Introduction to Next Generation Sequencing

RNA-Seq: Differential Expression of Genes

Bioinformatics Workshop 31 March 2017



Overview

- Differential Expression Principles
- Splice-aware Alignment and Counting
- Differential Expression Table



A Typical RNA-Seq Analysis at GC

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Project identification

Project Type RNA seq Number Of Samples 16 Number Of Conditions 2 Condition 1 MMP-9-KO_water Condition 2 MMP-9-KO_DSS

Used Read Information

Sample Code	Condition	Used Read Count	Size Factor
CC024962	MMP-9 KO water	4962826	0.481151532775072
CC024963	MMP-9_KO_water	7160682	1.27716186751061
CC024964	MMP-9 KO water	6036545	1.0640993138704
GC024965	MMP-9_KO_water	4594610	0.931302721027977
CC024970	MMP-9_KO_DSS	6985397	0.951266712762552
CC024971	MMP-9_KO_DSS	5971470	0.931648601332944
CC024972	MMP-9_KO_DSS	7308085	1.120414569201
GC024973	MMP-9_KO_DSS	6299628	1.11078799446147
CC024978	MMP-9 KO water	5922351	1.20096919252668
GC024979	MMP-9_KO_water	3319976	0.543371024301831
CC024980	MMP-9_KO_water	5768708	1.21066962669347
GC024981	MMP-9_KO_water	6813443	1.45836741122796
CC024986	MMP-9_KO_DSS	5734337	0.813023637998365
GC024987	MMP-9_KO_DSS	10620259	1.63676485961185
CC024988	MMP-9_KO_DSS	7968821	1.25323666394006
GC024989	MMP-9_KO_DSS	6823721	1.28413830085057

Sample Relations

Data quality assument and quality control are essential steps of any data analysis. Here we define the term quality a threas for purpose. Or purpose is the detection of differentially expressed genos, and we are looking in particular for samples whose experimental treatment sufferf from an anormality this residen the data points obtained from the neutricular samples detrimental to or runnous.

Variance stabilized data is used to create sample to assupple distances. With those distances sample contrainty becomes boundle. The clustering should refact the experimental design correctly, samples are now similar when they have the same treatment. The hostmap with tree should show this effect (Figure \S). The Principal Component Analysis pic (PCA-plot) (Figure \S) is a 2 dimensional version of these analysis. Expected is that samples with a same treatmen cluster together. Outliers and possible bias are oney to elected.

By taking a look at the top 50 highly expressed genes, a first impression of the data can be made. The heatmap below shows this expression data (Figure 9). The data is normalized by using the variance stabilisation transformation Sample should cluster together according the experimental factor. However if this is not the case, this doesn't imply that then is no difference. This job above only the highest expressed genes, not the differently expressed genes.





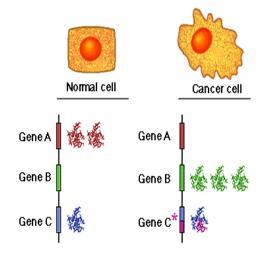
3GB of raw and analyzed data: Fastq, BAM, counts, normalized counts, gene expression files, heatmaps...



RNA-Seq Differential Expression Analysis

RNA-Seq is a technique that allows transcriptome studies based on nextgeneration sequencing technologies

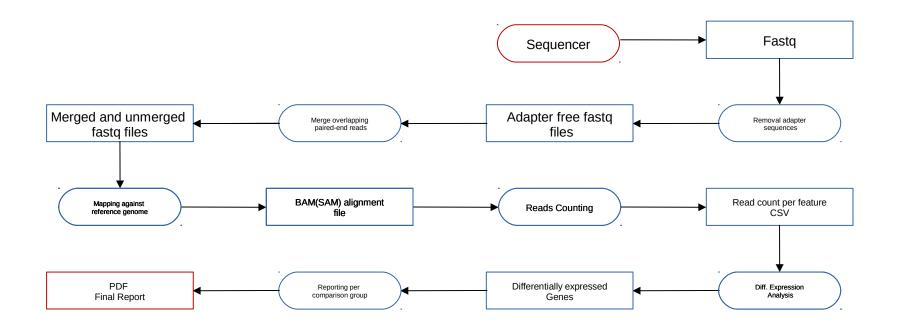
- SNP calling
- Fusion gene detection
- Differential expression (DE)



