Practical Guide to Interpreting RNA-seq Data

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Overview

I. Experimental Design Hypothesis-driven Overview of Best Practice II. Quality-control Pre- and post- alignment QC metrics Interpretation III. Pipeline FastQ Files -> Counts matrix Reproducibility IV. Downstream Analysis
 Principal Components Analysis (PCA)
 Differential Expression
 Pathway Analysis
 V. Advanced Visualizations
 Group comparisons
 Alternative Splicing Events
 Pathway Diagrams

Experimental Design

I. Experimental Design: Overview

Hypothesis-driven

Addresses a well thought-out quantifiable question

Considerations:

Library Construction: mRNA versus total RNA Single-end versus Paired-end Sequencing Sequencing Depth: quantifying gene-level or transcript-level expression Number of Replicates: statistical-power and ability drop a *bad* sample Reducing Batch Effects

I. Experimental Design: Library Construction

Total RNA contains high-levels of ribosomal RNA (rRNA): 80%

mRNA

poly(A) selection ~ standard profiling for gene expression Low RIN may results in 3' bias **Total RNA** rRNA depletion mRNA + non-coding RNA species (IncRNA) Prokaryotic samples

I. Experimental Design: Sequencing Depth

mRNA: poly(A)-selection

Recommended Sequencing Depth: 10-20M paired-end reads (or 20-40M reads)

RNA must be high quality (RIN > 8)

Total RNA: rRNA depletion

Recommended Sequencing Depth: 25-60M paired-end reads (or 50-120M reads) RNA must be high quality (RIN > 8)

* *Differential Isoform regulation or alternative splicing events*: > 100M paired-end reads

I. Experimental Design: Number of Replicates

Recommended

Biological Replicates > Technical Replicates

Number of Replicates: 4

Peace-of-mind: Ability drop a *bad* sample without compromising statistical power

Bare Minimum

Biological Replicates > Technical Replicates Number of Replicates: 3

I. Experimental Design: Reducing Batch Effects

Unwanted sources of technical variation					
Decrease batch effects by uniform process	ing				
Protocol-driven					
Different Lab Technicians					
Different processing times					
Different Reagent Lots					
Sequencing					
Lane effect					

Sai	mple Name	Group	Batch	Batch*
Trea	tment_r1	КО	1	1
Trea	tment_r2	КО	2	1
Trea	tment_r3	КО	1	1
Trea	tment_r4	КО	2	1
Cntr	l_r1	WT	1	2
Cntr	l_r2	WT	2	2
Cntr	l_r3	WT	1	2
Cntr	l_r4	WT	2	2

* Confounded Groups and Batches!

Quality Control

II. Quality-control: Overview

No need to reinvent the wheel... but there are a lot of wheels!

Pre-alignment Quality-control Sequencing Quality Contamination Screening Post-alignment Quality-control Alignment Quality Aggregation and Interpretation MultiQC Report QC metric guidelines

II. Quality-control: Pre-alignment

Sequencing Quality



II. Quality-control: Pre-alignment

FastQC (raw)

Adapter Trimming

FastQC (trimmed)

FastQC

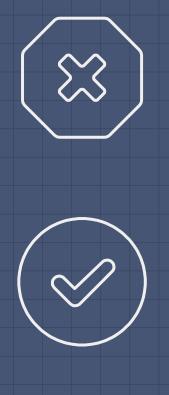
Identify potential problems that can arise during sequencing or library prep Run on raw reads (pre-adapter removal) and trimmed reads (post-adapter removal) Summarizes:

- Per base and per sequence quality scores
- Per sequence GC content
- Per sequence adapter content
- Per sequence read lengths
- Overrepresented sequences

