

RNA-Seq data analysis

http://genoweb.toulouse.inra.fr/~formation/4_Galaxy_RNAseq/

Delphine Labourdette Get-Biopuce / Céline Noirot Bioinfo Genotoul



Material

http://genoweb.toulouse.inra.fr/~formation/4_Galaxy_RNAseq/

Slides & Exercise leaflet (doc)

- pdf: one per page
- pdf: three per page with comment lines

Data & results files (data)



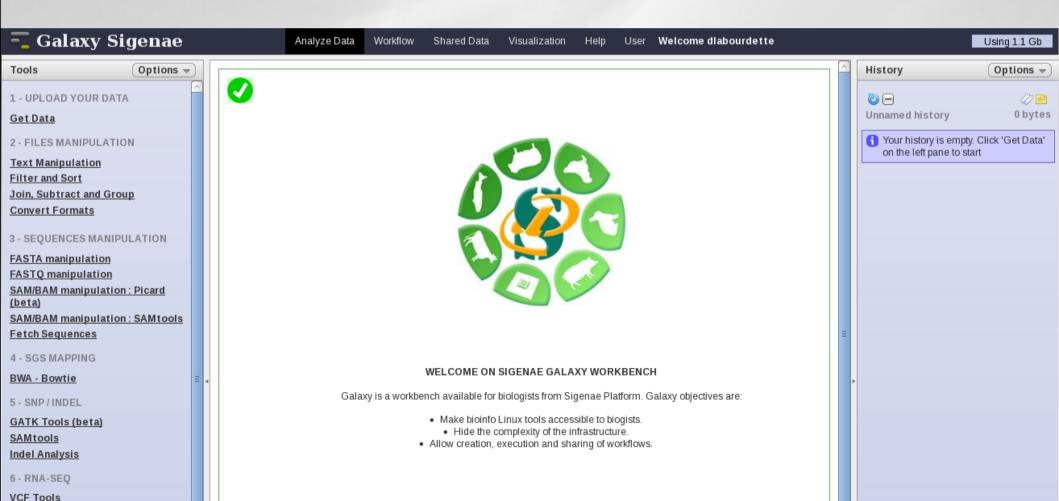
Session organisation

- Sequence quality
 - Theory + exercises
 - Spliced read mapping Visualisation
 - Theory + exercises
- expression measurement
 - Theory + exercises
- mRNA calling
 - Theory + exercises



What you should know

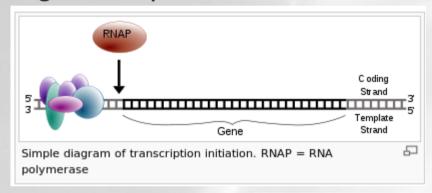
How to connect to Sigenar galaxy workbench? http://sigenae-workbench.toulouse.inra.fr/galaxy/

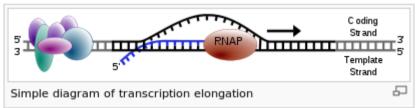


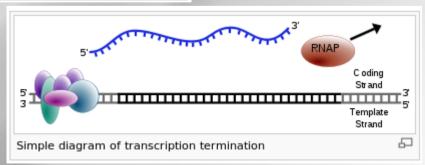


Transcription

Transcription is the process of creating a complementary RNA copy of a sequence of DNA. Transcription is the first step leading to gene expression.





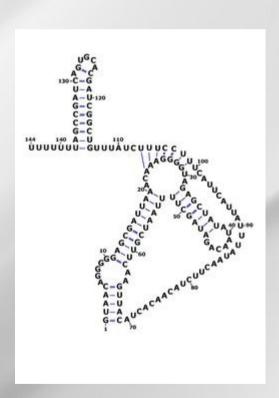




Transcription products

Protein coding gene: transcribed in mRNA ncRNA: highly abundant and functionally important RNA

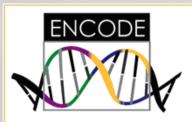
- tRNA,
- rRNA,
- snoRNAs,
- microRNAs,
- siRNAs,
- PiRNAs
- lincRNA



http://en.wikipedia.org/wiki/User:Amarchais/RsaOG_RNA



ENCODE



Project
Data
Statistics
Participants
Publications
RGASP 1/2
RGASP 3
Contact us

Statistics about the current GENCODE freeze (version 13)

Statistics of previous Gencode freezes are found archived here.

*The statistics derive from the **gtf files**, which include only the main chromosomes of the human reference genome.

Version 13 (March 2012 freeze, GRCh37)

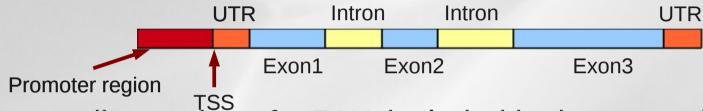
General stats

Total No of Genes	55123	Total No of Transcripts	182967
Protein-coding genes	20070	Protein-coding transcripts	77901
Long non-coding RNA genes	12393	- full length protein-coding:	55928
Small non-coding RNA genes	9173	- partial length protein-coding:	21973
Pseudogenes	13123	Nonsense mediated decay	11549
- processed pseudogenes:	9895	transcripts	19835
- unprocessed pseudogenes:	2550	Long non-coding RNA loci transcripts	19035
- unitary pseudogenes:	156		
- polymorphic pseudogenes:	31		
- pseudogenes:	298		
Immunoglobulin/T-cell receptor		Total No of distinct translations	78119
gene segments		Genes that have more than one	14235
 protein coding segments: 	364	distinct translations	
- pseudogenes:	193		



Vocabulary

Gene: functional units of DNA that contain the instructions for generating a functional product.



Exon: coding region of mRNA included in the transcript

Intron: non coding region

TSS: Transcription Start Site ≠ 1st amino acid

Transcript: stretch of DNA transcribed into an RNA molecule

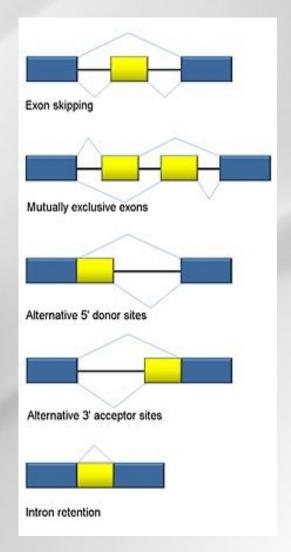




Alternative splicing

Alternative splicing (or differential splicing) is a process by which the exons of the RNA produced by transcription of a gene (a primary gene transcript or pre-mRNA) are reconnected in multiple ways during RNA splicing. The resulting different mRNAs may be translated into different protein isoforms; thus, a single gene may code for multiple proteins.