DE RNA-Seq: compare gene expression between conditions



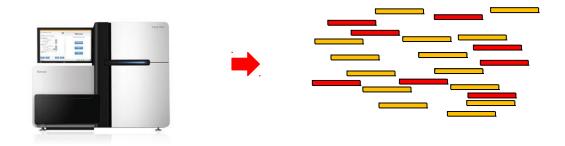
RNA-Seq Workflow (or pipeline) at GC





RNA-Seq Workflow at GC

Sequencer produces millions of reads and a qualification for each base call



How reads relate differential expression of genes?

Goal: discover changes in abundance between conditions

Read count is linearly related to the abundance of the target transcript



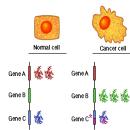
Differential Expression of Genes

- Count the number of reads that fall into annotated genes
 - Fall: Align reads w.r.t. a reference genome (transcriptome)
 - Count: number of aligned reads per feature (genes).



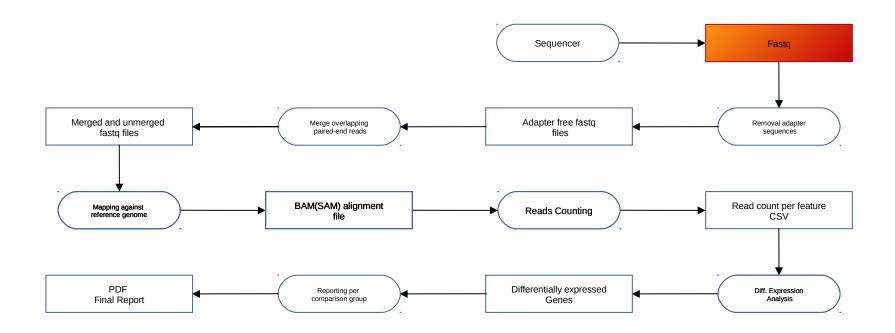
Reference Genome

- Perform statistical analysis on the counts to discover quantitative changes in expression levels between experimental groups
 - Normalization of counts
 - Probabilistic modeling of read counts
 - Estimate differential expression





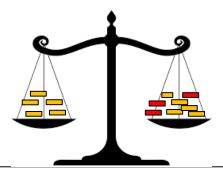
RNA-Seq Workflow at Genomics Core





Preprocessing or not?

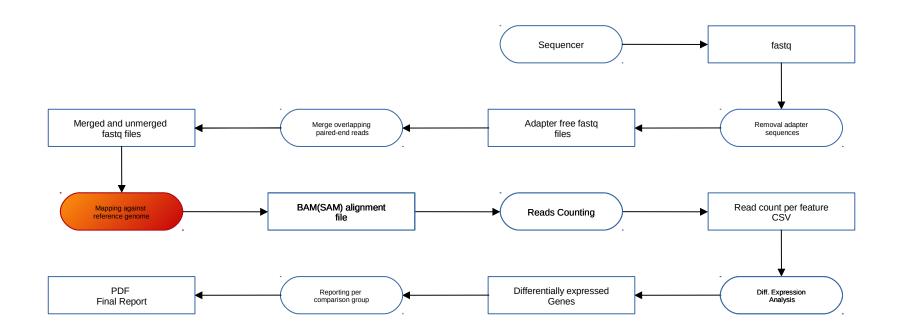
- Preprocessing remove/trimming reads with low quality data?
- Better quality input data with less noise...
 - Tradeoff: information is lost...can affect alignment