II. Quality-control: FastQC

% GC





II. Quality-control: Pre-alignment

Adapter Trimming

Contamination Screen

Alignment

FastQ Screen

Aligns to Human, Mouse, Fungi, Bacteria, Viral references

Easy to interpret and important QC step

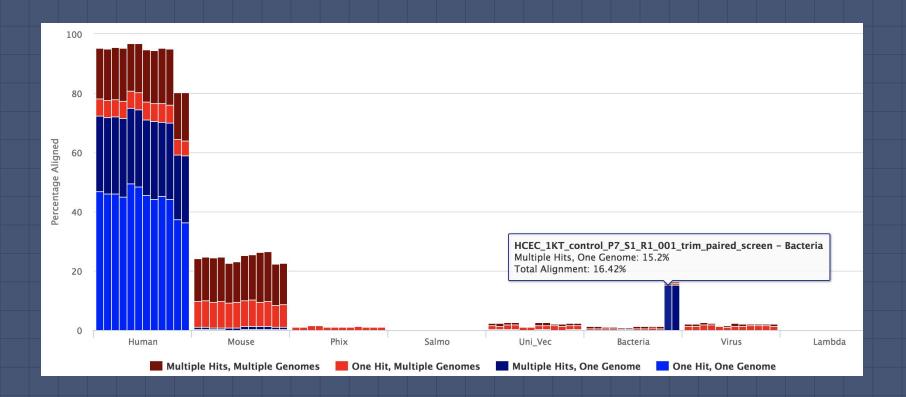
Kraken

Taxonomic composition of microbial contamination

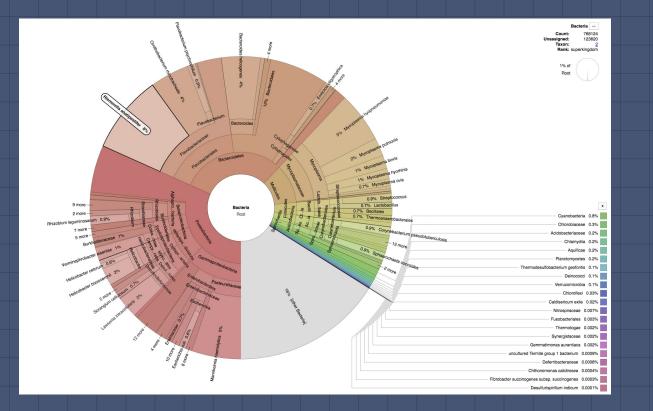
- Archaea
- Bacteria
- Plasmid
- Viral

16,7%

FastQ Screen Contamination Screening



Kraken + Krona Microbial Taxonomic Composition



II. Quality-control: Post-alignment

Alignment

Alignment Quality

Quantify Counts

Preseq

Estimates library complexity

Picard RNAseqMetrics

Number of reads that align to coding, intronic, UTR, intergenic, ribosomal regions

Normalize gene coverage across a meta-gene body

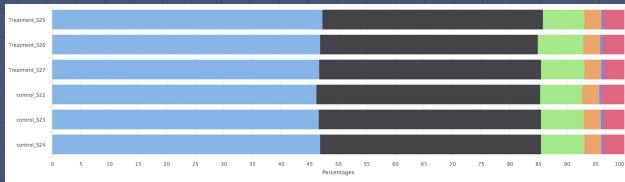
- Identify 5' or 3' bias

RSeQC

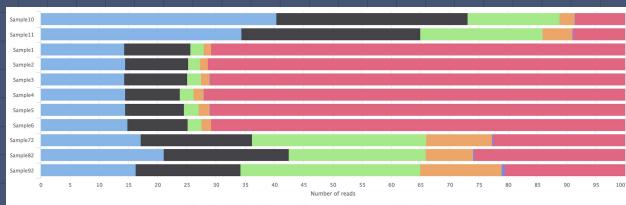
Suite of tools to assess various post-alignment quality

- Calculate distribution of Insert Size
- Junction Annotation (% Known, % Novel read spanning splice junctions)
- BAM to BigWig (Visual Inspection with IGV)

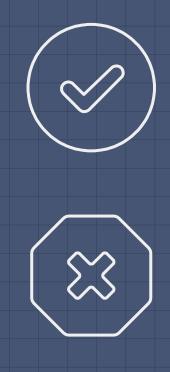
CollectRnaseqMetrics Alignment Summary



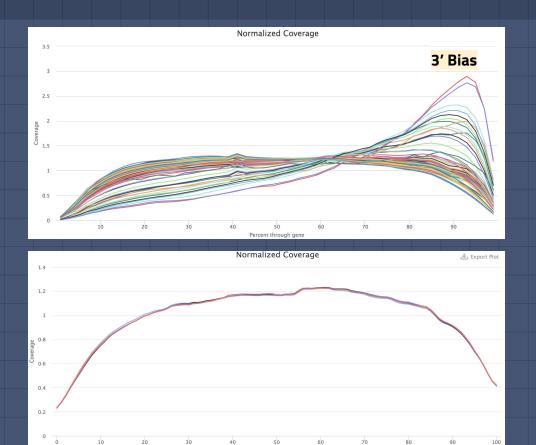




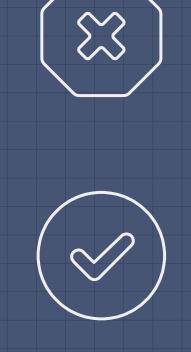
Coding UTR Intronic Intergenic Ribosomal PF not aligned