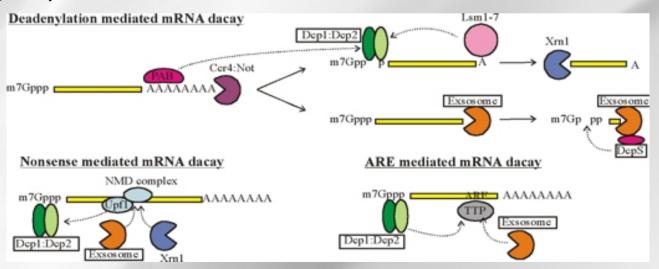
Post-transcriptional modification is a process in cell biology by which, in eukaryotic cells, primary transcript RNA is converted into mature RNA. A notable example is the conversion of precursor messenger RNA into mature messenger RNA (mRNA), which includes splicing and occurs prior to protein synthesis.





Transcript degradation

After export to the cytoplasm, mRNA is protected from degradation by a 5' cap structure and a 3' poly adenine tail. In the deadenylation dependent mRNA decay pathway, the polyA tail is gradually shortened by exonucleases. This ultimately attracts the degradation machinery that rapidly degrades the mRNA in both in the 5' to 3' direction and in the 3' to 5' direction. Additional mechanisms, including the nonsense mediated decay pathway, bypass the need for deadenylation and can remove the mRNA from the transcriptional pool independently. Interestingly, the same enzymes are responsible for the actual degradation of the mRNA independent of the pathway taken (see figure).

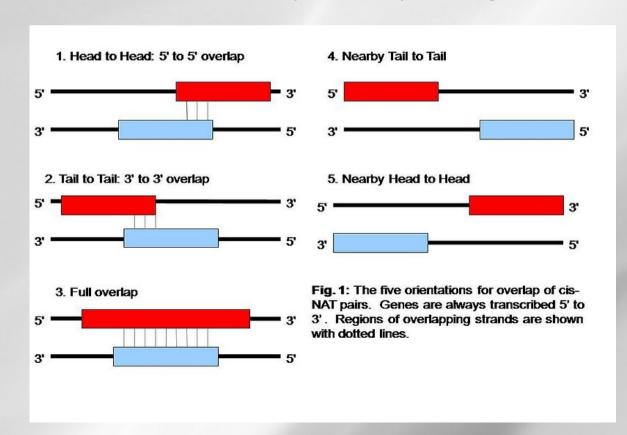




Cis-natural antisense transcript

 Natural antisense transcripts (NATs) are a group of RNAs encoded within a cell that have transcript complementarity to other RNA transcripts.

http://en.wikipedia.org/wiki/Cis-natural_antisense_transcript





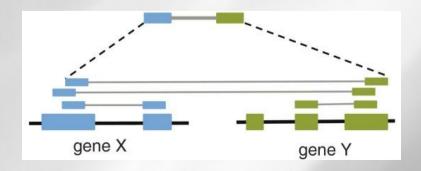
Fusion genes

- A fusion gene is a hybrid gene formed from two previously separate genes. It can occur as the result of a translocation, interstitial deletion, or chromosomal inversion. Often, fusion genes are oncogenes.
- They often come from trans-splicing: Trans-splicing is a special form of RNA processing in eukaryotes where exons from two different primary RNA transcripts are joined end to end and ligated.

Genome Biol. 2011 Jan 19;12(1):R6. [Epub ahead of print]

Identification of fusion genes in breast cancer by paired-end RNA-sequencing.

Edgren H, Murumaqi A, Kanqaspeska S, Nicorici D, Honqisto V, Kleivi K, Rye IH, Nyberg S, Wolf M, Borresen-Dale AL, Kallioniemi O. Institute for Molecular Medicine Finland (FIMM), Tukholmankatu 8, Helsinki, 00290, Finland. olli.kallioniemi@fimm.fi.



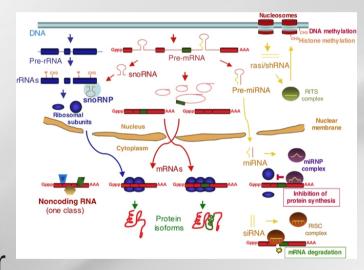
http://en.wikipedia.org/wiki/Fusion_gene

http://en.wikipedia.org/wiki/Trans-splicing



Transcriptome variability summary

- Number of transcripts
 - *possible variation factor between transcripts: 10⁶ or more,
 - *expression variation between samples.
- Many types of transcripts *mRNA, ncRNA,...
- Isoforms (with non canonical splice sites)
- Intron retention
 - *The splicing is not always completed
 - *Is a new isoform or a transcription error
- Transcript decay (degradation)
- Allele specific expression





UTR length

Lengthening of 3'UTR Increases with Morphological Complexity in Animal Evolution

Cho-Yi Chen^{1,2}, Shui-Tein Chen², Hsueh-Fen Juan^{1,*} and Hsuan-Cheng Huang^{3,*}

¹Genome and Systems Biology Degree Program, Department of Life Science, Institute of Molecular and Cellular Biology, Graduate Institute of Biomedical Electronics and Bioinformatics, National Taiwan University, Taipei, Taiwan,

²Institute of Biological Chemistry, Academia Sinica, Taipei, Taiwan

³Institute of Biomedical Informatics, Center for Systems and Synthetic Biology, National Yang-Ming University, Taipei, Taiwan