Quality scores are exploited by aligners

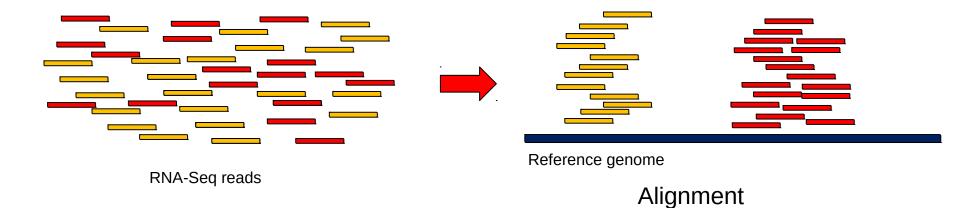


RNA-Seq Workflow at Genomics Core





From Raw Reads to Alignment





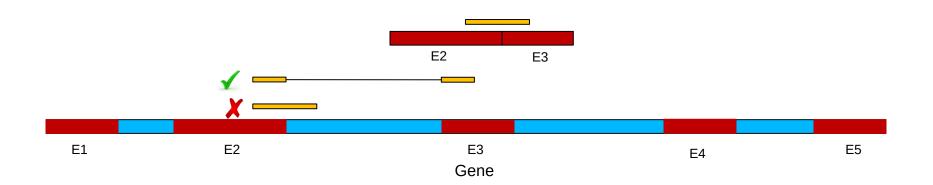
Tophat: Splice-Aware Alignment

Individual reads are aligned to a reference genome

RNA-seq read alignment differs from standard alignment:

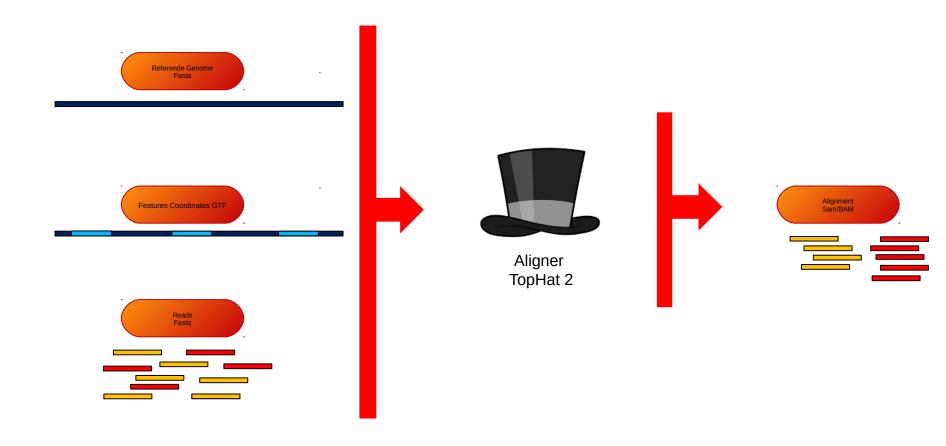
If an RNA-Seq read spans an exon boundary, part of the map will not map contiguosly to the reference

This causes the standard mapping procedure to fail





Reference-Based Alignment with Tophat 2





Reference Sequence in Fasta Format

genome.fa human-readable nucleotide sequence

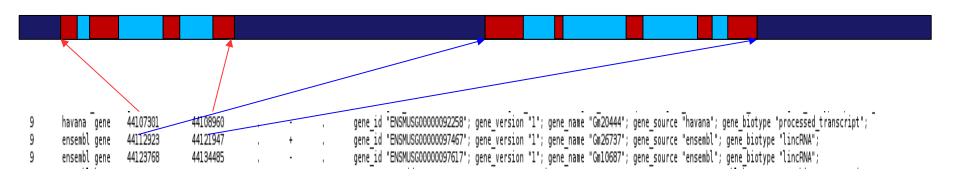
Mouse genome: 2.6GB

And it looks like this:

