99%
30 (Q30)	1 in 1000	99.9%

#### Back to our read:

@SRR098401.109756285
GACTCACGTAACTTTAAACTCTAACAGAAATATACTA...
+
CAEFGDG?BCGGGEEDGGHGHGDFHEIEGGDDDD...

 $C \rightarrow Q = 34 \rightarrow Probability < 1/1000 of an error$ 

https://www.illumina.com/science/education/sequencing-quality-scores.html

#### Raw read quality control

#### Fastq File

@SRR497699.30343179.1 HWI-EAS39X\_10175\_FC61MK0\_4\_117\_4812\_10346 length=75 CAGATGGCCGCAGAGGAAGCCCTGCAGGGAGACCGGGAAGAGCGGTTCAGCAGGAATGCCGAGAC

+

+

+

HHHHHHHHHHHGGGGGHHHGHGEBEEGGEDGGGGGGHHHHHGGEGBDGGGDDGBGGC < EADBEBE < GGGGBEEDGD

#### **Metrics**

Sequence Quality

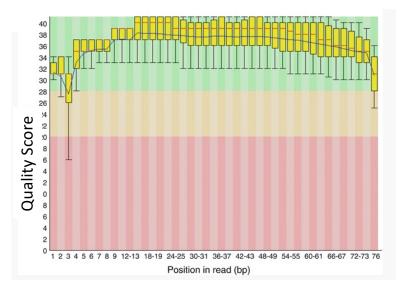
GC content

FastQC Tool

• Per base sequence content

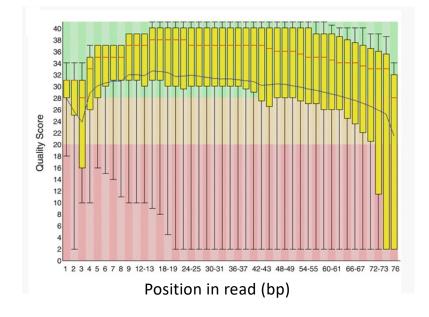
Adapters in Sequence

### FastQC: Sequence Quality Histogram



Position in read (bp)

GOOD
High quality over the length of the read

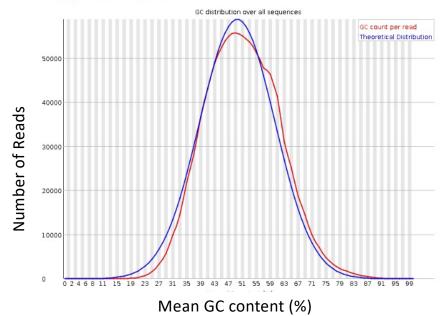


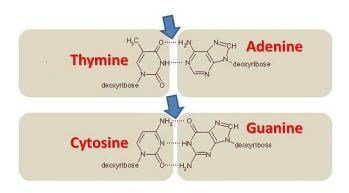
BAD
Read quality drops at the beginning and end



### FastQC: Per sequence GC content

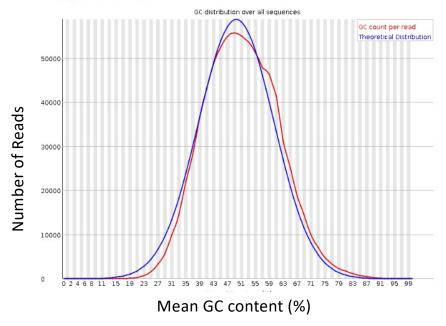
#### Per sequence GC content





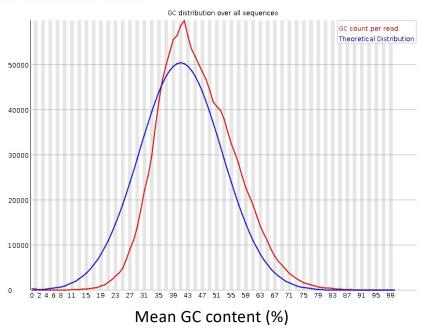
#### FastQC: Per sequence GC content

#### Per sequence GC content



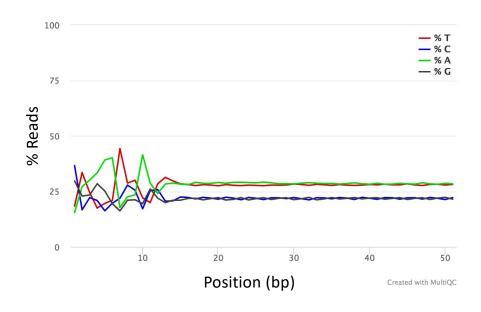
GOOD: follows normal distribution (sum of deviations is < 15% of reads)

#### **Per sequence GC content**



BAD: can indicate contamination with adapter dimers, or another species

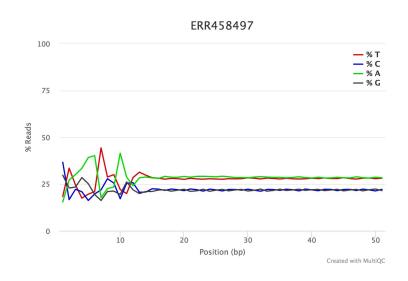
#### FastQC: Per Base Sequence Content



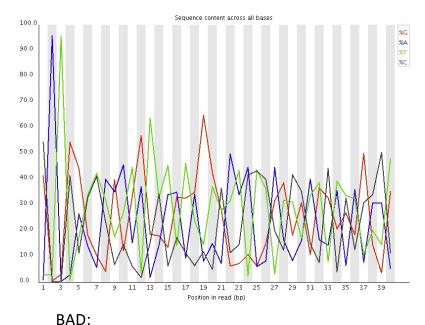
- Proportion of each position for which each DNA base has been called
- RNAseq data tends to show a positional sequence bias in the first ~12 bases
- The "random" priming step during library construction is not truly random and certain hexamers are more prevalent than others

sequencing.qcfail.com

#### FastQC: Per Base Sequence Content

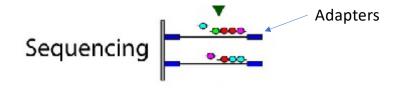


**EXPECTED** for RNAseq



Shows a strong positional bias throughout the reads, which in this case is due to the library having a certain sequence that is overrepresented