Associate Editor: Martin Bishop

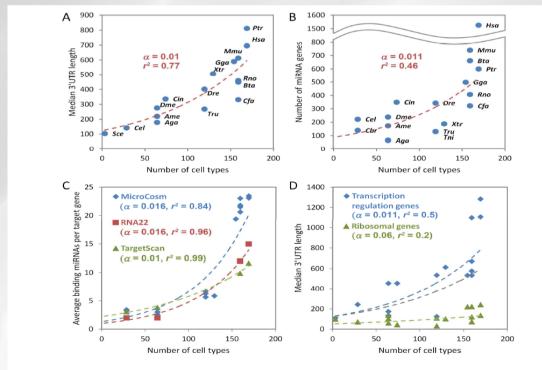


Fig. 1. Exponential correlation between miRNA-mediated regulation and morphological complexity. (A) A strong exponential correlation exists between the median length of 3 UTRs and the morphological complexity among 15 metazoan species, as measured by distinct cell types (Vogel and Chothia, 2006). Budding yeast (S.~cerevtstae) is included for comparison as a unicellular eukaryote. The dashed line indicates a single exponential fit, together with the fitting parameter α and the coefficient of determination r^2 . (B) The number of miRNA genes in each genome and (C) miRNA binding complexity (average numbers of putative binding miRNAs per target gene) correlate exponentially with morphological complexity. See also Supplementary Figure S3 for species labels. (D) The growth profiles of median 3 UTR length for transcription regulation genes (GO: 0006355) and ribosomal genes (GO: 0005840) show different trends. Budding yeast is included for comparison. The gray dash line, showing the global trend, is adapted from (A) for comparison.



Techniques classification?

EST	PCR/RT-QPCR	SAGE	MicroArrays
No quantification	Quantification	Quantification	Indirect quantification
Low throughput	Low throughput (up to hundreds)	Low throughput (up to thousands)	High throughput (up to millions)
Discovery (Yes)	No	No	Discovery (Yes)

- → Need transcript sequence partially known
- → Difficulties in discovering novels splice events



What is RNA-Seq?

- use of high-throughput sequencing technologies to sequence cDNA in order to get information about a sample's RNA content
- Thanks to the deep coverage and base level resolution provided by next-generation sequencing instruments, RNAseq provides researchers with efficient ways to measure transcriptome data experimentally

Nature Reviews Genetics 10, 57-63 (January 2009) | doi:10.1038/nrg2484

O ARTICLE SERIES: Applications of next-generation sequencing

INNOVATION

RNA-Seq: a revolutionary tool for transcriptomics

Zhong Wang¹, Mark Gerstein¹ & Michael Snyder¹ About the authors

top 🛧

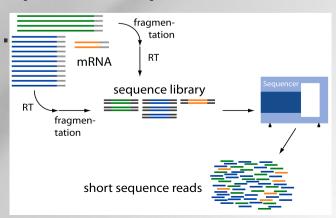
RNA-Seq is a recently developed approach to transcriptome profiling that uses deep-sequencing technologies. Studies using this method have already altered our view of the extent and complexity of eukaryotic transcriptomes. RNA-Seq also provides a far more precise measurement of levels of transcripts and their isoforms than other methods. This article describes the RNA-Seq approach, the challenges associated with its application, and the advances made so far in characterizing several eukaryote transcriptomes.

http://en.wikipedia.org/wiki/RNA-Seq



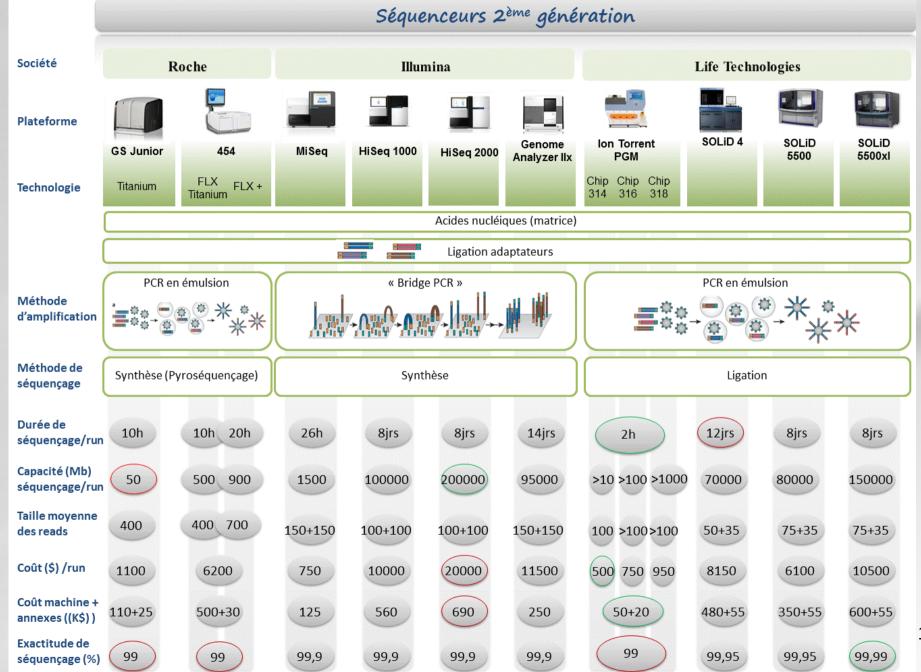
What is different with RNA-Seq?

- No prior knowledge of sequence needed
- Specificity of what is measured
- Increased dynamic range of measure, more sensitive detection
- Direct quantification
- Good reproducibility
- Different levels : genes, transcripts, allele specificity, structure variations
- New feature discovery: transcripts, isoforms, ncRNA, structures (fusion...)
- Possible detection of SNPs, ...





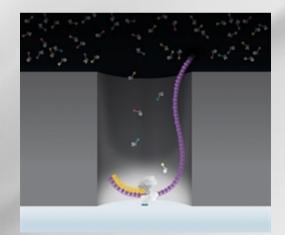
RNA-Seq platforms comparison





Third Generation RNA-Seq

- No more amplification
- Single Molecule Sequencing Technology (tSMS)
- Single Molecule Real Time (SMRT) sequencing
 - technology (PacBio RS)
- One read per transcript

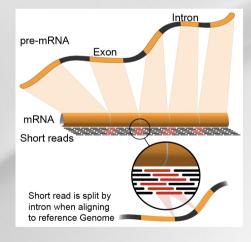




Different approaches:

Alignment to

- De novo
 - No reference genome, no transcriptome available
 - Very expensive computationally
 - Lots of variation in results depending on the software used
- Reference transcriptome
 - Most are incomplete
 - Computationally inexpensive
- Reference genome
 - When available
 - Allow reads to align to unannotated sites
 - Computationally expensive
 - Need a spliced aligner





What are we looking for?

Identify genes

List new genes

Identify transcripts

List new alternative splice forms



Quantify these elements → differential expression



Usual questions on RNA-Seq!