Picard CollectRnaseqMetrics Normalized Gene Coverage



Percent through gene



II. Quality-control: Aggregation

MultiQC

- HTML report that aggregates information across all samples
 - Plots, filtering, and highlighting
- Highly customizable with great documentation
 - Add text and embed custom figures
 - Create your own module to extend missing functionality
- Supports over 73 commonly-used open source bioinformatics tools

QC Metric Guidelines	mRNA	total RNA
RNA Type(s)	Coding	Coding + non-coding
RIN	> 8 [low RIN = 3' bias]	> 8
Single-end vs Paired-end	Paired-end	Paired-end
Recommended Sequencing Depth	10-20M PE reads	25-60M PE reads
FastQC	Q30 > 70%	Q30 > 70%
Percent Aligned to Reference	> 70%	> 65%
Million Reads Aligned Reference	> 7M PE reads (or > 14M reads)	> 16.5M PE reads (or > 33M reads)
Percent Aligned to rRNA	< 5%	< 15%
Picard RNAseqMetrics	Coding > 50%	Coding > 35%
Picard RNAseqMetrics	Intronic + Intergenic < 25%	Intronic + Intergenic < 40%

Pipeline

III. Processing Pipeline Conceptual Diagram

Adapters are composed of synthetic sequences and should be removed prior to alignment

Adapter Trimming

Raw data FastQ files

Alignment

Adding biological context to your data, find where reads align to the reference genome

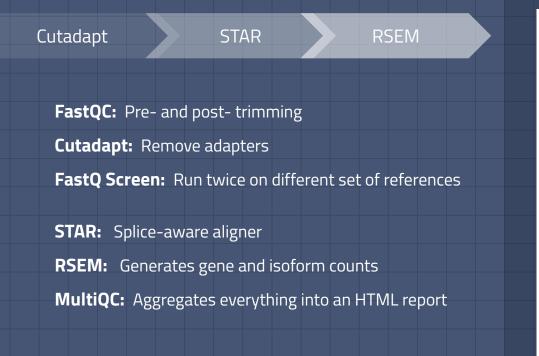
Counting the number of reads that align to particular feature of interest (genes, isoforms, etc)

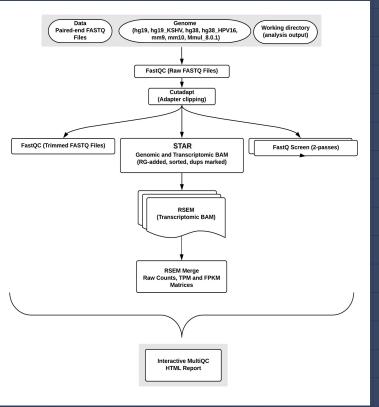
Quantification

Differential Expression

Summarizing differences between two groups or conditions (KO vs. WT)

III. Processing Pipeline Practical Example





FastQ files to raw counts matrix

III. Processing Pipeline: Reproducibility

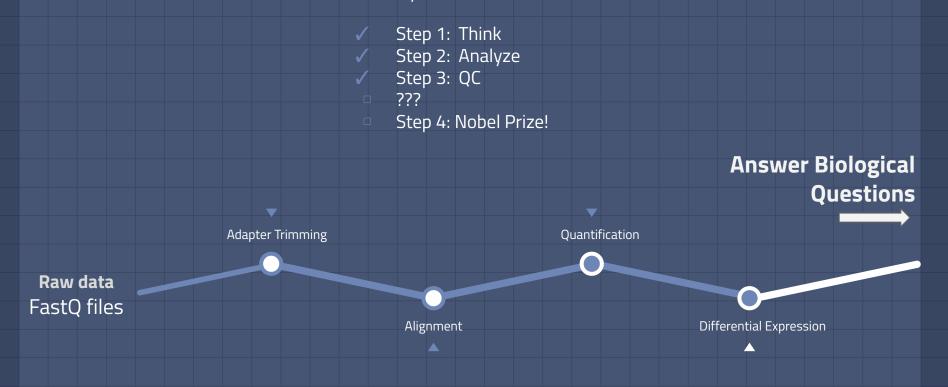
Workflow management systems

Snakemake, Nextflow

Package management

No active management: rat's nest of interdependencies prone to break Python: virtual environments Conda: Python, R, Scala, Java, C/C++, FORTRAN Docker or Singularity: Portability and high reproducibility

