Characterizing transcriptomes using ngs data

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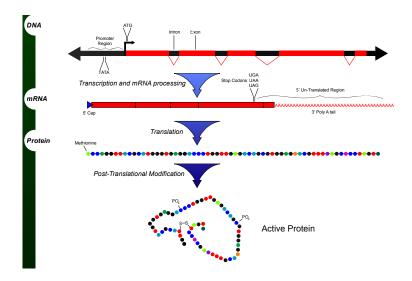


Outline

- The transcriptome
- 2 RNA sequence technologies
- 3 RNA-seq analysis
 - Mapping based approach
 - Gene expression from RNA-seq
 - de-novo assembly

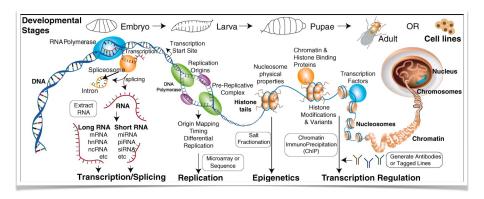


The Central Dogma





A more complex view



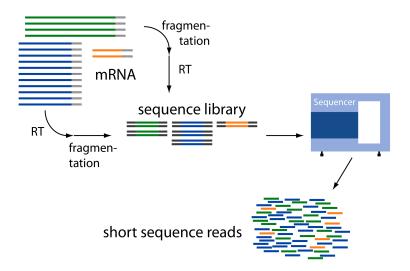


Transcriptomes vs genomes

- Dynamic, not the same over tissues and time points
- Smaller sequence space
- Less repetitive (but large gene families can be found)
- Fairly stable in size? (eg. 2-4 fold change among eukaryotes, whereas genome size can vary 1000-fold)
- Genes are often expressed in multiple different splice-variants
- RNA often from only one strand

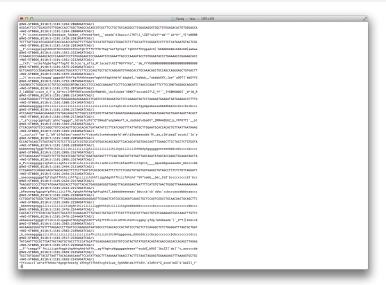


NGS data





Machine output



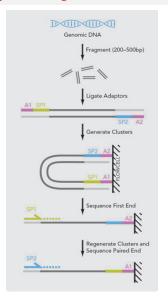
Machine output

```
@SRR038845.3 HWI-EAS038:6:1:0:1938 length=36
CAACGAGTTCACACCTTGGCCGACAGGCCCGGGTAA
+SRR038845.3 HWI-EAS038:6:1:0:1938 length=36
BA@7>B=>:>>7@7@>>9=BAA?:>52:>:9=8.=A
@SRR038845.41 HWI-EAS038:6:1:0:1474 length=36
CCAATGATTTTTTCCGTGTTTCAGAATACGGTTAA
+SRR038845.41 HWI-EAS038:6:1:0:1474 length=36
@SRR038845.53 HWI-EAS038:6:1:1:360 length=36
GTTCAAAAAGAACTAAATTGTGTCAATAGAAAACTC
+SRR038845.53 HWI-EAS038:6:1:1:360 length=36
BBCBBBBBB@@BAB?BBBBCBC>BBBBAA8>BBBAA@
```

Sequence quality

- Phred quality scores: Q = -10 x log P (High Q = high probability of the base being correct
- A Phred quality score of 20 to a base, means that the base is called incorrectly in 1 out of 100 times.

Pair-end (PE) sequencing



Pair-end reads

File format

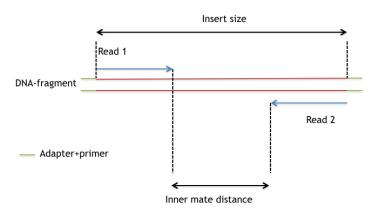
- Two files are created
- The order in files identical and naming of reads are the same with the exception of the end
- The way of naming reads are changing over time so the read names depend on software version

```
@61DFRAAXX100204:1:100:10494:3070/1
AAACAACAGGGCACATTGTCACTCTTGTATTTGAAAAACACTTTCCGGCCAT
+
ACCCCCCCCCCCCCCCCCCCCCCCCCCAC
```

```
@61DFRAAXX100204:1:100:10494:3070/2
ATCCAAGTTAAAACAGAGGCCTGTGACAGACTCTTGGCCCATCGTGTTGATA
+
_^_a^ccceqcqqhhqZc`qhhc^eqqqd^_[d]defcdfd^Z^0XWaQ^ad
```