GAAGTGAAAGATCTGTATGATAAAAACTTCAAGTCTCTGAAGAAAAAAATTAAAGAAGAT CTCAGAAGATGGAAAGATCTCCCATGCTCATGGATTGGCAGGATCAATATTGTAAAAATG GCTATCTTGCCAAAAGCAATCTACAGATTCAATGCAATCCCCATCAAAATTCCAACTCAA TTCTTCAACGAATTAGAAGGAGCAATTTGCAAATTCATCTGTAATAACAAAAACCTAGG ATAGCAAAAAGTCTTCTCAAGGATAAAAGAACCTCTGGTGGAATCACCATGCCTGACCTA GTAGACCAATGGAATAGAATTGAAGACCCAGAAATGAACCCACACACCTATGGTCACTTG ATCTTCGACAAGGGAGCTAAAACCATCCAGTGGAAGAAGACAGCATTTTCAACAAATGG TGCTGGCACAACTGGTTGTTATCATGTAGAAGAATGCGAATCGATCCATACTTATCTCCT TGTACTAAGGTCAAATCTAAATGGATCAAAGAACTTCACATAAAACCAGAGACACTGAAA CTTATAGAGGAGAAAGTGGGGAAAAGCCTTGAAGATATGGGCACAGGGGAAAAATTCCTG AACAGAACAGCAATGGCTTGTGCTGTAAGATTGAGAATTGACAAATGGGACCTAATGAAA CTCCAAAGTTTCTGCAAGGCAAAAGACACCGTCAATAAGAGAAAGAGACCACCAACAGAT TGGGAAAGGATCTTTACCTATCCTAAATCAGATAGGGGACTAATATCCAACATATATAAA GAACTCAAGAAGGTGGACTTCAGAAAATCAAACCACCCATTAAAAAAATGGGGCTCAGAA CTGAACAAAGAATTCTCACCTGAGTTATACCGAATGGCAGAGAAGCACCTGAAAAAATGC TCAACATCCTTAATCATCAGGGAAATGCAAATCAAAACAACCCTGAGATTCCACCTCACA CCAGTCAGAATGTCTAAGATCAAAAATTCAGGTGACAGCAGATGCTGGCGAGGATGTGGA GAAAGAAGAACACTCCTCCATTGTTGGTGGGATTGCAGGCTTGTACAACCACTCTGGAAA TCCGTCTGGCGGTTCCTCAGAAAATTGGACATAGTACTACCGGAGGATCCAGCAATACCT CTCCTGGGCATATATCCAGAAGATGCCCCAACTGGTAAGAAGGACACATGCTCCACTATG TTCATAGCAGCCTTATTTATAATAGCCAGAAGCTGGAAAGAACCCAGATGCCCCTCAACA GAGGAATGGATACAGAAAATGTGGTACATCTACACAATGGAGTACTACTCAGCTATTAAA AAGAATGAATTTATGAAATTCCTAGCCAAATGGATGGACCTGGAGGGCATCATCCTGAGT



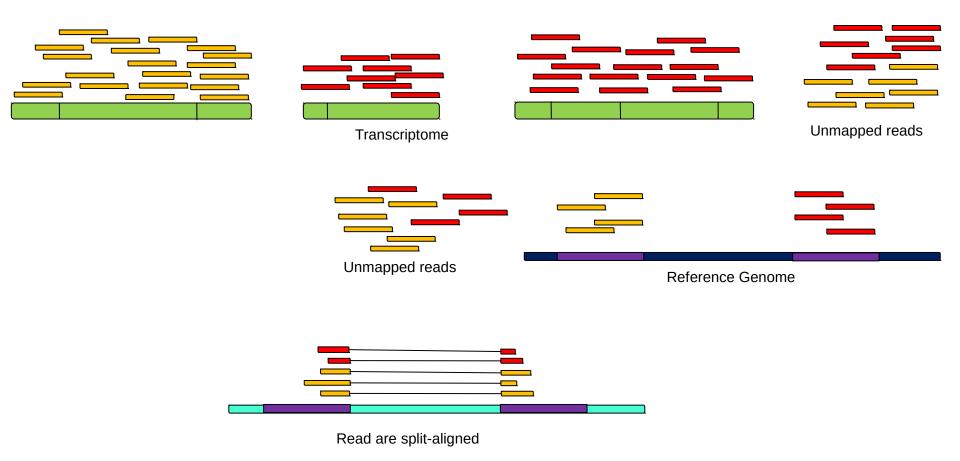
GTF Files: Gene Transfer Format



column-number	content	values/format
1	chromosome name	chr{1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,X,Y,M}
2	annotation source	{ENSEMBL,HAVANA}
3	feature-type	{gene,transcript,exon,CDS,UTR,start_codon,stop_codon,Selenocysteine}
4	genomic start location	integer-value (1-based)
5	genomic end location	integer-value
6	score (not used)	
7	genomic strand	{+,-}
8	genomic phase (for CDS features)	{0,1,2,.}