- How many replicates?
 - Technical or/and biological replicates?
- How many reads for each sample?
- How many conditions for a full transcriptome?
- How long should my reads be?
- Single-end or paired-end?



ENCODE answers

- RNA-Seq is not a mature technology.
- Experiments should be performed with two or more biological replicates, unless there is a compelling reason why this is impractical or wasteful
- A typical R² (Pearson) correlation of gene expression (RPKM) between two biological replicates, for RNAs that are detected in both samples using RPKM or read counts, should be between 0.92 to 0.98. Experiments with biological correlations that fall below 0.9 should be either be repeated or explained.
- Between 30M and 100M reads per sample depending on the study.
 - **NB.** Guidelines for the information to publish with the data.



Encyclopedia of DNA Elements



Statisticians answers

Efficient experimental design and analysis strategies for the detection of differential expression using RNA-Sequencing

BMC Genomics 2012, 13:484 doi:10.1186/1471-2164-13-484

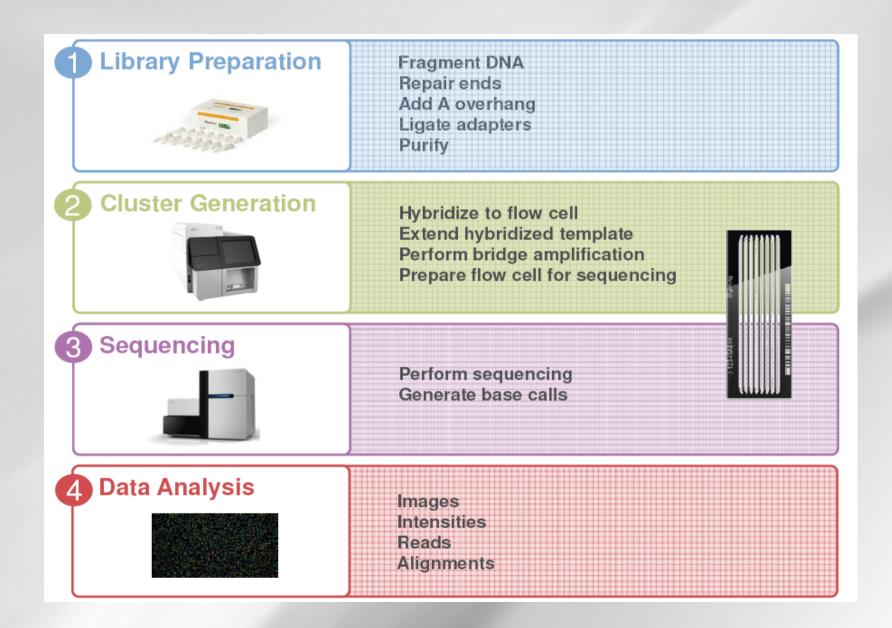
Jose A Robles (jose.robles@csiro.au)

Conclusions

This work quantitatively explores comparisons between contemporary analysis tools and experimental design choices for the detection of differential expression using RNA-Seq. We found that the DESeq algorithm performs more conservatively than edgeR and NBPSeq. With regard to testing of various experimental designs, this work strongly suggests that greater power is gained through the use of biological replicates relative to library (technical) replicates and sequencing depth. Strikingly, sequencing depth could be reduced as low as 15% without substantial impacts on false positive or true positive rates.

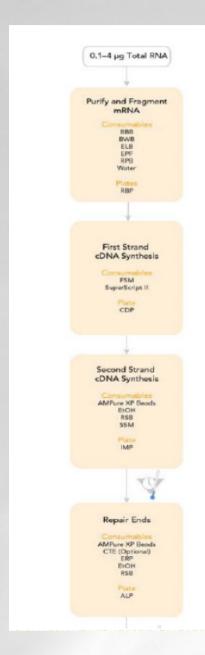


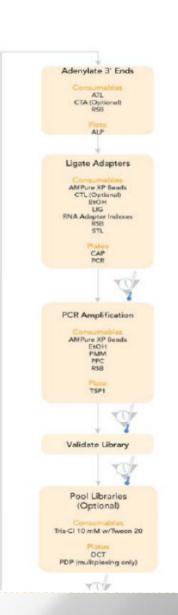
Illumina RNA-Seq protocol





RNA-Seq library preparation



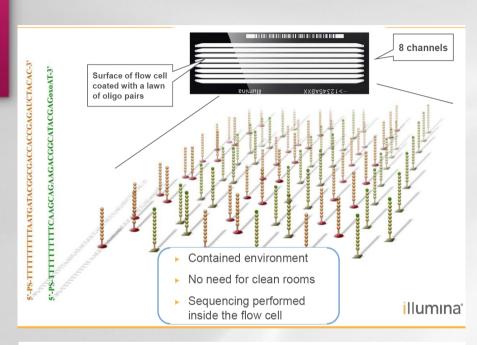


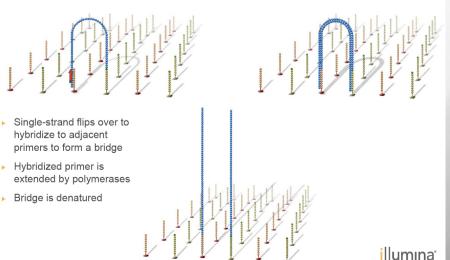
- Isolate poly-A containing mRNA
- capture mRNA with oligoT beads
- Randomly fragment RNA
- Random prime mRNA → cDNA
- Make 2nd strand cDNA
- Repair-Ends and 3' Ends Adenylate
- Ligate sequencing adapters
- Enrich up to 15 cycles of PCR
- gel purify
- validate library w/ Bioanalyzer

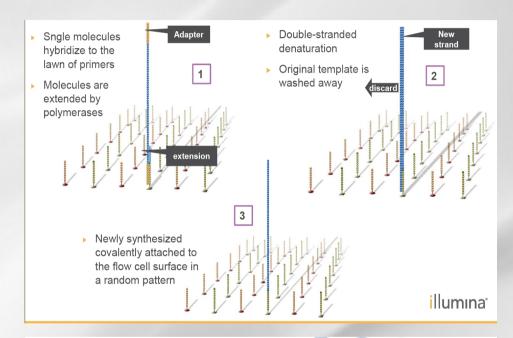
Library prep takes <2 days



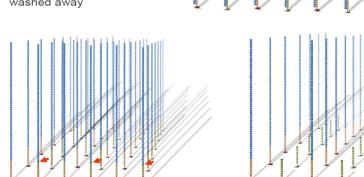
Clusters generation







- Bridge amplification cycle repeated until multiple bridges are formed
- Bridges denaturation
- Reverse strands cleaved and washed away