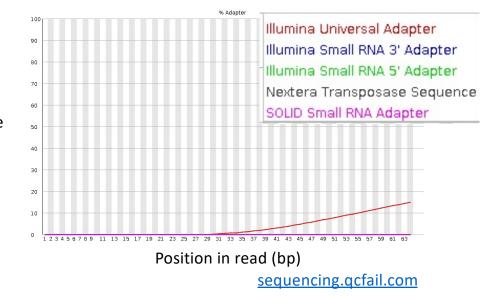
#### FastQC: Adapter content



FastQC will scan each read for the presence of known adapter sequences

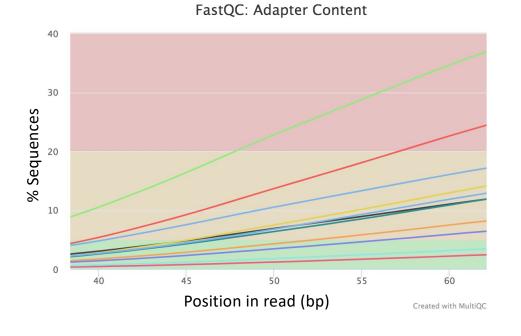
The plot shows that the adapter content rises over the course of the read

Solution – Adapter trimming!



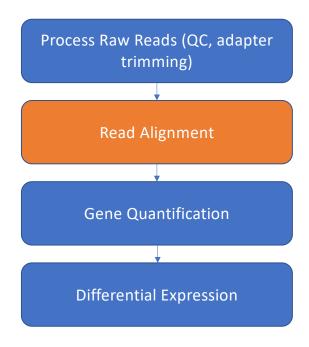
#### FastQC -> MultiQC

Should view all samples at once to notice abnormalities for our dataset.



We'll use a tool called "Trim Galore!" to trim adapters and remove low quality bases/reads.

#### Workflow



#### Read Alignment

- RNAseq data originates from spliced mRNA (no introns)
- When aligning to the genome, our aligner must find a spliced alignment for reads
- We use a tool called STAR (Spliced Transcripts Alignment to a Reference) that has a exon-aware mapping algorithm.

cDNA fragments

sequencing

aligned reads

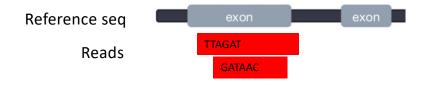
exon

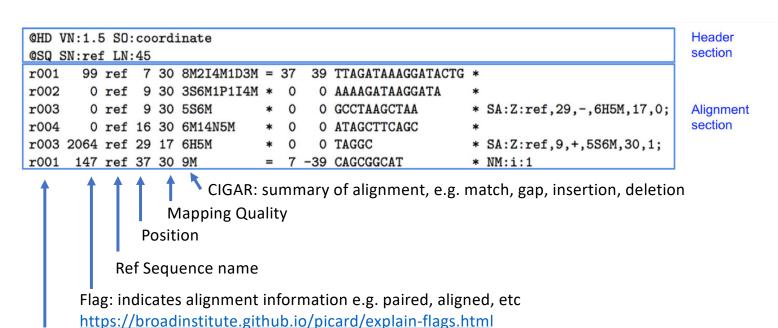
exon

Reference sequence

**Dobin et al Bioinformatics 2013** 

#### Sequence Alignment Map (SAM)

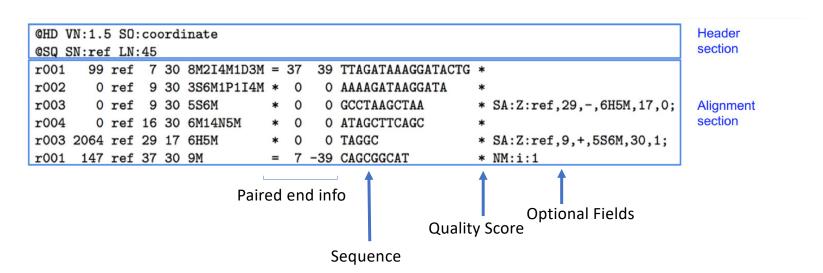




Read ID www.samformat.info

# Sequence Alignment Map (SAM)

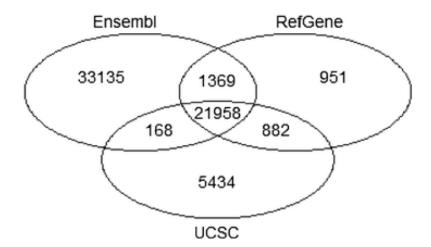




www.samformat.info

#### Genome Annotation Standards

- STAR can use an annotation file gives the location and structure of genes in order to improve alignment in known splice junctions
- Annotation is dynamic and there are at least three major sources of annotation
- The intersection among RefGene, UCSC, and Ensembl annotations shows high overlap. RefGene has the fewest unique genes, while more than 50% of genes in Ensembl are unique
- Be consistent with your choice of annotation source!



Zhao et al Bioinformatics 2015

## Gene Annotation Format (GTF)

In order to count genes, we need to know where they are located in the reference sequence STAR uses a Gene Transfer Format (GTF) file for gene annotation

							Ha	
						Stra	and	
Chrom	Source	Feature type	Start	Stop	(Scc			Attribute
			120465402	120155050				: LUECDAU
chr5	hg38_refGene	exon	138465492	138466068	<u> </u>	+		gene_id "EGR1";
chr5	hg38_refGene	CDS	138465762	138466068		+	0	gene_id "EGR1";
-					† ·	<del>                                     </del>	_	80,
chr5	hg38_refGene	start_codon	138465762	138465764		+		gene_id "EGR1";
chr5	hg38 refGene	CDS	138466757	138468078		+	2	gene_id "EGR1";
chr5	hg38 refGene	exon	138466757	138469315		+		gene id "EGR1";
			İ	İ				<u> </u>
chr5	hg38_refGene	stop_codon	138468079	138468081		+		gene_id "EGR1";