IV. Downstream Analysis



Principal Components Analysis (PCA)

Data summarization, visualization, and QC tool

Differential Expression

Find genes that are different between groups of interest

Pathway Enrichment

Analyze for broader biological patterns

Principal Components Analysis (PCA)

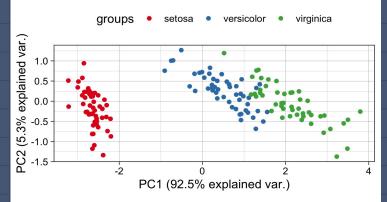
- Dimensionality reduction technique
- Captures patterns of variance into singular values
- Visualizes global transcriptomic patterns

Sepal.Length 🗘	Sepal.Width 🗘	Petal.Length 🗘	Petal.Width 🗘	Species 🗘	
4.9	2.5	4.5	1.7	virginica	
4.4	3.0	1.3	0.2	setosa	
4.8	3.0	1.4	0.1	setosa	
5.1	3.7	1.5	0.4	setosa	
5.7	3.8	1.7	0.3	setosa	
6.3	2.5	5.0	1.9	virginica	
6.3	3.3	6.0	2.5	virginica	
5.4	3.4	1.7	0.2	setosa	
6.4	3.1	5.5	1.8	virginica	
6.1	3.0	4.6	1.4	versicolor	
5.9	3.0	5.1	1.8	virginica	



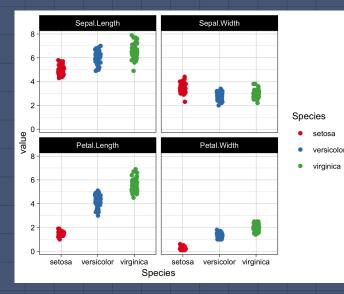
Iris Versicolor

Iris Virginica



Principal Components Analysis (PCA)

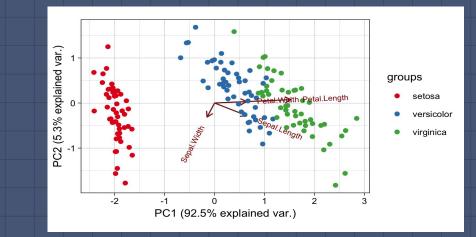
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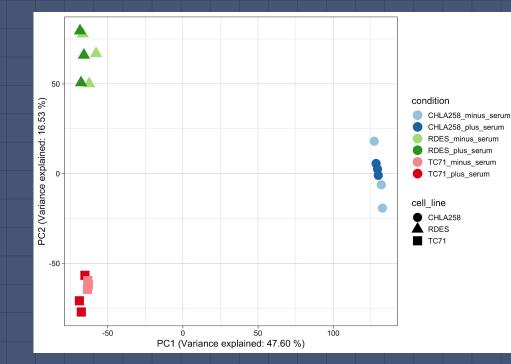


Iris Versicolor

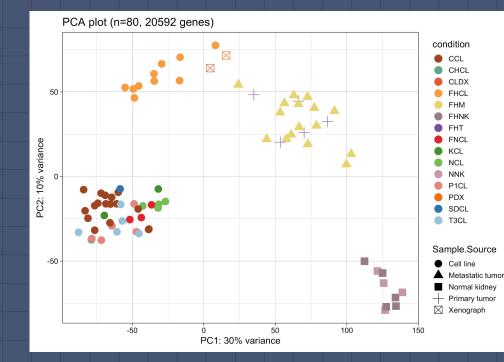
Iris Virginica



PCA can help drive biological insights...

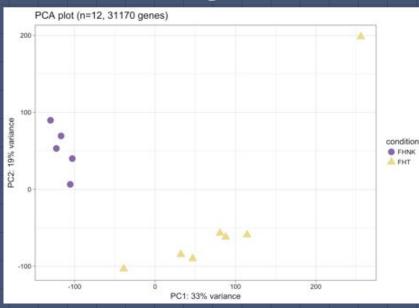


PCA can help drive biological insights...