Sequencing

Cluster generation:

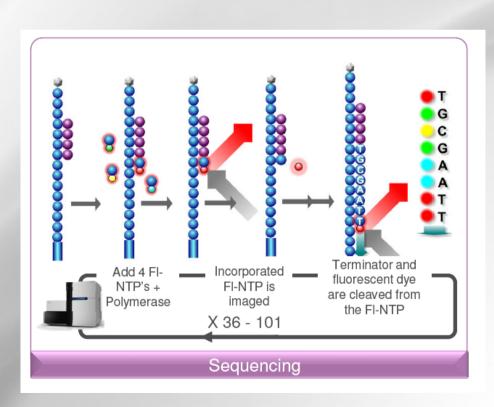
- 35 amplification cycles
- 1 cluster → 2 000 identical molecules
- 500 000 clusters / flocell

Sequencing:

- Image acquisition:

• 50 min / cycle

Ex: $2x100bp \rightarrow 2x100x50 min$



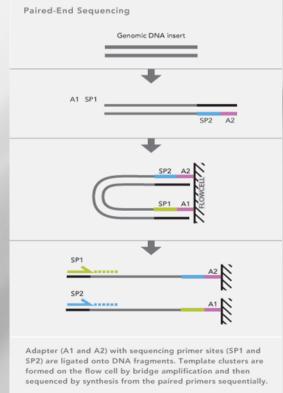


Paired-end sequencing

- Modification of the standard single-read DNA library preparation facilitates reading both ends of each fragment
- Improvement of mapping

 Help to detect structural variations in the genome like insertions or deletions, copy number variations, and

genome rearrangements





Strand specific RNA-Seq protocol

workflow comparison: mRNA-Seq vs directional mRNA-Seq

- 1. start with 1µg (or less) total RNA
- purify poly-A mRNA
- randomly fragment mRNA



- 1st strand cDNA synthesis
- 2nd strand cDNA synthesis
- end repair
- adenylate 3' ends
- ligate adaptors
- gel purify

- end repair with phosphatase and PNK
- column purify PNK treated mRNA
- ligate 3' adaptor
- ligate 5' adaptor
- reverse transcribe

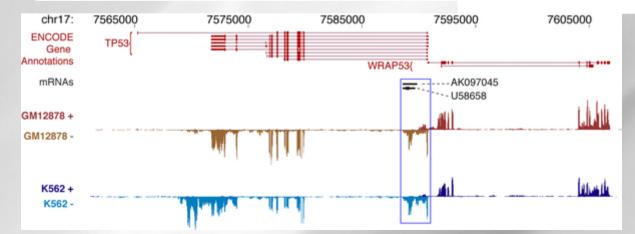


Nat Methods. 2010 Sep;7(9):709-15. Epub 2010 Aug 15.

Comprehensive comparative analysis of strand-specific RNA sequencing methods.

Levin JZ, Yassour M, Adiconis X, Nusbaum C, Thompson DA, Friedman N, Gnirke A, Regev A.

Broad Institute of Massachusetts Institute of Technology and Harvard University, Cambridge, Massachusetts, USA. jlevin@broadinstitute.org



- 10. enrich with PCR
- 11. validate library
- 12. grow clusters
- 13. sequence on HiSeq2000 (SR or PE)



Analysis workflow

Data quality control

Spliced mapping

Quantification

Gene and transcript discovery



fastq file formats

Published online 16 December 2009

Nucleic Acids Research, 2010, Vol. 38, No. 6 1767–1771 doi:10.1093/nar/gkp1137

SURVEY AND SUMMARY

The Sanger FASTQ file format for sequences with quality scores, and the Solexa/Illumina FASTQ variants

Peter J. A. Cock^{1,*}, Christopher J. Fields², Naohisa Goto³, Michael L. Heuer⁴ and Peter M. Rice⁵

@EAS54_6_R1_2_1_413_324
CCCTTCTTGTCTTCAGCGTTTCTCC
+
;;3;;;;;;;;;;;;88

 $Q_{\rm PHRED} = -10 \times \log_{10}(P_e)$



RNAseq specific bias

- Influence of the library preparation
- Random hexamer priming
- Positional bias and sequence specificity bias.

Robert et al. Genome Biology, 2011,12:R22

- Transcript length bias
- Some reads map to multiple locations



Hexamer random priming bias

Published online 14 April 2010

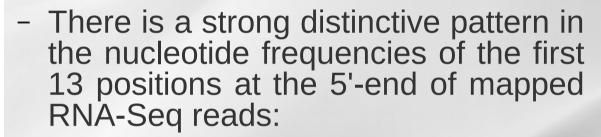
Nucleic Acids Research, 2010, Vol. 38, No. 12 e131 doi:10.1093/nar/gkq224

Biases in Illumina transcriptome sequencing caused by random hexamer priming

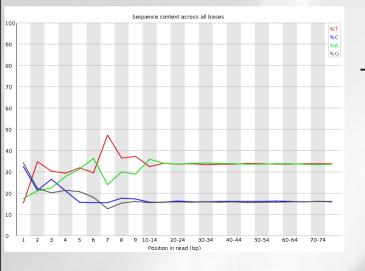
Kasper D. Hansen^{1,*}, Steven E. Brenner² and Sandrine Dudoit^{1,3}

ABSTRACT

Generation of cDNA using random hexamer priming induces biases in the nucleotide composition at the beginning of transcriptome sequencing reads from the Illumina Genome Analyzer. The bias is independent of organism and laboratory and impacts the uniformity of the reads along the transcriptome. We provide a read count reweighting scheme, based on the nucleotide frequencies of the reads, that mitigates the impact of the bias.