https://useast.ensembl.org/info/website/upload/gff.html

#### A note on standards

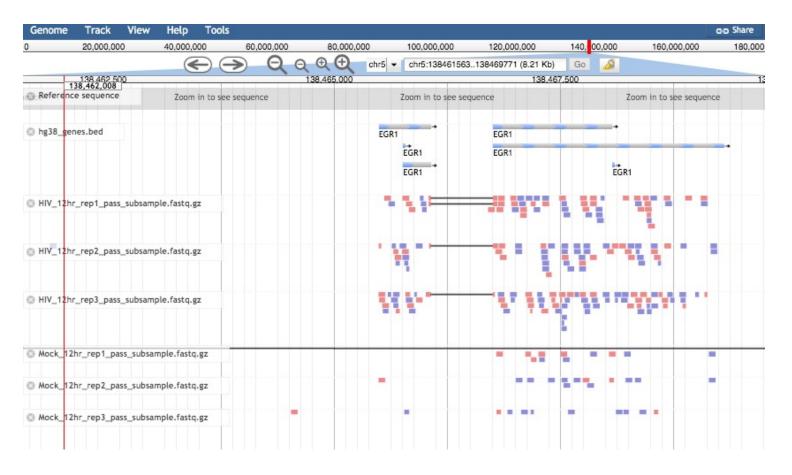
HOW STANDARDS PROLIFERATE: (SEE: A/C CHARGERS, CHARACTER ENCODINGS, INSTANT MESSAGING, ETC.)

SITUATION: THERE ARE 14 COMPETING STANDARDS.

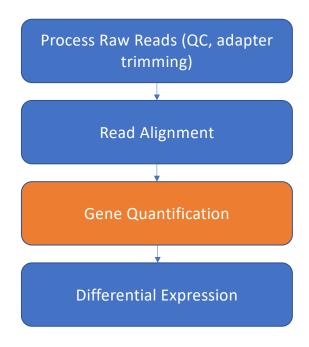


SOON: SITUATION: THERE ARE 15 COMPETING STANDARDS.

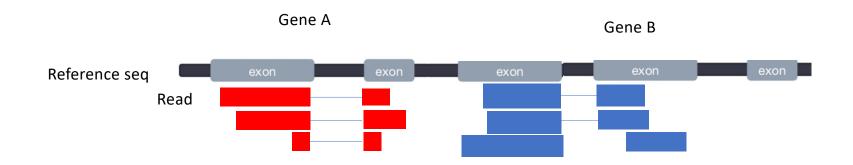
# Visualizing reads with JBrowse



### Workflow

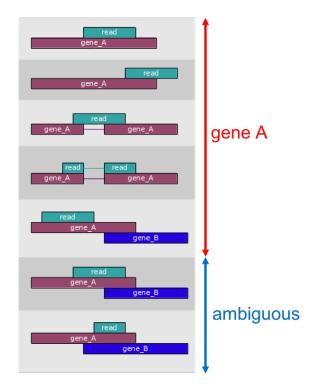


# Counting reads for each gene



# Counting reads: featurecounts

- The mapped coordinates of each read are compared with the features in the GTF file
- Reads that overlap with a gene by >=1 bp are counted as belonging to that feature
- Ambiguous reads will be discarded

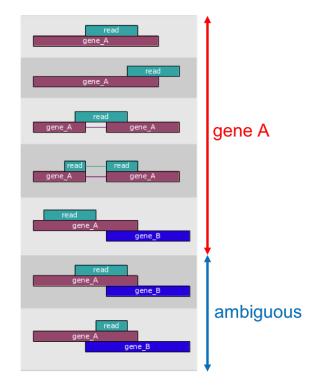


# Counting reads: featurecounts

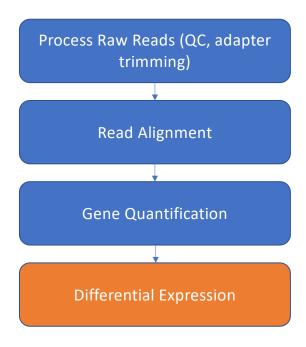
- The mapped coordinates of each read are compared with the features in the GTF file
- Reads that overlap with a gene by >=1 bp are counted as belonging to that feature
- Ambiguous reads will be discarded

#### Result is a gene count matrix:

Gene	Sample 1	Sample 2	Sample 3	Sample 4
Α	1000	1000	100	10
В	10	1	5	6
С	10	1	10	20

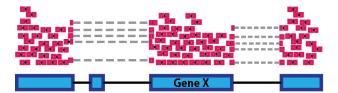


### Workflow



- Raw Count != Expression strength
- Normalization:
  - Eliminates factors that are not of interest for our experiment
  - Enables accurate comparison between samples or genes

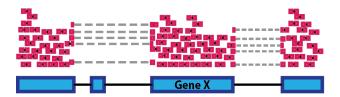
#### **Sample A Reads**

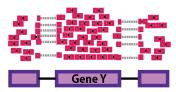


The number of reads mapped to a gene depends on

• Gene Length

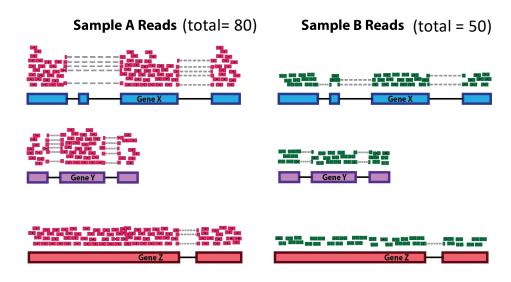
#### **Sample A Reads**





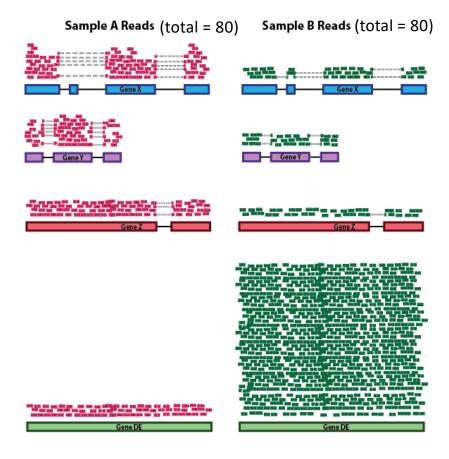
The number of reads mapped to a gene depends on

- Gene Length
- Sequencing depth



The number of reads mapped to a gene depends on

- Gene Length
- Sequencing depth
- The expression level of other genes in the sample (RNA Composition)