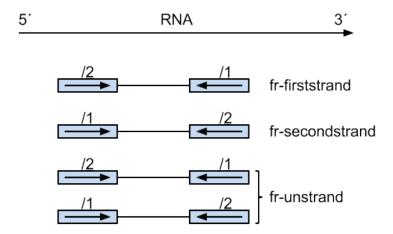


Pair-end data



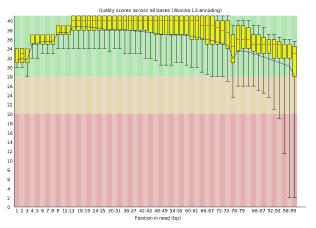


Stranded or not



Basic quality control of raw reads

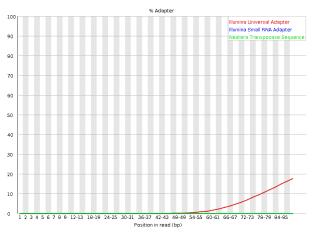
FastQC





Basic quality control of raw reads

FastQC

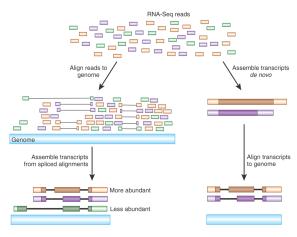




Basic quality control of raw reads

- RNA-seq is not random sample from the genome eg. GC content might be different
- Highly expressed genes can be frequent and create warnings in quality controls that assumes whole genome data
- Random hexamer in cDNA synthesis might create 'biases' in base frequencies in the beginning of reads

Two main routes for analysis



Haas & Zody (2010), Nature Biotechnology 28, 421-423

Aligning short reads from RNA to genomes

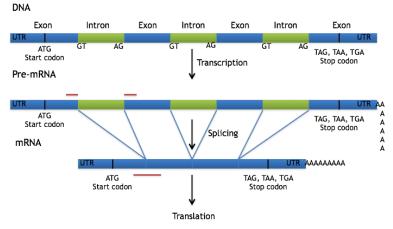
- If available map to the genome sequence
- If no genome sequence one can also map to transcriptome reference
- Make use of available genome annotation (GTF, GFF, BED files)





Aligning short reads from RNA to genomes

- Large number of programs available: Star, Tophat, Subread etc
- Important feature: Allow for spliced mapping



Aligning short reads from RNA to genomes

After mapping perform QC of the output

read_distribution.py -i Pairend_StrandSpecific_51mer_Human_hg19.bam -r hg19.refseq.bed12

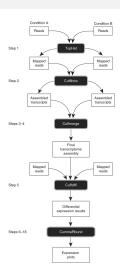
Output:

Group	Total_bases	Tag_count	Tags/Kb
CDS_Exons	33302033	20002271	600.63
5'UTR_Exons	21717577	4408991	203.01
3'UTR_Exons	15347845	3643326	237.38
Introns	1132597354	6325392	5.58
TSS_up_1kb	17957047	215331	11.99
TSS_up_5kb	81621382	392296	4.81
TSS_up_10kb	149730983	769231	5.14
TES_down_1kb	18298543	266161	14.55
TES_down_5kb	78900674	729997	9.25
TES down 10kb	140361190	896882	6.39



Example workflow

- Tophat: Aligns reads to genome (allows for spliced read mapping)
- Cufflinks: Extract transcripts from spliced read alignments
- Cuffmerge: Merge results from multiple Cufflinks results
- Cuffdiff: Detect differential gene expression



Trapnell et al. (2012), Nature Protocols 7, 562-578



Tophat

- Efficient and fast alignment to the genome using bowtie2
- 2 Create a data base of putative splice junctions from the reads mapping in step 1
- 3 Map reads that did not map in step 1 using the splice information

QC of mapped reads

TES down 10kb

140361190

896882

6.39

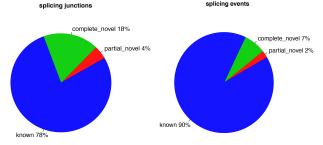
Reads should mostly map to known (annotated genes)

read distribution.py -i Pairend StrandSpecific 51mer Human hg19.bam -r hg19.refseq.bed12 Output: Total bases Tag count Tags/Kb Group CDS Exons 33302033 20002271 600.63 5'UTR Exons 21717577 4408991 203.01 3'UTR Exons 15347845 3643326 237.38 5.58 Introns 1132597354 6325392 11.99 TSS up 1kb 17957047 215331 TSS up 5kb 81621382 392296 4.81 TSS up 10kb 149730983 769231 5.14 TES down 1kb 18298543 266161 14.55 TES down 5kb 9.25 78900674 729997