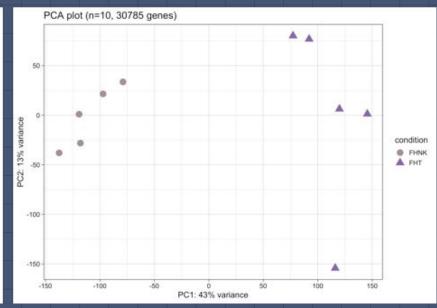


... or be used as a QC tool

Original



Outliers Removed

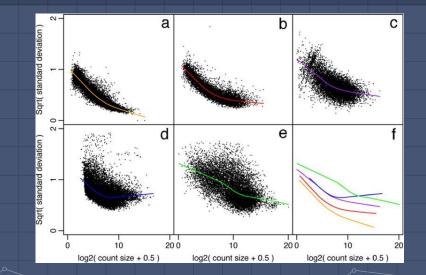


IV. Downstream Analysis: Differential Expression

Goal: Identify genes or transcripts that vary due to *biological* effects

Question: Can't I just use a t-test to do that? **Answer:** Sure. But data are noisy... bad idea

So we apply normalization and/or employ specialized statistical tests.



Law, C. W., et al. (2014). "voom: Precision weights unlock linear model analysis tools for RNA-seq read counts." Genome Biol **15**(2): R29.

IV. Downstream Analysis: Differential Expression

Table 1:

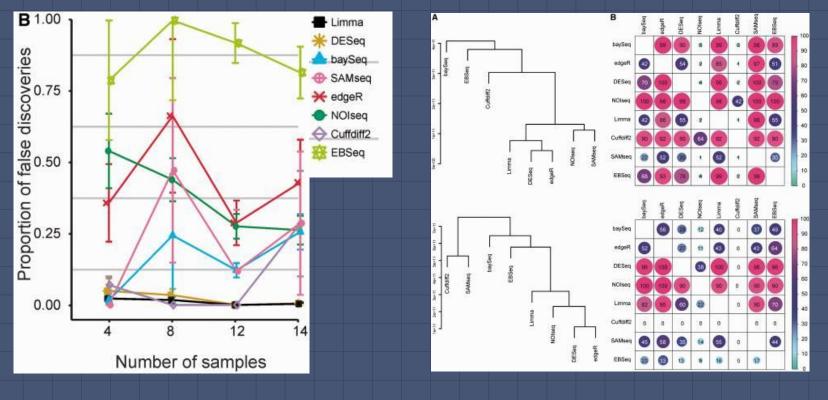
Software packages for detecting differential expression

Method	Version	Reference	Normalization ^a	Read count	Differential expression test
				distribution	
				assumption	
edgeR	3.0.8	[<u>4]</u>	TMM/Upper quartile/RLE (DESeq-like)/None	Negative binomial	Exact test
			(all scaling factors are set to be one)	distribution	
DESeq	1.10.1	[<u>5]</u>	DESeq sizeFactors	Negative binomial	Exact test
				distribution	
baySeq	1.12.0	[6]	Scaling factors (quantile/TMM/total)	Negative binomial	Assesses the posterior probabilities of models for differentially and non-differentially
				distribution	expressed genes via empirical Bayesian methods and then compares these posterior
					likelihoods
NOIseq	1.1.4	[7]	RPKM/TMM/Upper quartile	Nonparametric	Contrasts fold changes and absolute differences within a condition to determine the null
				method	distribution and then compares the observed differences to this null
SAMseq	2.0	[8]	SAMseq specialized method based on the mean	Nonparametric	Wilcoxon rank statistic and a resampling strategy
(samr)			read count over the null features of the data set	method	
Limma	3.14.4	[9]	TMM	voom	Empirical Bayes method
				transformation of	
				counts	
Cuffdiff 2	2.0.2-	[10]	Geometric (DESeq-like)/quartile/classic-fpkm	Beta negative	t-test
(Cufflinks)	beta			binomial	
				distribution	
EBSeq	1.1.7	[11]	DESeq median normalization		Evaluates the posterior probability of differentially and non-differentially expressed entities
				distribution	(genes or isoforms) via empirical Bayesian methods

^aIn case of availability of several normalization methods, the default one is underlined.

Seyednasrollah, F., et al. (2015). "Comparison of software packages for detecting differential expression in RNA-seq studies." Brief Bioinform **16**(1): 59-70.

IV. Downstream Analysis: Differential Expression



Seyednasrollah, F., et al. (2015). "Comparison of software packages for detecting differential expression in RNA-seq studies." Brief Bioinform **16**(1): 59-70.