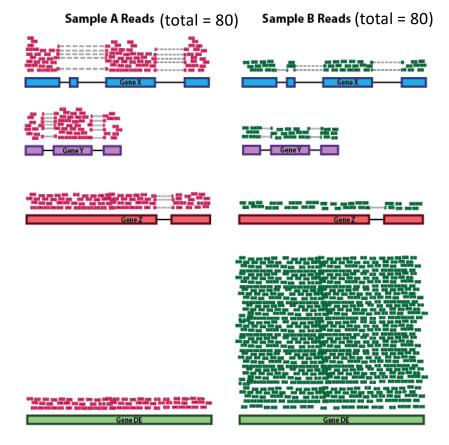


Adapted from https://hbctraining.github.io/DGE\_workshop

The number of reads mapped to a gene depends on

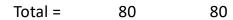
- Gene Length
- Sequencing depth
- The expression level of other genes in the sample (RNA Composition)

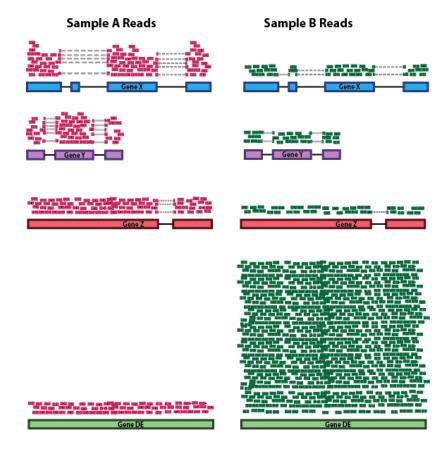
**DESeq2 Median of Ratios** 



Adapted from https://hbctraining.github.io/DGE workshop

Gene	Sample A	Sample B
Χ	26	10
Υ	26	10
Z	26	10
DE	2	50





1. Take a row-wise average to produce an average sample (geometric mean)  $\sqrt[n]{x_1}$ 

$\sqrt[n]{x_1 x_2}$	•	•	•	$\overline{x_r}$
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Gene	Sample A	Sample B	Avg. Sample
Χ	26	10	 16
Υ	26	10	16
Z	26	10	16
DE	2	50	10

1. Take a row-wise average to produce an average sample (geometric mean)  $\sqrt[n]{x_1x_2\cdots x_n}$ 

Gene	Sample A	Sample B	Avg. Sample
Χ	26	10	 16
Υ	26	10	16
Z	26	10	16
DE	2	50	10

2. Divide all rows by the Average Sample for that gene (Ratio)

Gene	Sample A/Avg.	Sample B /Avg.
X	26/16 = 1.6	10/16 = 0.6
Υ	1.6	0.6
Z	1.6	0.6
DE	0.2	5

1. Take a row-wise average to produce an average sample (geometric mean)  $\sqrt[n]{x_1x_2\cdots}$ 

Gene	Sample A	Sample B	A
Χ	26	10	
Υ	26	10	
Z	26	10	
DE	2	50	

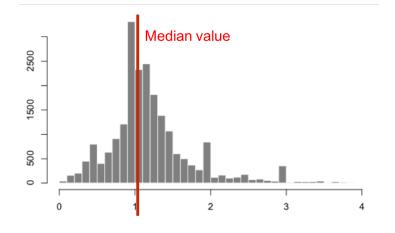
Avg. Sample
16
16
16
16

2. Divide all rows by the Average Sample for that gene (Ratio)

Gene	Sample A/Avg.	Sample B /Avg.
X	26/16 = 1.6	10/16 = 0.6
Υ	1.6	0.6
Z	1.6	0.6
DE	0.2	5

3. Take the **median** of each column. Should be ~1 for all

		Size factor	1.6	0.6
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1. Take a row-wise average to produce an average sample (geometric mean)  $\sqrt[n]{x_1x_2\cdots x_n}$ 

Gene	Sample A	Sample B	Avg. Sample
Х	26	10	16
Υ	26	10	16
Z	26	10	16
DE	2	50	16

2. Divide all rows by the Average Sample for that gene (Ratio)

Gene	Sample A/Avg.	Sample B /Avg.
X	26/16 = 1.6	10/16 = 0.6
Υ	1.6	0.6
Z	1.6	0.6
DE	0.2	5

4. Divide all counts by sample specific size factor

Gene	Sample A / S <sub>A</sub>	Sample B / S <sub>B</sub>
Χ	16.3	16.7
Υ	16.3	16.7
Z	16.3	16.7
DE	1.3	83.3

Normalized counts for non-DE genes are similar!

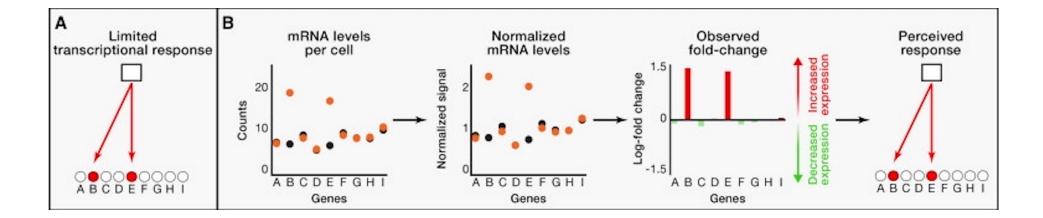
3. Take the **median** of each column. Should be ~1 for all

Size factor	1.6	0.6
-------------	-----	-----

estimateSizeFactors(dds)

## Assumption of DESeq2 Median of Ratios

Median of Ratios method assumes that most genes are not Differentially Expressed between samples.

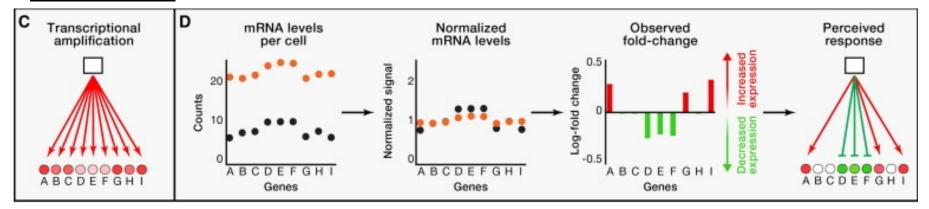


Loven et al "Revisiting Global Gene Expression Analysis" Cell 2012 https://doi.org/10.1016/j.cell.2012.10.012

## Assumption of DESeq2 Median of Ratios

Median of Ratios method assumes that most genes are not Differentially Expressed between samples.