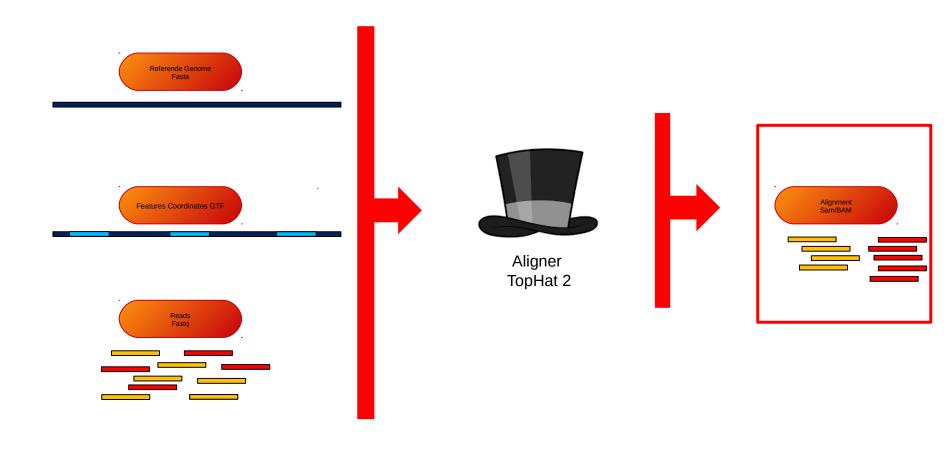


TopHat Alignment Strategy – GTF





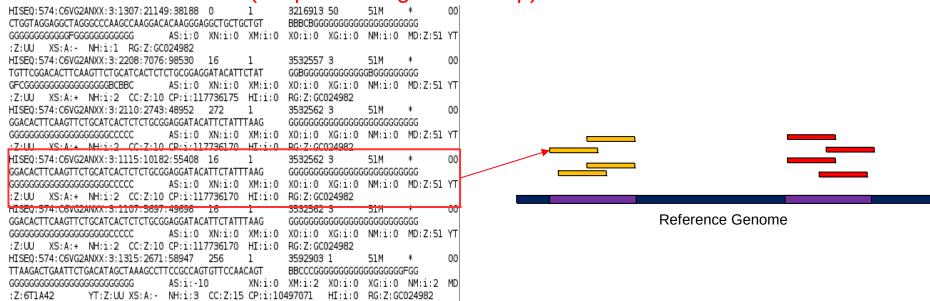
Reference-Based Alignment with Tophat 2





RNA-Seq BAM/SAM

Extract SAM (Sequence Alignment Map) file



BAM files are machine-readable versions of SAM files



RNA-Seq BAM/SAM

HISEQ:574:C6VG2ANXX:3:2208:7076:98530: Query Name

16 00000010000 Decimal bitwise: Mapped? Strand?

1 Chromosome

3532557 Position

3 Mapping Quality

51M CIGAR: match? Skipped bases on reference?

* Unpaired or paired (=)?