IV. Downstream Analysis: Differential Expression

Practical Rules of Thumb

Limma, DESeq2, and EdgeR will work be very similarly in most cases

Consensus or intersection of the three is sometimes used

Limma works better with larger cohorts (7 or more samples per group)
DESeq2 works better with small cohorts (3 or less per group)

May also be more sensitive for low depth data

EdgeR provides convenience functions for converting to various normalized values

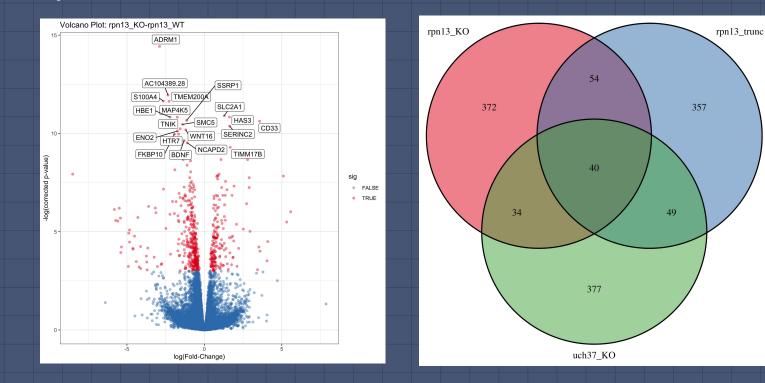
IV. Downstream Analysis: Differential Expression

Output

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Н	lome Insert Draw	Page Layout Formula	s Data	Review	View				
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A1 $\oint \times \sqrt{f_x}$ gene_id									
7	A	В	С	D	E	F	G	Н	I
1	gene_id 💌	gene_symbol 🔻	baseMea 🔻	log2FoldC 🔻	IfcSE 💌	stat 🔻	pvalue 🔻	padi 🔻	
2	ENSG00000175287.18	PHYHD1	105.506727	-8.8636152	0.40719938	-21.767261	4.74E-105	1.12E-100	
3	ENSG00000197928.10	ZNF677	41.5611751	-7.4872309	0.52508083	-14.259197	3.93E-46	4.65E-42	
4	ENSG00000172346.14	CSDC2	88.017538	-7.7697659	0.5624097	-13.815135	2.07E-43	1.63E-39	
5	ENSG00000131094.3	C1QL1	3105.41497	9.1301863	0.68595857	13.3101134	2.02E-40	1.20E-36	
6	ENSG00000117472.9	TSPAN1	825.466933	-5.0610375	0.43424916	-11.654686	2.17E-31	8.58E-28	
7	ENSG00000145103.12	ILDR1	11.5394187	-5.3294612	0.45687139	-11.665123	1.92E-31	8.58E-28	
8	ENSG00000133477.16	FAM83F	21.3385083	-7.452384	0.66149914	-11.265901	1.93E-29		
9	ENSG00000140839.11	CLEC18B	58.2303036		0.51491504	-10.903892	1.10E-27	3.27E-24	
10	ENSG0000090776.5	EFNB1	849.156295		0.35309448	-10.763215	5.13E-27	1.35E-23	
11	ENSG00000100918.12	REC8	268.126523		0.45924441	-10.358877	3.81E-25	9.04E-22	
12	ENSG00000164434.11	FABP7	126.9278		2.34880941		1.56E-24		
13	ENSG00000100181.22	TPTEP1	42.0025572		0.5693855		2.91E-24		
14	ENSG00000182379.9	NXPH4	880.551373		0.73582601		1.71E-23		
15	ENSG00000113805.8	CNTN3	18.0584932		0.69162958		6.15E-23	1.04E-19	
16	ENSG00000111319.12 ENSG00000240747.7	SCNN1A KRBOX1	156.135846		0.38466023	-9.8461079 -9.5462195	7.12E-23 1.35E-21	1.13E-19 1.99E-18	
17 18		FGD5	12.5149416		0.81085494		1.35E-21 1.41E-20		
18	ENSG00000154783.11 ENSG00000074211.13	PPP2R2C	956.880491		0.63226125		5.31E-20		
20		WNT7A	157.383259		1.07831546		5.68E-20		
10	LIN300000134704.3	WINT /A	131.303239	-9.0009140	1.07851546	-9.100049	J.06E-20	1.000-17	

