RNA Sequencing

Kasper D Hansen <<u>khansen@jhsph.edu</u>> Statistical Methods for Next Generation Sequencing ENAR 2012 Slides contain material from Ben Langmead, Margaret Taub

The Question(s) and the assay

RNAs

poly-adenylated (coding) RNAs, "genes"

short non-coding RNAs (ncRNA), "microRNA"

Total RNA

long non-coding RNAs

ribosomal RNA

RNAs



RNAs





Only one transcript per gene No (little) splicing Overlapping genes Little space between genes

TP53 (human gene)

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	Heverse strand				25.76 Kb							
Gene Legend	protein coding processed transcript											
	merged Ensembl/Havana											
	There are currently 423 tracks turne	d off.										

Ensembl Homo sapiens version 66.37 (GRCh37) Chromosome 17: 7,565,097 - 7,590,856

TP53 (human gene)



Questions

- What is the structure of known and unknown transcripts
- Changes in splicing
- Gene expression
- Transcript expression
- Allele specific expression

Technical variation (broad overview)

- Take tissue sample from individual
- Extract RNA from tissue sample
- Convert RNA to DNA
- Sequence DNA

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- All of the above induces technical variation.
- Several steps are independent of technology.
- Also: day-to-day, laboratory, experimenter, machine

Standard protocol

The current standard protocol for RNA-Seq is

Extraction of RNA, polyA purification Fragmentation of RNA Reverse transcription of RNA to cDNA (using random hex.) Ligation of adapters Size selection ~ 200bp (perhaps ~300bp) PCR amplification (15 rounds or so) Injection into flowcell

This produces reads from polyadenylated RNA without strand information.

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<u>Variants</u>

ribominus instead of polyA purification strand specificity small RNA sequencing (direct ligation of adaptors to RNA) [oligo(dT) priming instead of random hexamer priming]

Overview



Pepke (2009) Nat. Methods

Data from D. melanogaster



Image from Brenton Gravely

Gene by Sample

Gene models



Union-intersection

("every base belonging to every transcript")

Gene models



Union ("every base belonging to any transcript")

Gene level data

Gene model + overlap rule = gene x sample matrix

(like microarrays)

- Much work by statisticians re. inferring changes between conditions (differential expression).
- Count data (many zeroes, very large range)
- how do we model biological variability

We need to control for sequencing depth gene length

Mortazavi (2008) Nat. Methods introduced "RPKM".

$$\operatorname{RPKM}(g, i) = \frac{X(g, i)}{L(g)N(i)}$$

The big deal



Mortazavi (2008) Nat. Methods

Marioni (2008) Genome Res. showed that technical replicates are poisson.

 $X(g,i) \sim \text{Poisson}(\lambda_g N(i))$

Bullard (2010) BMC Bioinformatics confirmed and extended to library preparation.

None of these papers looked at biological replicates or RNA extraction. Only the technical variation introduced by the sequencing machine.

Several papers have considered more complicated count models, especially the negative binomial.

We have tricks for borrowing strength across genes.

$$X(g,i) \sim F(\theta(g), N(i))$$

Key papers are Anders (2010) Genome Biology ["DESeq"] Hardcastle (2010) BMC Bioinformatics ["baySeq"] McCarthy (2012) Nucleic Acids Res ["edgeR"]

Implementations in Bioconductor. Things change fast.

We need values of N(i) ("sequencing depth") or ("size factor")

Naive estimates: Number of reads Number of mapped reads

Several (scale) normalization methods exist. Bullard (2010) BMC Bioinformatics ("upper quartile") Robinson (2010) Genome Biology ("TMM") Anders (2010) Genome Biology

This is especially an issue when comparing very different samples. For example, between tissue types.

Langmead (2010) Genome Biology shows that it may be a good idea to use a gene-specific normalization factor.

Biological variability



Hansen (2011) Nat. Biotech

Problems: length bias



Oshlack (2009) Biology Direct

Problems: GC content bias



- **Biological variability**
- Need for normalization
- Issues with length, GC content, ?
- Models for count data, borrowing strength across genes

.... but all of this addresses a question we could have answered using microarrays

A look at the data

Data from D. melanogaster



Image from Brenton Gravely

Base effect - single sample



position

Base effect - multiple samples



yeast, Data from Lee (2008) PLoS Genet

Base effect - different study (and prep)



Base effect - conclusions

Reproducible base effect - like probe affinities in microarrays.

Seems to be prep dependent.

Creates issues for comparing different regions in the genome.

Less of an issue for comparing the same region across samples?

Nucleotide content bias



Hansen (2010) Nucleic Acids Res

Correcting for spatial heterogeneity

A sample of papers

Hansen (2010) Nucleic Acids Res Li (2010) Genome Biology Roberts (2011) Genome Biology Jones (2012) Bioinformatics





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Junction reads



Image from Brenton Gravely

Junction reads, zoom



Image from Brenton Gravely

Mapping reads to the transcriptome



Mapping transcripts



Mapping transcripts



The basic approaches

a

De novo assembly of the transcriptome



Pepke (2009) Nat Methods

or inferred

Strategies for mapping to junctions

Map to known junctions (or to known transcripts, but that involves a lot of bookkeeping).

Map to combination of known exons.

Map completely de-novo using canonical acceptor and donor sites. (huge!)

Map de-novo, but constrain the search to canonical acceptor and donor sites between and in transcribed region: transcript assembly. (TopHat).

Paired-end data will help with this.

FP rates for junctions



Hard to map near splice sites (both de-novo and known)

Similar regions of the genome + error in reads + differences between sample and reference = possibility of mapping errors. Still no real understanding.

Do not underestimate this aspect of the data.

Assembly

TopHat



Tuxedo tools



Trapnell (2012) Nat. Protocols