#### **COUNTER EXAMPLE**



- Late stage cell death (total RNA DOWN)
- High c-Myc cells (total RNA UP)

Known quantity spike-in transcripts (ERCC) can be used to normalize in these cases.

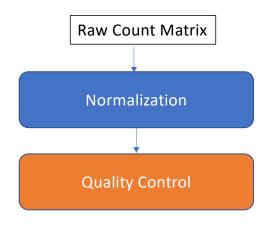
Loven et al "Revisiting Global Gene Expression Analysis" Cell 2012 https://doi.org/10.1016/j.cell.2012.10.012

### Normalization methods

Normalization method	Description	Accounted factors	Recommended use	
CPM (counts per million)	K <sub>i</sub> Total Reads per Sample/10 <sup>6</sup>	sequencing depth	Comparison between replicates of the sample group	
<b>R/FPKM</b> (reads/fragments per kilobase of exon per million reads/fragments mapped)	$\frac{K_{i}}{\textit{Gene Length}/10^{3}*\;\textit{Total Reads per Sample}/10^{6}}$	sequencing depth and gene length	Comparison between genes in a sample	
DESeq2's median of ratios [1]	$K_{i}$ divided by sample-specific size factors	sequencing depth and RNA composition	Differential Expression between samples	

Similar to DESeq2: EdgeR, limma-voom

# **Quality Control Visualizations**



Examine sources of variation in the data

- Principal Component Analysis
- Hierarchical Clustering

(Log2 + 1) Transformed, Normalized Count Table

Gene	Sample A	Sample B	Sample C
1	1	1.6	0.5
2	2.2	-0.2	1
3	-1	1	3.1

# Principle Component Analysis

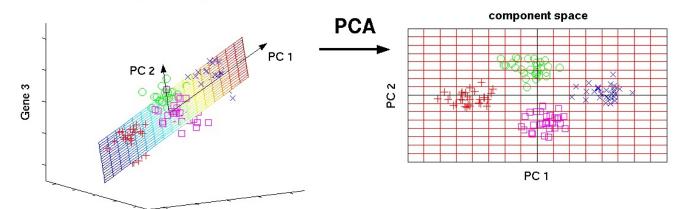
Dimension reduction technique Example: 3 gene dimensions -> 2 PC

Gene	Mock_12h	Mock_12h	Mock_24h	Mock_24h	HIV_12h	HIV_12h	HIV_24h	HIV_24h
Gene 1	8.9	8.9	8.9	9.0	8.9	8.9	9.0	6.8
Gene 2	0.6	-1.0	0.6	-1.0	0.6	-1.0	0.6	3.8
Gene 3	4.1	11.9	4.1	-0.5	4.1	8.7	4.0	4.4

#### original data space

Gene 1

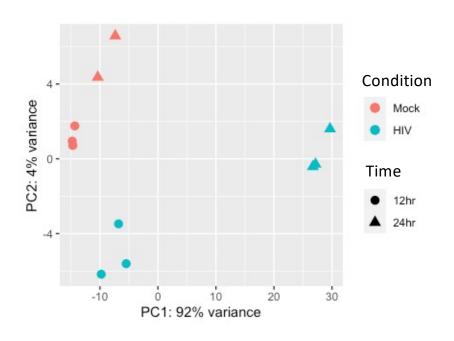
Gene 2



Do your samples cluster as expected?

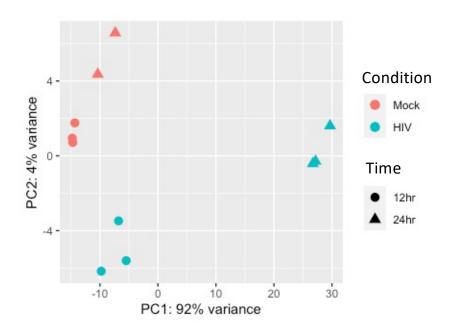
What are the major sources of variation in the data?

# Principle Component Analysis



- ✓ Do your samples cluster as expected?
- ✓ What are the major sources of variation in the data?

# Principle Component Analysis



- ✓ Do your samples cluster as expected?
- ✓ What are the major sources of variation in the data?
- ✓ Is there a batch effect?

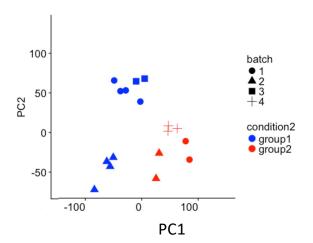
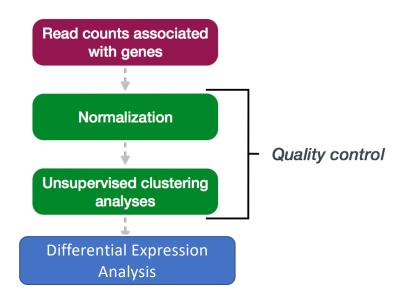
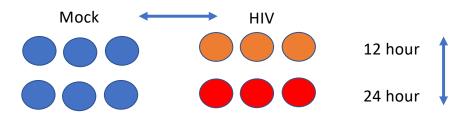


Image https://support.bioconductor.org/p/111491/

# Differential Expression with DESeq2



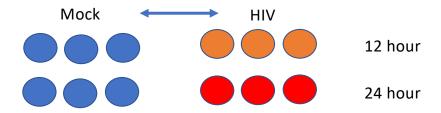
# Multi-factor experiment design



Factor 1: Infection status (Mock or HIV)

Factor 2: Time (12 or 24 hr)

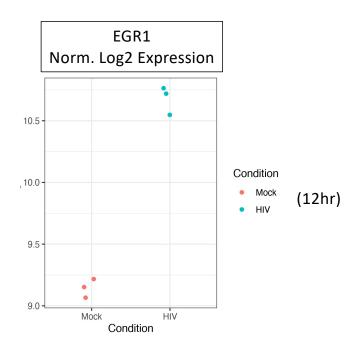
## Multi-factor experiment design



- Differential Expression compares two conditions
- We'll choose Infection status at 12 hr (Mock or HIV) for comparison
- We could also choose time, or a combination of multiple factors