IV. Downstream Analysis: Differential Expression

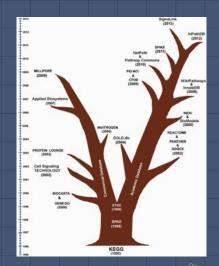
Output



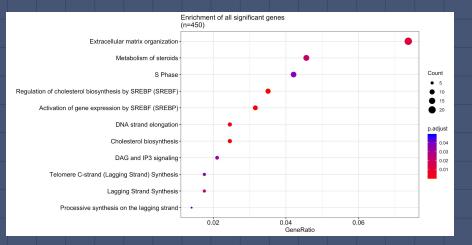
Gene annotation and network databases capture biological meaning Manual curation, text mining Gene function and/or interactions

Dozens of databases and hundreds of tools

Depends on how you want to look at gene-pathway relationships



Types of pathway analysis Simple enrichment test: Qualitative - Fisher's Exact Test - Hypergeometric test Enrichment algorithms: Quantitative - GSEA (Broad Institute) Network Analysis Commercial vs. open source



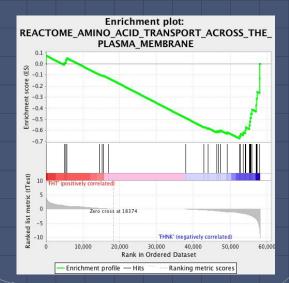
Types of pathway analysis

Simple enrichment test: Qualitative

- Fisher's Exact Test
- Hypergeometric test

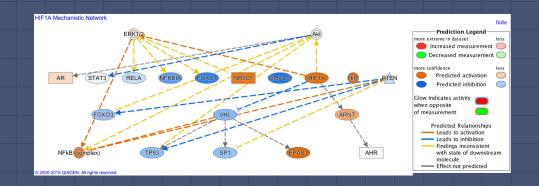
Enrichment algorithms: Quantitative - GSEA (Broad Institute)

Network Analysis Commercial vs. open source



Types of pathway analysis

- Simple enrichment test: Qualitative
 - Fisher's Exact Test
 - Hypergeometric test
- Enrichment algorithms: Quantitative - GSEA (Broad Institute)
- **Network Analysis**
- Commercial vs. open source



Types of pathway analysis

	Com	mercial	Open-source					
	IPA	MetaCore	GSEA	Reactome	KEGG	PANTHER	DAVID	
Enrichment Test	х	х	х	x	(x)	х	х	
Enrichment Scoring Algorithm	х	х	х		(x)			
Network Analysis	х	х		х	(x)			
Graphical Interface	х	х	х	х	х	х	х	