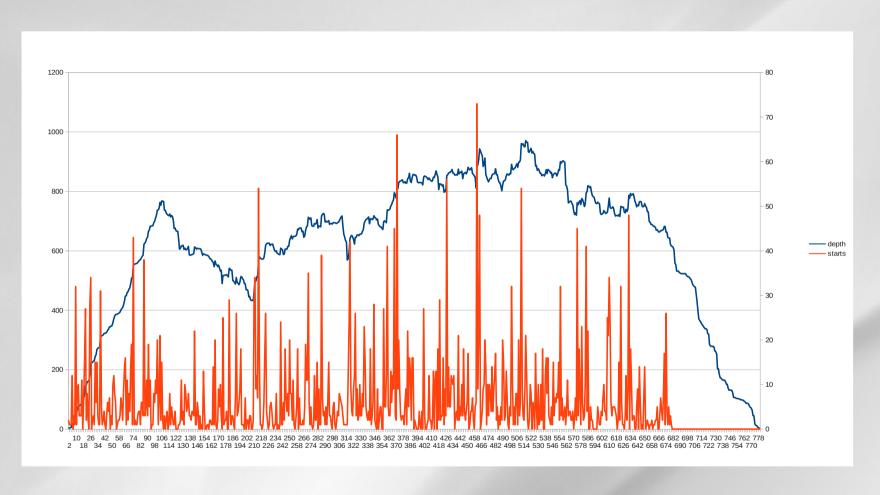


- sequence specificity of the polymerase
- due to the end repair performed
- Reads beginning with a hexamer overrepresented in the hexamer distribution at the beginning relative to the end are down-weighted





Hexamer random effect



- Orange = reads start sites
- Blue = coverage



Transcript length bias

Biol Direct. 2009 Apr 16;4:14.

Transcript length bias in RNA-seq data confounds systems biology.

Oshlack A, Wakefield MJ.

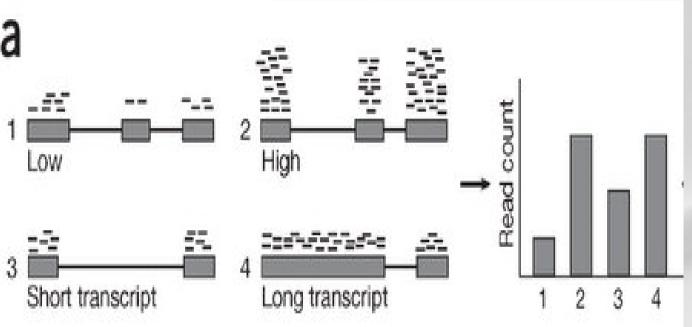
Abstract

Background: Several recent studies have demor transcriptome analysis (RNA-seq) in mammals. genome transcriptional profiling is likely to becor genomic sequences. As yet, a rigorous analysis m still in the stages of exploring the features of the

Results: We investigated the effect of transcript published data sets. For standard analyses using a call differentially expressed genes between samp transcript.

Conclusion: Transcript length bias for calling diff current protocols for RNA-seq technology. This expressed genes, and in particular may introduce other multi-gene systems biology analyses.

Reviewers: This article was reviewed by Rohan 3 Cloonan (nominated by Mark Ragan) and James B



 the differential expression of longer transcripts is more likely to be identified than that of shorter transcripts

BIOINFORMATICS	ORIGINAL PAPER	Vol. 27 no. 5 2011, pages 662-669 doi:10.1093/bioinformatics/b1r005		
Gene expression	Advano	Access publication January 19, 2011		
Length bias correction for RNA-seq data in gene set analyses				
Liyan Gao ^{1,†} , Zhide Fang ^{2,†} , Kui Zhang ¹ , Degui Zhi ¹ and Xiangqin Cui ^{1,*}				

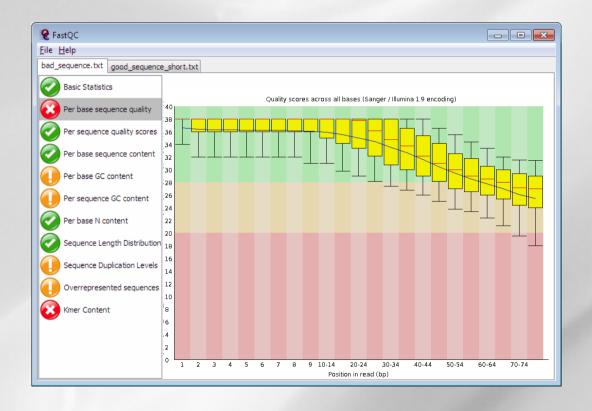


Verifying RNA-Seq raw data

FastQC:

http://www.bioinformatics.bbsrc.ac.uk/projects/fastqc/



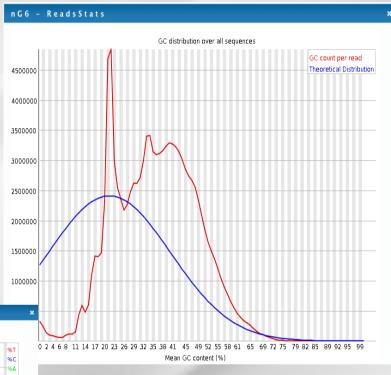




Fourmiz !!!









Take home message on quality analysis

Elements to be checked:

- Random priming effect
- K-mer (polyA, polyT)

Alignment on reference for the second quality check and filtering.

A good run?:

- Expected number of reads produced (2x500millions / flowcell),
- Length of the reads expected (100pb),
- Random selection of the nucleotides and the GC%,
- Good alignment: very few unmapped reads, pairs mapped on opposite strands.



Analysis workflow

Data quality control

Spliced mapping

Quantification

Gene and transcript discovery



Where to find a reference genome?

Retrieving the genome file (fasta):

- The Genome Reference Consortium

http://www.ncbi.nlm.nih.gov/projects/genome/assembly/grc/

- ! NCBI chromosome naming with « | » not well supported by mapping software
- Prefer EMBL:

http://www.ensembl.org/info/data/ftp/index.html



Reference transcriptome file

What is a GTF file ?:

- derived from GFF (General Feature Format, for description of genes and other features)
- Gene Transfer Format:

http://genome.ucsc.edu/FAQ/FAQformat.html#format4

<seqname> <source> <feature> <start> <end> <score> <strand> <frame> [attributes] [comments]

The [attribute] list must begin with:

gene_id value : unique identifier for the genomic source of the sequence. transcript_id value : unique identifier for the predicted transcript.