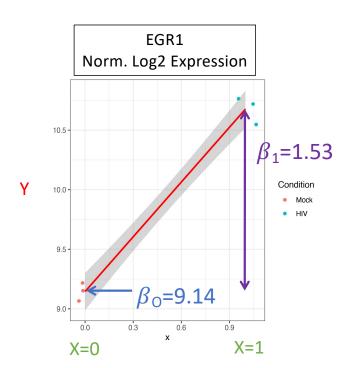
# Step 1: Modeling gene expression values

All leading DE tools use regression models to estimate the fold change between conditions for each gene



# Step 1: Modeling gene expression values

All leading DE tools use **regression models** to estimate the fold change between conditions for **each gene** Example, simple linear regression:

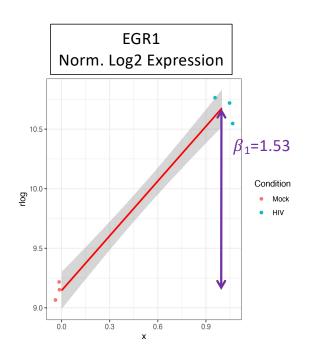


Intercept Condition (0-Mock, 1-HIV) 
$$Y = \beta_o + \beta_1 X + e$$
 Log2 Slope: Gifference difference between Mock/HIV

DESeq2 uses a Generalized Linear Model with a Negative Binomial error Distribution, which has been shown to be best fit for RNAseq data.

Love, M.I., Huber, W. & Anders, S. Moderated estimation of fold change and dispersion for RNA-seq data with DESeq2. *Genome Biol* **15**, 550 (2014).

### Step 2: Hypothesis Testing



Is EGR1 differentially expressed?

Yes! p << 0.05

$$H_0: \beta_1 = 0$$
 vs.  $H_A: \beta_1 \neq 0$ 

H<sub>o</sub>: there is no systematic difference between the average read count values for Mock vs. HIV

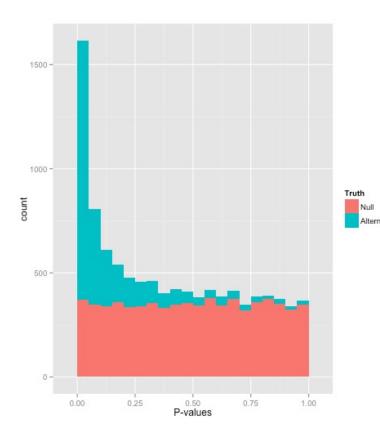
- Statistical test Wald test (similar to t-test) on  $\beta_1$
- $Z = \beta_1/SE_{\beta_1}$
- Z-statistic is compared to the normal distribution and probability of getting a statistic at least as extreme is computed

# DESeq2 Results table

GenelD	Base mean	log2FoldChange	StdErr	P-value	P-adj
EGR1	1273	1.55	0.13	1.19e-77	1.52e-73
MYC	5226	-1.53	0.14	1.63e-36	1.03e-32

- Mean of normalized counts averaged over all samples from two conditions (HIV, Mock)
- · Log of the fold change between two conditions
- StdErr Standard error of coefficient (e.g. b<sub>1</sub>)
- P-value the probability that the Wald statistic is as extreme as observed if H<sub>O</sub> were true
- P-adj accounting for multiple testing correction

# DESeq2 P-value histogram



- Histogram of raw p-values for all genes examined
- P-value: Probability of getting a log2FoldChange as extreme as observed if the true log2FoldChange = 0 for that gene (null hypothesis)

#### How to interpret:

 Random P-values are expected to be uniform, if you have true positives you should see a peak close to zero

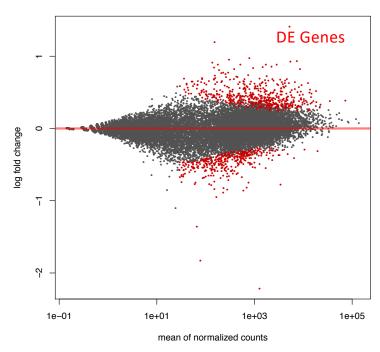
http://varianceexplained.org/statistics/interpreting-pvalue-histogram/

# DESeq2 MA plot

#### Shows the relationship between

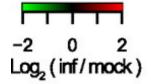
- M: The difference in expression Log(HIV) – Log(Mock) = Log(HIV/Mock)
- A: Average expression strength Average(Mock, HIV)
- Genes with adjusted p-value < 0.1 are in red</li>
- Gives an overview of your results

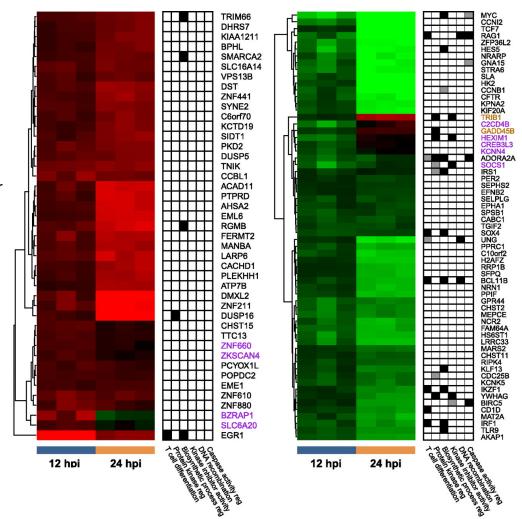
#### MA-plot for condition: mock vs hiv



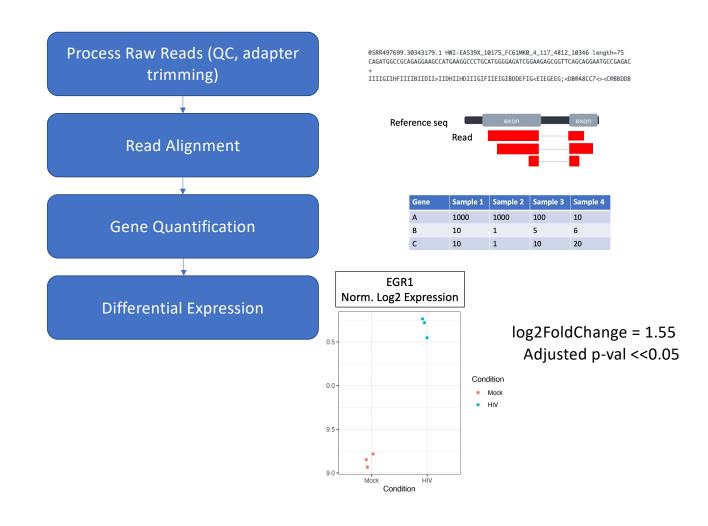
# Study findings

- T cell differentiation-related genes were overrepresented in the DEG at 24hr
- 'Large-scale disruptions to host transcription' at 24hr