Visualizations

 \bigvee

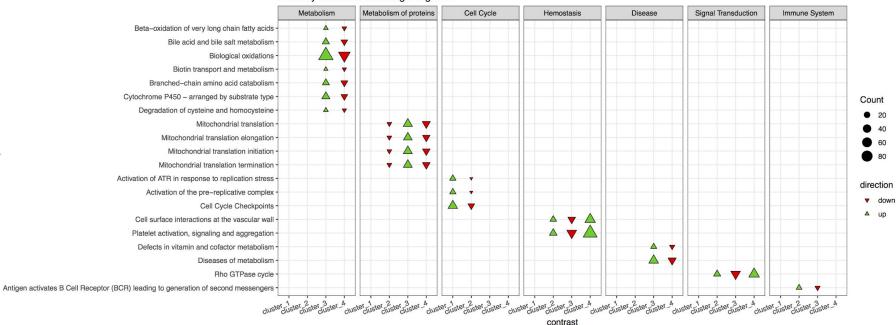
V. Visualizations of RNA-Seq Data

Group comparisons of pathway enrichment

Heatmaps Visualizing Set Overlap Dotplots Sashimi plots Alternative Splicing

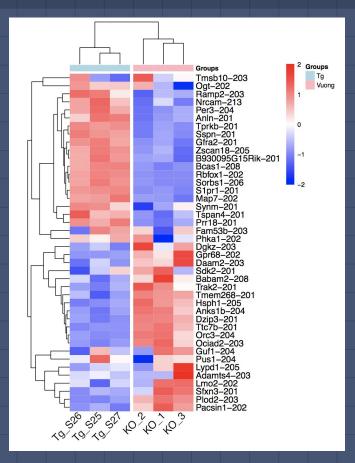
V. Visualizations: Group Enrichment

Group comparison of pathway enrichment: Simple Enrichment Test

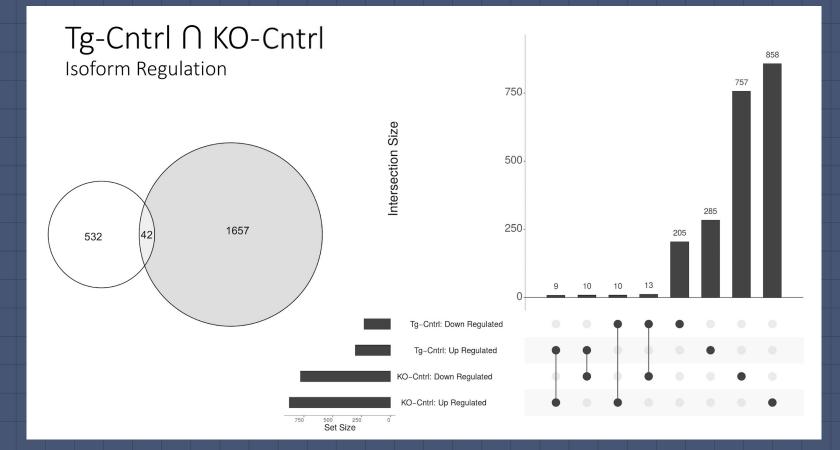


Pathway enrichment among DE genes

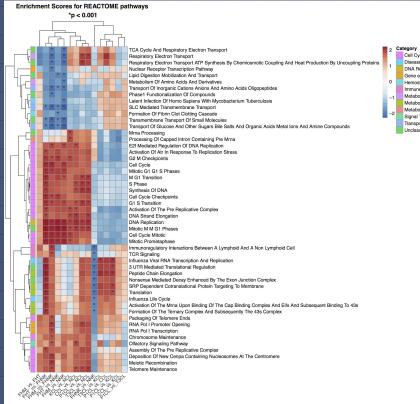
V. Visualizations: Expression Heatmap



V. Visualizations: Set Intersection

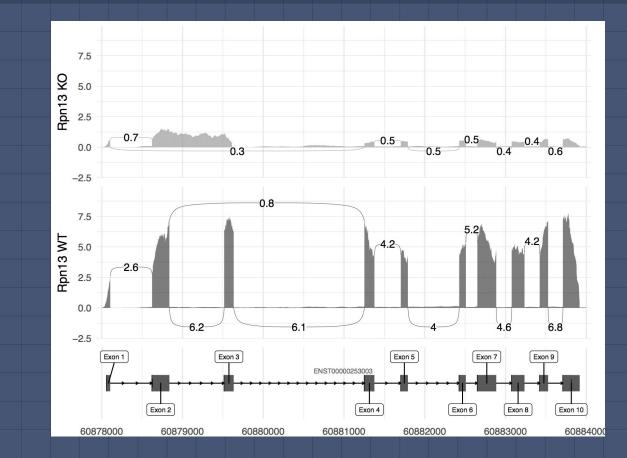


V. Visualizations: Pathway enrichment



Category Cell Cycle Desase DNA Replication Gene expression (Transcription) Hemostaals Immune System Metabolism of proteins Metabolism of RNA Signal Transcuction Transport of small molecules Unclassifie

V. Visualizations: Sashimi Plot



Conclusions

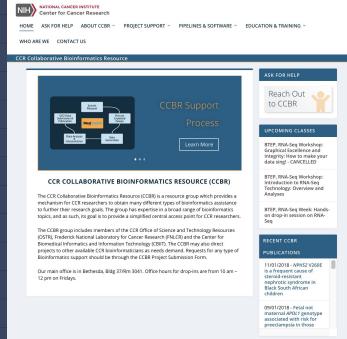
Think BEFORE you sequence!

THANKS!

Acknowledgements

CCBR, NCBR, and GAU members

Any questions?



Cost-Benefit Considerations

Caveats:

Expected reads/sample based on **maximum possible yield**

Typical runs likely yield 80% of max

Different platforms may have different turnaround times depending on queue length and popularity

Library Prep cost is not included here: \$50-84 depending on type of kit

	MiSeq	NextSeq	HiSeq 4000	Novaseq
Run Time	4–55 hours	12–30 hours	< 1–3.5 days	~13 - 44 hours
Max Output	15 Gb	120 Gb	1500 Gb	6000 Gb
Max Reads Per Run	25 million	400 million	5 billion	20 billion
Lanes	1	1	8	4
Maximum Read Length	2 × 300 bp	2 × 150 bp	2 × 150 bp	2 x 250**
Cost from SF	\$623	\$1956	\$1007/lane	\$4382/lane
Max Coverage (12 samples)	2 million reads	33 million reads	52 million reads	416 million reads
\$ per sample (12 samples)	\$51.91	\$163.92	\$83.92	\$365.16