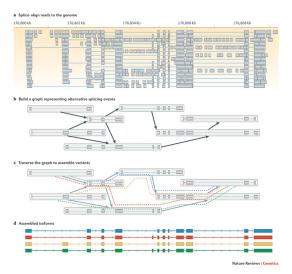
QC of mapped reads

Most splice event should be known and canonical (GU-AG)





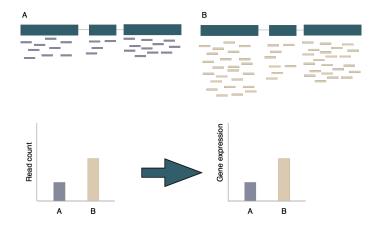
Cufflinks



Cuffdiff

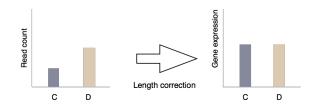
- Program that estimate expression levels and identify differentially expressed genes from ngs alignments
- Basically uses the read data to estimate dispersion parameters (the amount of deviation from a Poisson distr.)
- Genes that show patterns deviating from the above expectations are differentially expressed between treatments
- Will work also for detection of isoform differential expression

From counts to gene expression



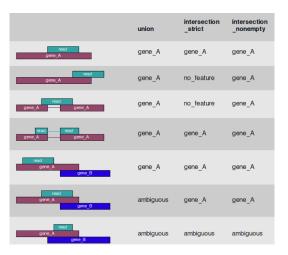
From counts to gene expression







Not all reads are the same

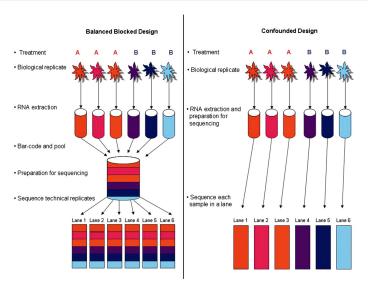


from: http://www-huber.embl.de/users/anders/HTSeq/doc/count.html

Normalized expression Values

- Mapped read counts are normalized for both length of the transcript they map to and total depth of sequencing.
- Count data is hence converted to: Reads/Fragments per kb of transcript length and million mapped reads (RPKM or FPKM)

Experimental design





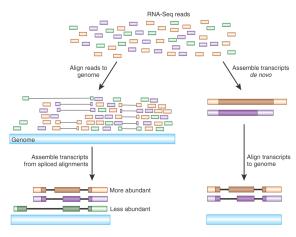
Experimental design

- Count reads (convert to RPKM/FPKM?)
- Small number of reads (= low RPKM/FPKM values) often non-significant
- Remember that Fold change is not the same as significance

	Condition	Condition 2	i old_ollalige	Significants
Gene A	1	2	2-fold	No
Gene B	100	200	2-fold	Yes



Two main routes for analysis



Haas & Zody (2010), Nature Biotechnology 28, 421-423

Major challenges in relation to genome assembly

- Genes show different levels of gene expression, hence uneven coverage among genes
- Many genes are expressed in different isoforms
- As sequence depth increase detected number of loci increase.
 (What is actually expressed?)
- Sequence error from highly expressed genes might be seen more often than "true" sequences from lowly expressed genes

Several programs available

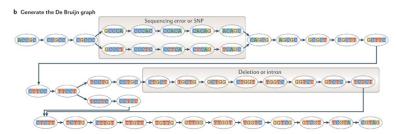
- SOAP-denovo TRANS
- Oases
- Trans-ABYSS
- Trinity

All of them uses de Bruijn graphs to cope with the data and many of them have been developed from a genome assembly program

Trinity

a Generate all substrings of length k from the reads

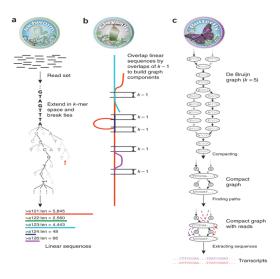






c Collapse the De Bruijn graph

Trinity



Summary - with ref.

- Map to genome allow for spliced alignment
- If novel transcripts of interest: use method that can re-create transcripts from mapped reads (Cufflinks, Scripture or Bayesembler)
 NB! In well annotated genomes most reads should map to known genes
- If interest is expression of known genes/exons: Use available annotation for analysis
- Spend time on experimental design and more replicates gives more power in gene expression analysis

Summary - without ref.

- Assemble using your favourite assembler
- Spend lots of time in assessing the results (compare to related species, look for ORFs etc)
- Often large number of partial transcripts (hence often large number of contigs).
- Merge with other data from transcripts?