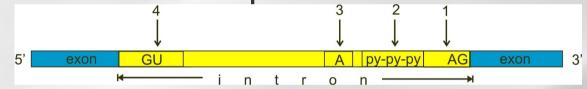


The chromosome name should be the same in the gtf file and fasta file



Splice sites

Canonical splice site:
 which accounts for more than 99% of splicing
 GT and AG for donor and acceptor sites



http://en.wikipedia.org/wiki/RNA_splicing

Non-canonical site:
 GC-AG splice site pairs, AT-AC pairs

Nucleic Acids Res. 2000 Nov 1;28(21):4364-75.

Analysis of canonical and non-canonical splice sites in mammalian genomes.

Burset M, Seledtsov IA, Solovyev VV.

- Trans-splicing :

splicing that joins two exons that are not within the same RNA transcript



Spliced alignment

- The recognition of exon/intron junctions can be inferred from the reads that overlap the splicing sites. The resulting spliced reads can produce very short alignments, part of the read will not map contiguously to the reference.
 - → therefore this approach requires a dedicated algorithm

Generation :

Genome Res. 1998 Sep;8(9):967-74.

A computer program for aligning a cDNA sequence with a genomic DNA sequence.

Florea L, Hartzell G, Zhang Z, Rubin GM, Miller W.

• Sim4

Department of Computer Science and Engineering, The Pennsylvania State University, University Park, Pennsylvania 16802 USA.

- Seqanswer : http://seqanswers.com/wiki/Software/list
- Idea:
 - Database of potential splice junction sequences (known)
 - splice canonical / non canonical site search (seed then mapping)



TopHat

BIOINFORMATICS

ORIGINAL PAPER

Vol. 25 no. 9 2009, pages 1105-1111 doi:10.1093/bioinformatics/btp120

Sequence analysis

TopHat: discovering splice junctions with RNA-Seq

Cole Trapnell^{1,*}, Lior Pachter² and Steven L. Salzberg¹

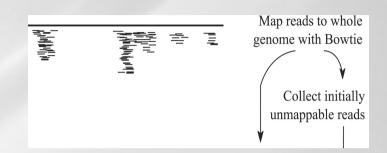
http://tophat.cbcb.umd.edu/

- Aligns RNA-Seq reads to a reference genome with Bowtie
- splice junction mapper for reads without knowledges
- identify splice junctions between exons.



TopHat algorithm: first step

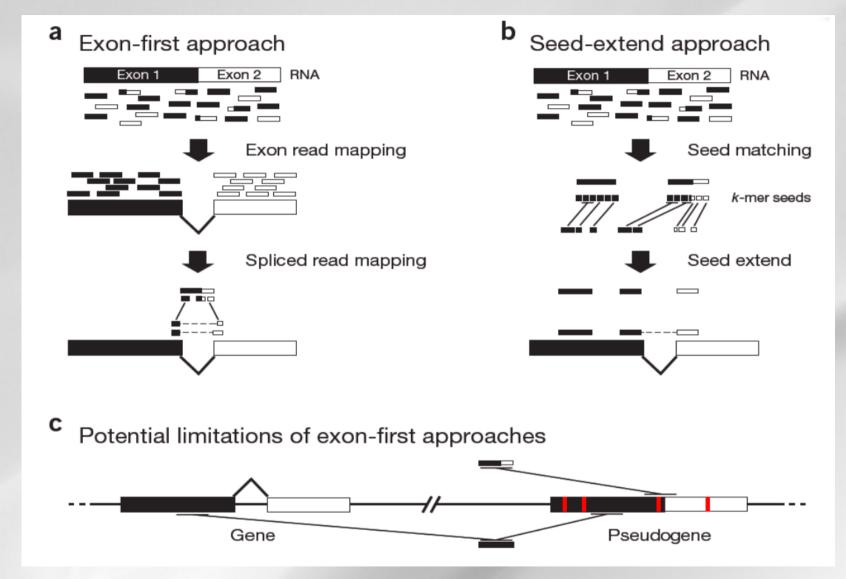
 TopHat finds junctions by mapping reads to the reference:



- all reads are mapped to the reference genome using Bowtie
- reads not mapped to the genome are set aside as IUM (initially unmapped)
- low complexity reads are discarded
- for each read : allow until 20 alignments



Exon first approach limitation

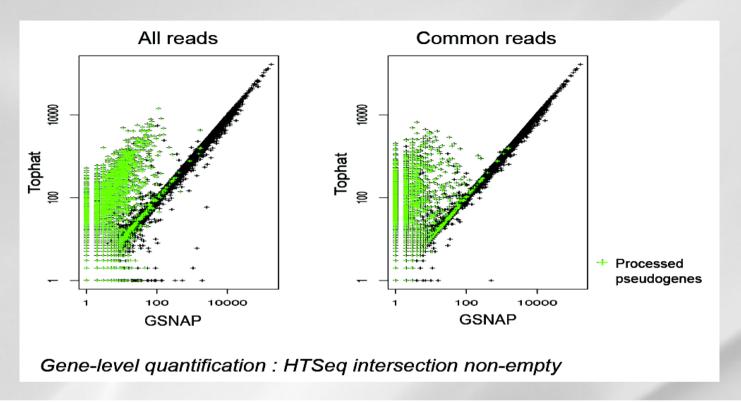


REVIEW

Computational methods for transcriptome annotation and quantification using RNA-seq



TopHat and pseudogenes



--read-realign-edit-dist

Some of the reads spanning multiple exons may be mapped incorrectly as a contiguous alignment to the genome even though the correct alignment should be a spliced one - this can happen in the presence of processed pseudogenes that are rarely (if at all) transcribed or expressed. This option can direct TopHat to re-align reads for which the edit distance of an alignment obtained in a previous mapping step is above or equal to this option value. If you set this option to 0, TopHat will map every read in all the mapping steps (transcriptome if you provided gene annotations, genome, and finally splice variants detected by TopHat), reporting the best possible alignment found in any of these mapping steps. This may greatly increase the mapping accuracy at the expense of an increase in running time. The default value for this option is set such that TopHat will not try to realign reads already mapped in earlier steps.



Why does it find small exons?