## Conclusions



### References

#### DESeq2 vignette (R/Rstudio):

http://www.bioconductor.org/packages/release/bioc/vignettes/DESeq2/inst/doc/DESeq2.html#differential-expression-analysis

HBC Training (Command line/R):

https://hbctraining.github.io/DGE workshop

Galaxy Training:

https://galaxyproject.org/tutorials/rb\_rnaseq/

# Outline

Bulk and single cell RNA sequencing

Intro to Galaxy Platform for Bioinformatics (Tufts network or VPN required)

https://galaxy.cluster.tufts.edu/

Work through RNAseq example together on Galaxy

https://rbatorsky.github.io/in tro-to-rnaseq-with-galaxy/

Turn in workshop questions on Canvas



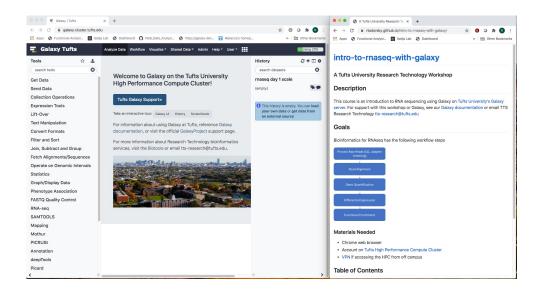
- \* Web-based platform for running data analysis and integration, geared towards bioinformatics
  - > Open-source
  - > Developed at Penn State, Johns Hopkins, OHSU and Cleveland Clinic with many more outside contributions
  - Large and extremely responsive community

## Access Galaxy

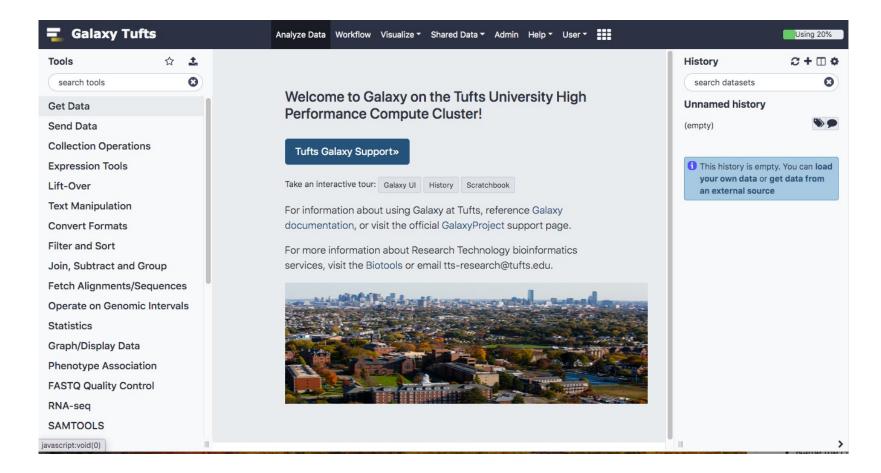
- 1. Connect to Tufts Network, either on campus or via <a href="VPN">VPN</a>
- 2. Visit <a href="https://galaxy.cluster.tufts.edu/">https://galaxy.cluster.tufts.edu/</a>
- 3. Log in with you cluster username and password
- 4. In another browser window go to course workflow:

https://rbatorsky.github.io/intro-to-rnaseq-with-galaxy/

#### **Suggested screen layout**



#### User Interface



### User Interface

**TOOLS** 

**Collection Operations** 

**Expression Tools** 

**Text Manipulation** 

**Convert Formats** 

Join, Subtract and Group

Fetch Alignments/Sequences
Operate on Genomic Intervals

Filter and Sort

Statistics

RNA-seq
SAMTOOLS
javascript:void(0)

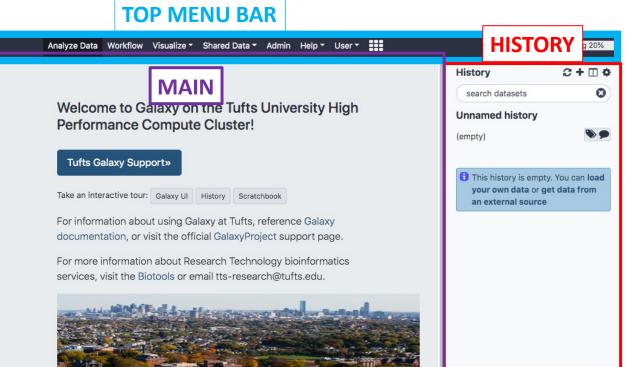
Graph/Display Data
Phenotype Association
FASTQ Quality Control