AS:i:0 XN:i:0 XM:i:0 XO:i:0 XG:i:0 NM:i:0 MD:Z:51 YT

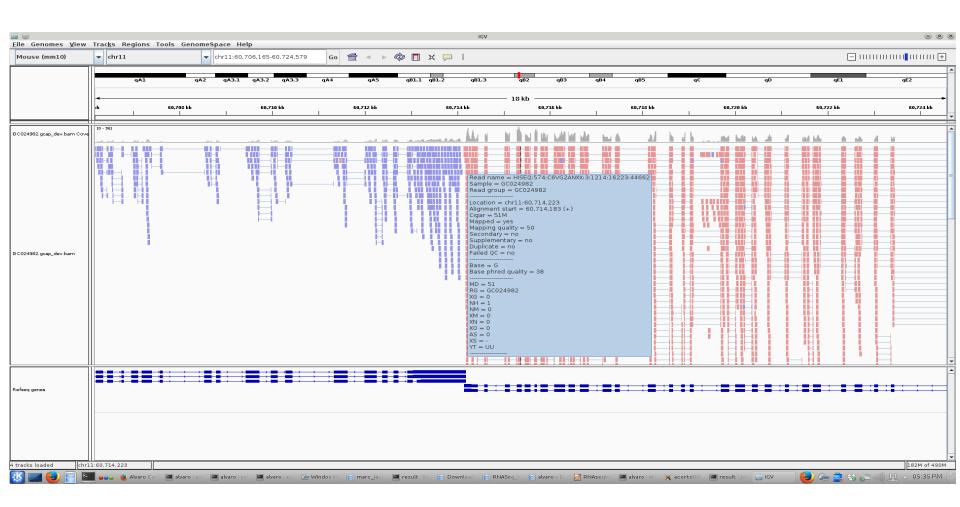


Reference Genome

Reference Base Qualities Base Qualities

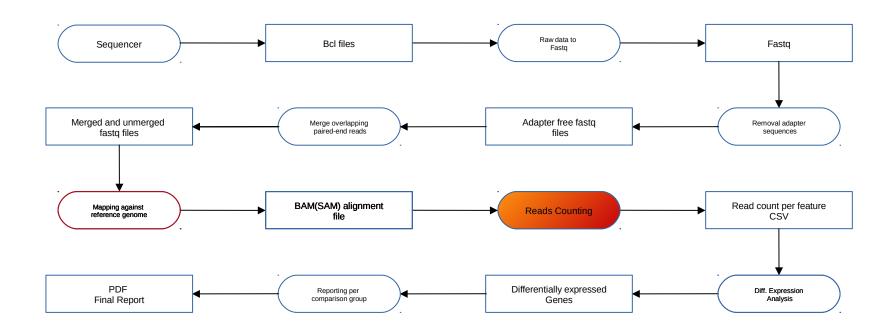


RNA-Seq BAM/SAM



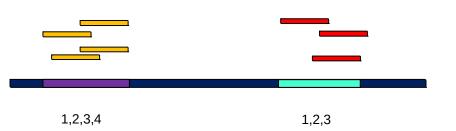


RNA-Seq Workflow



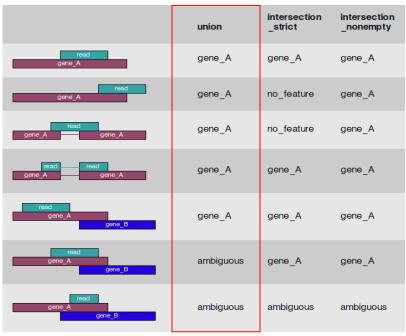


Counting Reads in HTSeq



Method

- Count each read only once
- Multi-mapping reads and reads overlapping multiple features discarded



Simon Anders

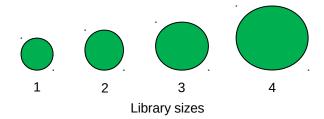


Counting Reads in HTSeq(*)

(*) Simon Anders, Wolfgang Huber (EMBL)

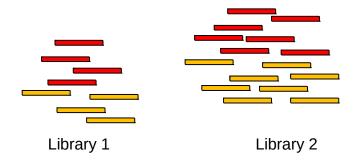
Resulting table of absolute counts for each sample and feature:

	Sample 1		Sample 2	Sample 3	Sample4
FBgn0000003	0	0	0	1	
FBgn0000008	76	70	88	70	
FBgn0000014	0	0	0	0	
FBgn0000015	1	2	0	0	
FBgn0000017	3564	3150	3072	3334	
FBgn0000018	245	310	299	308	





Normalization of Counts: Impact Library Size



A bigger library produces more reads...But in slide 3:

"Read Counts is linearly related to the abundance of the target transcript"



Normalization of Counts: Size Factors

Adjust for library sizes to produce count values in a common scale:

