RNA Sequencing Examples

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Overview

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

Today's Goals

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Jigsaw Activity

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- Good overview of current "best practices"

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- Compare and contrast during the activity

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 - Have to use with bacterial samples (lack polyA)

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- Use a "Saturation Curve" to assess results at given depth

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- 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 %

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- Reads accumulating at the 3' end of transcripts could be a sign of poor RNA quality (polyA enrichment only)

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- Discovery of new transcripts must be done separately

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- Montebello quantification AND isoforms! (project idea?)

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- Is necessary for correctly <u>ranking</u> gene expression levels

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- Not necessally memory intensive software (DESeq runs in R)

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- Tools:
- GOseq, Blast2GO, Gene Set Variation Analysis, SeqGSEA

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- 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