search tools

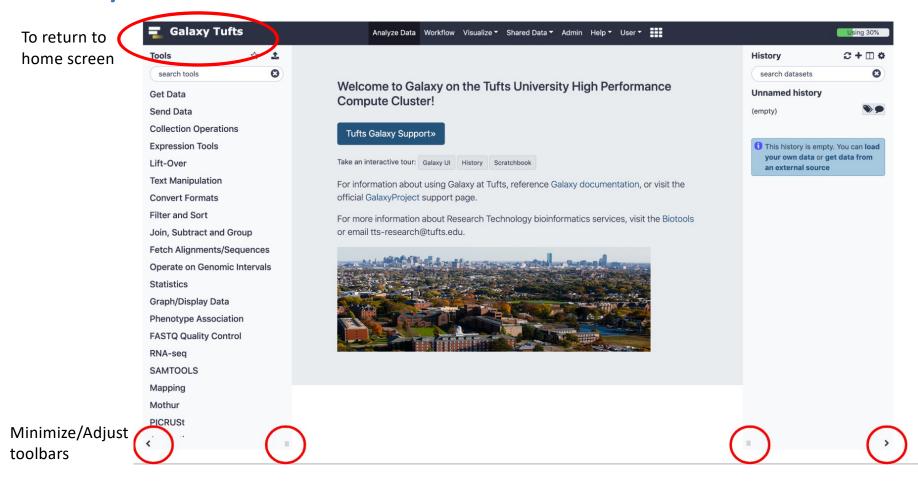
**Get Data** 

Send Data

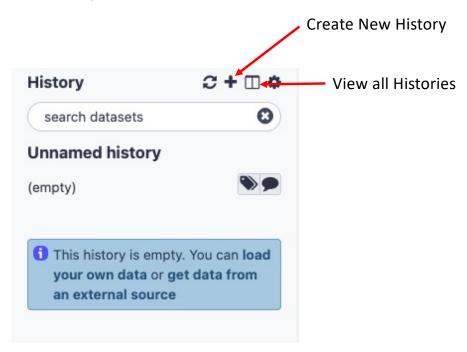
Lift-Over



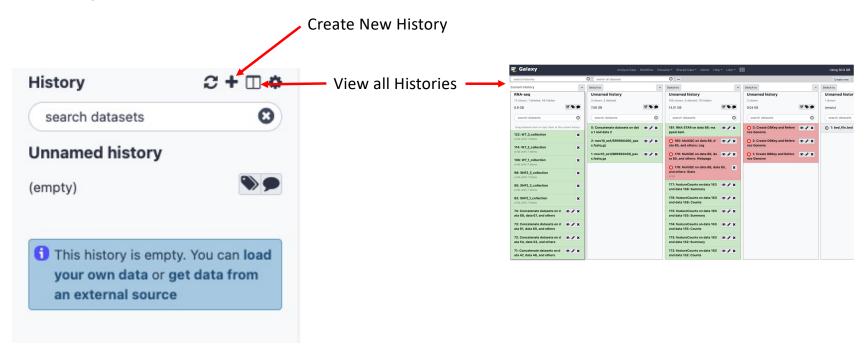
## Galaxy User Interface



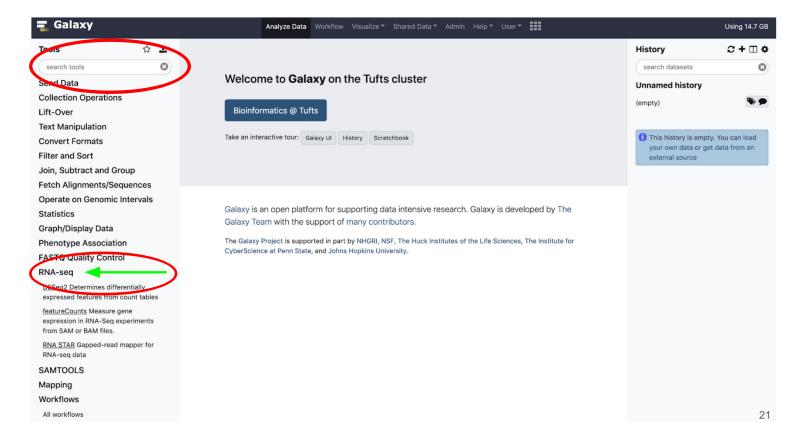
# History



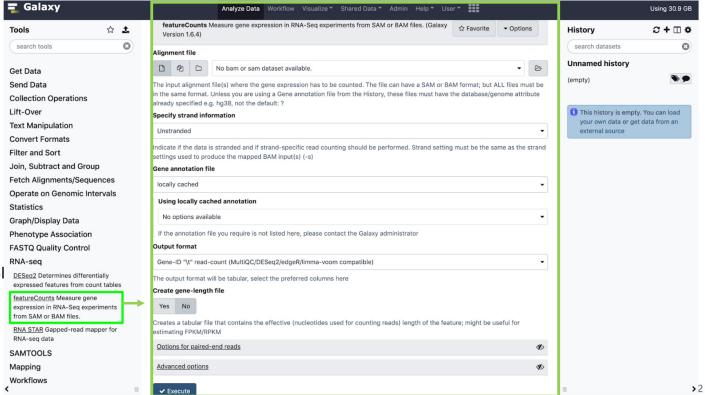
# History



### **Tools**

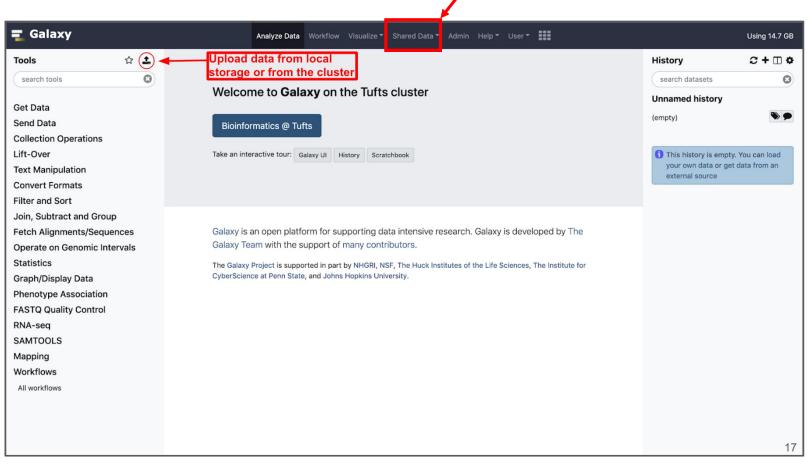


#### **Tools**



Click on the name of the tool to open it in the main panel

# Importing data



Import shared data libraries

## Access Galaxy

- 1. Connect to Tufts Network, either on campus or via <a href="VPN">VPN</a>
- 2. Visit <a href="https://galaxy.cluster.tufts.edu/">https://galaxy.cluster.tufts.edu/</a>
- 3. Log in with you cluster username and password
- 4. In another browser window go to course workflow: <a href="https://rbatorsky.github.io/intro-to-rnaseq-with-galaxy/">https://rbatorsky.github.io/intro-to-rnaseq-with-galaxy/</a>
- 5. Under Table of Contents click on "Introduction and Setup"

#### **Suggested screen layout**