	Sample 1 0.873	Sample 2 1.011	Sample 3 1.022	Sample4 1.115	→ Size factors
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Sample 1	Sample 2	Sample 3	Sample4						
FBgn0000003	. 0	0	0	1					
FBgn0000008	76	70	88	70					
FBgn0000014	0	0	0	0					
FBgn0000015	1	2	0		0				
FBgn0000017	3564 31	50 3072	2 3	334		1	2	3	4
FBgn0000018	245 3	10 299	9	308			L	ibrary sizes	

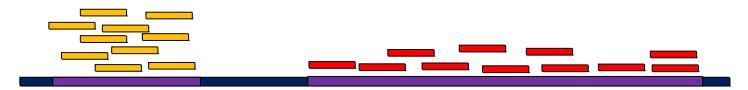
FeatureSample	e 1 Sam	ple 2	Sample 3		Sample4
FBgn0000003	0.00	0.0	0	0.0	0.897
FBgn0000008	87.05	69.2	7	86.1	62.803
FBgn0000014	0.00	0.0	0	0.0	0.000
FBgn0000015	1.15	1.9	3	0.0	0.000
FBgn0000017	4082.023116	.933004.5	29	91.23	8
FBgn0000018	280.61	306.7	5 2	92.4	276.335

76/0.873 = 87.05



Normalized counts

More on Counting and Normalization



- Possible extra normalization:
 - Longer transcripts are more likely to have sequences mapped to their genes
 - Higher counts, biasing comparisons between transcripts of different lengths.
 - RPKM Reads per kilo base per million mapped reads

"based on three real mRNA and one miRNA-seq datasets,we confirm previous observations that RPKM and TC, both of which are still widely in use [40,41], are ineffective and should be definitively abandoned

in the context of differential analysis"

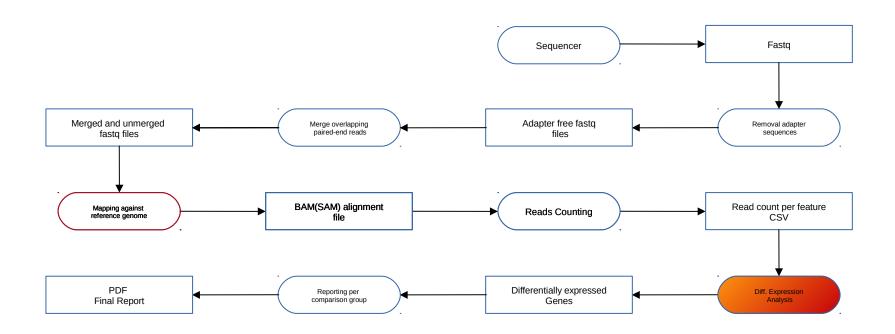
Briefings in Bioinformatics Advance Access published September 17, 2012 ժությությեն իրան ու թագալ ի օր ը

A comprehensive evaluation of normalization methods for Illumina high-throughput RNA sequencing data analysis

Marie-Agnès Dillies', Andrea Rau', Julie Aubert', Christelle Hennequet-Antier', Marine Jeanmougin', Nicolas Servari, Caline Keime', Gullemette Maru, David Castel, Jord Estelle, Gregory Guernec, Bernd Japla, Luc Joureau, Deris Labe, Garnile in God Jehigita Schaëffer, Stejhane Le Crom', Mickaël Guedi', Florence Joffrézic and on behalf of The French StatiOmique Consortium



RNA-Seq Workflow

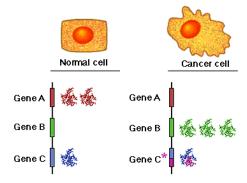




Differential Expression

Statistical test: Decide whether for a given gene, an observed difference in reads counts is significant

Comparison between different biological conditions



Read counts per gene are modeled by a probability distribution



Read Count Distribution Assumption

Method	Read Count Distribution Assumption
EdgeR	Negative binomial distribution
DESeq	Negative binomial distribution
Cuffdiff2 (CuffLinks)	Beta negative binomial distribution



Package Selection

DESeq or edgeR?

