# RNA Sequencing Best Practices and Jigsaw

#### C. Ryan Campbell

Duke University c.ryan.campbell@duke.edu

3 Oct 2017

• What is your project going to be?

- What is your project going to be?
- Graded on 5 points:

- What is your project going to be?
- Graded on 5 points:
  - Has your data been downloaded? (Group)

- What is your project going to be?
- Graded on 5 points:
  - Has your data been downloaded? (Group)
    - Have you picked software to handle/clean it? (Group)

- What is your project going to be?
- Graded on 5 points:
  - Has your data been downloaded? (Group)
  - Have you picked software to handle/clean it? (Group)
  - What is your question?

- What is your project going to be?
- Graded on 5 points:
  - Has your data been downloaded? (Group)
  - Have you picked software to handle/clean it? (Group)
  - What is your question?
  - What is your hypothesis?

- What is your project going to be?
- Graded on 5 points:
  - Has your data been downloaded? (Group)
  - Have you picked software to handle/clean it? (Group)
  - What is your question?
  - What is your hypothesis?
  - Which software will you use (different than group)?

- What is your project going to be?
- Graded on 5 points:
  - Has your data been downloaded? (Group)
  - Have you picked software to handle/clean it? (Group)
  - What is your question?
  - What is your hypothesis?
  - Which software will you use (different than group)?
- Each item is graded for 0-5 points, rubric (will be) on the git repo

#### Overview

- Goals
- Experimental Design
  - Number of Replicates
- Data Analysis
  - Handling Reads
  - Transcripts
  - Differential Expression
  - Functional Profiling

## Today's Goals

• What are RNAseq best practices?

## Today's Goals

- What are RNAseq best practices?
- How did the assigned papers address these recommendations?

## Today's Goals

- What are RNAseq best practices?
- How did the assigned papers address these recommendations?

Jigsaw Activity

#### Review to Read

• This is a summary from:

#### Review to Read

- This is a summary from:
- Conesa et al. 2016. A survey of best practices for RNA-seq data analysis.

#### Review to Read

- This is a summary from:
- Conesa et al. 2016. A survey of best practices for RNA-seq data analysis.
- Good overview of current "best practices"

# **Jigsaw Activity**

 Each of your papers took a different approach to this problem

# **Jigsaw Activity**

- Each of your papers took a different approach to this problem
- As I'm covering these practices make a note of what your paper did

# Jigsaw Activity

- Each of your papers took a different approach to this problem
- As I'm covering these practices make a note of what your paper did
- Compare and contrast during the activity

Enrichment method

- Enrichment method
  - Deplete rRNA

- Enrichment method
  - Deplete rRNA
  - Enrich mRNA via polyA selection

- Enrichment method
  - Deplete rRNA
  - Enrich mRNA via polyA selection
- Library Type (single v paired-end)

- Enrichment method
  - Deplete rRNA
  - Enrich mRNA via polyA selection
- Library Type (single v paired-end)
- Sequencing Depth

- Enrichment method
  - Deplete rRNA
  - Enrich mRNA via polyA selection
- Library Type (single v paired-end)
- Sequencing Depth
- Number of Replicates

Deplete rRNA

Deplete rRNA

Enrich mRNA via polyA selection

- Deplete rRNA
  - Requires good quality RNA

Enrich mRNA via polyA selection

- Deplete rRNA
  - Requires good quality RNA
  - High RIN (RNA Integrity Number)
- Enrich mRNA via polyA selection

- Deplete rRNA
  - Requires good quality RNA
  - High RIN (RNA Integrity Number)
  - Often not possible with tissue
- Enrich mRNA via polyA selection

- Deplete rRNA
  - Requires good quality RNA
  - High RIN (RNA Integrity Number)
  - Often not possible with tissue
- Enrich mRNA via polyA selection
  - Have to use with bacterial samples (lack polyA)

Single End

Single End

Paired End

- Single End
  - Better for well-annotated organisms
- Paired End

- Single End
  - Better for well-annotated organisms
  - Cost can go towards more reads, better coverage
- Paired End

- Single End
  - Better for well-annotated organisms
  - Cost can go towards more reads, better coverage
- Paired End
  - More crucial for de novo

#### Library Type

- Single End
  - Better for well-annotated organisms
  - Cost can go towards more reads, better coverage
- Paired End
  - More crucial for de novo
  - Improve mappability to "dicey" genomes

Deeper is better

- Deeper is better
- Lower end ranges from:

- Deeper is better
- Lower end ranges from:
  - 5mil reads (for common mRNA)

- Deeper is better
- Lower end ranges from:
  - 5mil reads (for common mRNA)
  - 100mil reads (for rare mRNA)

- Deeper is better
- Lower end ranges from:
  - 5mil reads (for common mRNA)
  - 100mil reads (for rare mRNA)
- What else would effect necessary depth?