Box 2 | Differences between DESeq and edgeR

The two packages described in this protocol, DESeq and edgeR, have similar strategies to perform differential analysis for count data. However, they differ in a few important areas. First, their look and feel differs. For users of the widely used limma package⁶⁰ (for analysis of microarray data), the data structures and steps in edgeR follow analogously. The packages differ in their default normalization: edgeR uses the trimmed mean of M values⁵⁶, whereas DESeq uses a relative log expression approach by creating a virtual library that every sample is compared against; in practice, the normalization factors are often similar. Perhaps most crucially, the tools differ in the choices made to estimate the dispersion. edgeR moderates feature-level dispersion estimates toward a trended mean according to the dispersion-mean relationship. In contrast, DESeq takes the maximum of the individual dispersion estimates and the dispersion-mean trend. In practice, this means DESeq is less powerful, whereas edgeR is more sensitive to outliers.

Recent comparison studies have highlighted that no single method dominates another across all settings^{27,61,62}.

PROTOCOL

Count-based differential expression analysis of RNA sequencing data using R and Bioconductor

Simon Anders¹, Davis J McCarthy^{2,3}, Yunshun Chen^{4,5}, Michal Okoniewski⁶, Gordon K Smyth^{4,7}, Wolfgang Huber¹ & Mark D Robinson^{8,9}

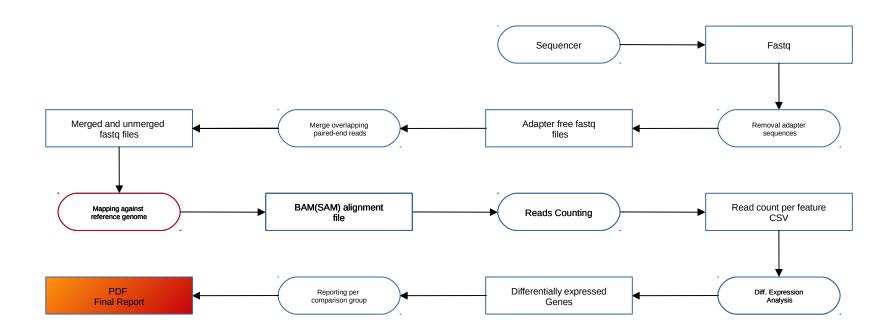


Differential Expression Table (DeSeq)

id	baseMean	baseMeanA	baseMeanB	foldChange	log2FoldChange	pval	padj
TTp9	61.2142079613	114.5039786047	7.9244373179	0.0692066548	-3.8529454185	3.18278695454205E-038	7.8910836963961E-034
Roums4	111.7253852962	3.3863424303	220.064428162	64.9858756734	6.0220542852	3.14004006066747E-016	3.89255066120643E-012
Serinc3	5049.0292624521	. 2783.4853979737	7314.5731269304	2.6278467752	1.3938811573	8.88017567331908E-011	7.33887318228667E-007
Apoba	687.9674505131	478.6234549012	897.3114461251	1.8747753311	0.9067177166	3.02197214770456E-005	0.1833853013
Psiga	318.5920273479	219.6643392529	417.519715443	1.9007168704	0.926543645	3.69832818348108E-005	0.1833853013
lgdskv12-98	3.4254621585	0.697231647	6.1536926701	8.8258940866	3.1417424346	7.3351076233012E-005	0.2589065108
Ssdlc12a5	17.8775194124	28.617735224	7.1373036008	0.249401413	-2.0034584562	8.04863286246797E-005	0.2589065108
Treb3l3	31.0676067843	13.9815013501	48.1537122185	3.444101675	1.7841277338	8.35418096347497E-005	0.2589065108
Tm16316	1.205992866	2.4119857321	0	0	-Inf	0.0001326348	0.3653795179
Ces1d	553.0344051691	424.629437072	681.4393732662	1.604785994	0.6823809198	0.0002487961	0.6168402322
Vsig1	134.705417607	168.1043611548	101.3064740591	0.6026403679	-0.7306307796	0.0005224394	1



RNA-Seq Workflow





Thanks!