- Deeper is better
- Lower end ranges from:
  - 5mil reads (for common mRNA)
  - 100mil reads (for rare mRNA)
- What else would effect necessary depth?
  - Genome complexity of the organism matter

- Deeper is better
- Lower end ranges from:
  - 5mil reads (for common mRNA)
  - 100mil reads (for rare mRNA)
- What else would effect necessary depth?
  - Genome complexity of the organism matter
- Use a "Saturation Curve" to assess results at given depth

Depends on:

- Depends on:
  - Technical Variability

- Depends on:
  - Technical Variability
    - Technical replicates should result in an R-squared > 0.9

- Depends on:
  - Technical Variability
    - Technical replicates should result in an R-squared > 0.9
  - Biological Variability

- Depends on:
  - Technical Variability
    - Technical replicates should result in an R-squared > 0.9
  - Biological Variability
  - Desired Statistical Power

- Depends on:
  - Technical Variability
    - Technical replicates should result in an R-squared > 0.9
  - Biological Variability
  - Desired Statistical Power
- Minimum of 3 replicates per group

- Depends on:
  - Technical Variability
    - Technical replicates should result in an R-squared > 0.9
  - Biological Variability
  - Desired Statistical Power
- Minimum of 3 replicates per group
- Conduct a power analysis

**Table 1** Statistical power to detect differential expression varies with effect size, sequencing depth and number of replicates

	Replicates per group		
	3	5	10
Effect size (fol	d change)		
1.25	17 %	25 %	44 %
1.5	43 %	64 %	91 %
2	87 %	98 %	100 %
Sequencing d	epth (millions of read	s)	
3	19 %	29 %	52 %
10	33 %	51 %	80 %
15	38 %	57 %	85 %

#### Handling Reads

Clean reads with FASTX-Toolkit or Trimmomatic

### Handling Reads

- Clean reads with FASTX-Toolkit or Trimmomatic
- Expect 70-90% of reads aligning (model organism)

## Handling Reads

- Clean reads with FASTX-Toolkit or Trimmomatic
- Expect 70-90% of reads aligning (model organism)
- Reads accumulating at the 3' end of transcripts could be a sign of poor RNA quality (polyA enrichment only)

## Transcripts

If a genome/annotation exists you can map to it

#### **Transcripts**

- If a genome/annotation exists you can map to it
- but, you can only quantify expression

### **Transcripts**

- If a genome/annotation exists you can map to it
- but, you can only quantify expression
- Discovery of new transcripts must be done separately

Need high coverage to discvoer new transcripts

- Need high coverage to discvoer new transcripts
- Paired end data helps, hard to get complete transcript (see: IsoSeq)

- Need high coverage to discvoer new transcripts
- Paired end data helps, hard to get complete transcript (see: IsoSeq)
- Several software to tackle this question:

- Need high coverage to discvoer new transcripts
- Paired end data helps, hard to get complete transcript (see: IsoSeq)
- Several software to tackle this question:
- Cufflinks, iReckon, SLIDE, StringTie

- Need high coverage to discvoer new transcripts
- Paired end data helps, hard to get complete transcript (see: IsoSeq)
- Several software to tackle this question:
- Cufflinks, iReckon, SLIDE, StringTie
- Montebello quantification AND isoforms! (project idea?)

Count transcripts to measure expression

- Count transcripts to measure expression
- Raw counts of mapped reads are converted... (to what?)

- Count transcripts to measure expression
- Raw counts of mapped reads are converted... (to what?)
- to RPKM (reads per kilobase of exon model per million reads)

- Count transcripts to measure expression
- Raw counts of mapped reads are converted... (to what?)
- to RPKM (reads per kilobase of exon model per million reads)
- Not necessary when comparing within the same gene across samples

- Count transcripts to measure expression
- Raw counts of mapped reads are converted... (to what?)
- to RPKM (reads per kilobase of exon model per million reads)
- Not necessary when comparing within the same gene across samples
- Is necessary for correctly <u>ranking</u> gene expression levels

 Find which genes are expressed at different levels

- Find which genes are expressed at different levels
- Possible software to use:

- Find which genes are expressed at different levels
- Possible software to use:
- Cufflinks, TMM, DESeq, PoissonSeq, UpperQuartile

- Find which genes are expressed at different levels
- Possible software to use:
- Cufflinks, TMM, DESeq, PoissonSeq, UpperQuartile
- COMBAT and ARSyN can be used to correct batch effects

#### Differential Expression

- Find which genes are expressed at different levels
- Possible software to use:
- Cufflinks, TMM, DESeq, PoissonSeq, UpperQuartile
- COMBAT and ARSyN can be used to correct batch effects
- Not necessaily memory intensive software (DESeq runs in R)

• Genes are nice, but what do they do?

- Genes are nice, but what do they do?
- Characterize the function of the differentially expressed genes

- Genes are nice, but what do they do?
- Characterize the function of the differentially expressed genes
- Also compare functional patheways for over or under-expression

- Genes are nice, but what do they do?
- Characterize the function of the differentially expressed genes
- Also compare functional patheways for over or under-expression
- Tools:

- Genes are nice, but what do they do?
- Characterize the function of the differentially expressed genes
- Also compare functional patheways for over or under-expression
- Tools:
- GOseq, Blast2GO, Gene Set Variation Analysis, SeqGSEA

Form a group with everyone else who read the same paper

- Form a group with everyone else who read the same paper
- Discuss your paper by answering the questions on the next slide – 10-15 mins

- Form a group with everyone else who read the same paper
- Discuss your paper by answering the questions on the next slide – 10-15 mins
- Get together with a new group, with a single representative from each paper covered

- Form a group with everyone else who read the same paper
- Discuss your paper by answering the questions on the next slide – 10-15 mins
- Get together with a new group, with a single representative from each paper covered
- Share your results and discuss the differences 15-20 mins

- Mouse Olf -Sisi, Kevin, Alan
- Lemurs Alvin, Rahul, Helena
- AD Austin, Othmane, Jenn
- Obese
   Chickens Hank, Nayib,
   Jake

- Number (and type) of replicates
- Software used
- What functional analysis was done?
- What conclusions were drawn?

# The End