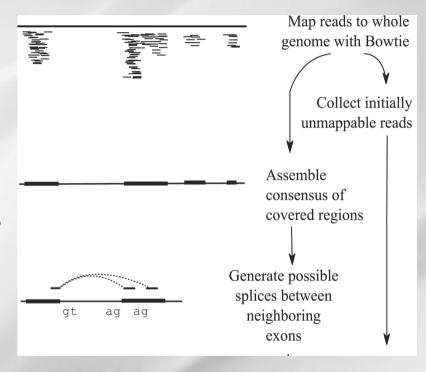
- In the last tophat versions:

Short read sequencing machines can currently produce reads 100bp or longer but many exons are shorter than this so they would be missed in the initial mapping. **TopHat solves this problem mainly by splitting all input reads into smaller segments which are then mapped independently**. The segment alignments are put back together in a final step of the program to produce the end-to-end read alignments.



Exon assembly process

- TopHat then assembles the mapped reads
- Define island: aggregates mapped reads in islands of candidate exons
 - Generate potential donor/acceptor splice sites using neighbouring exons



- Extend islands to cover eventually splice junctions
 - +/- 45 bp from reference on either side of island



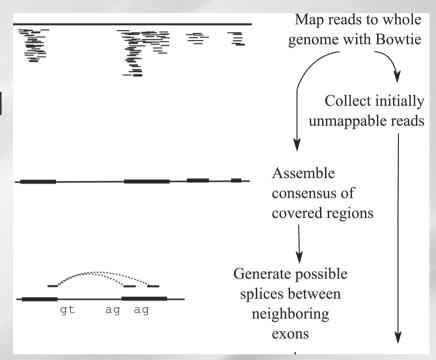
Spice junction reference

To map reads to splice junction:

- Enumerate all canonical donor and acceptor sites in islands
 - long (>= 75 bp) reads:

"GT-AG", "GC-AG" and "AT-AC" introns

- Shorter reads:
- only "GT-AG" introns
- Find all pairings which produce
 GT-AG introns between islands
 - 50 bp < Intron size < 500,000 bp

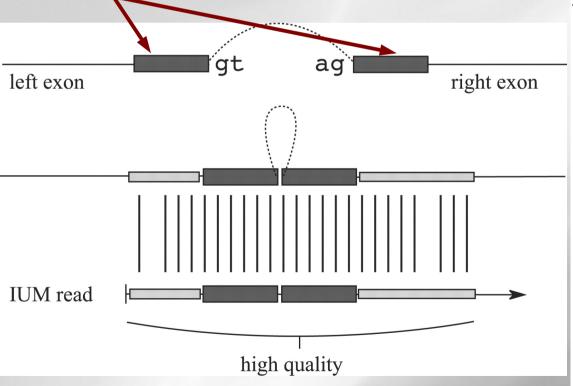


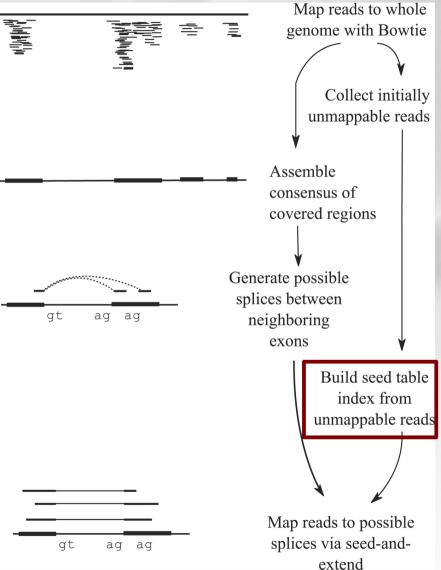


IUM alignment

 Each possible intron is checked against the IUM

→ seed and extend alignment







TopHat Inputs

Inputs:

- bowtie2 index of the genome
 ftp://ftp.cbcb.umd.edu/pub/data/bowtie_indexes/
 http://bowtie-bio.sourceforge.net/index.shtml
- file fasta (.fa) of the reference or will be build by bowtie,
 in the index directory
- File fastq of the reads



! the GTF file and the Bowtie index should have same name of chromosome or contig

Command lines:

bowtie2-build <reference.fasta> <index_base>
tophat [options] <index_base> <reads1_1]> <[reads1_2]>



TopHat Options

Some useful options (command line):

```
-h/--help
```

- -v/--version
- - bowtie1 (instead of bowtie2)
- o/--output-dir
- -r/--mate-inner-dist: no default value
- -m/--splice-mismatches : default 0
- -i/--min-intron-length: default 50
- -I/--max-intron-length: default 500000, prefer 25000 for non human
- --max-insertion-length: default 3
- --max-deletion-length: default 3
- -p/--num-threads



Special note on the website

Please Note TopHat has a number of parameters and options, and their default values are tuned for processing mammalian RNA-Seq reads.

If you would like to use TopHat for another class of organism, we recommend setting some of the parameters with more strict, conservative values than their defaults.

Usually, setting the maximum intron size to 4 or 5 Kb is sufficient to discover most junctions while keeping the number of false positives low.



More topHat options

Your own junctions:

```
-G/--GTF <GTF2.2file>
```

-j/--raw-juncs <.juncs file>

--no-novel-juncs (ignored without -G/-j)

Your own insertions/deletions:

--insertions/--deletions <.juncs file>

--no-novel-indels



Library types

library-type	TopHat will treat the reads as strand specific. Every read alignment will have an XS attribute tag. Consider
	supplying library type options below to select the correct RNA-seq protocol.

Library Type	Examples	Description
fr-unstranded	Standard Illumina	Reads from the left-most end of the fragment (in transcript coordinates) map to the transcript strand, and the right-most end maps to the opposite strand.
fr-firststrand	dUTP, NSR, NNSR	Same as above except we enforce the rule that the right-most end of the fragment (in transcript coordinates) is the first sequenced (or only sequenced for single-end reads). Equivalently, it is assumed that only the strand generated during first strand synthesis is sequenced.
fr-secondstrand	Ligation, Standard SOLiD	Same as above except we enforce the rule that the left-most end of the fragment (in transcript coordinates) is the first sequenced (or only sequenced for single-end reads). Equivalently, it is assumed that only the strand generated during second strand synthesis is sequenced.



TopHat Outputs

Outputs:

- accepted_hits.bam : list of read alignments in SAM format compressed
- *junctions.bed* : track of junctions, scores : number of alignments spanning the junction
- *insertions.bed* and *deletions.bed* : tracks of insertions and deletions
- logs directory files
- unmapped.bam : Unmapped or multi-mapped (over the threshold) reads
- prep_reads.info: number of reads and read length for input and output



Spliced cigar line

Extend CIGAR strings

Op	BAM	Description
M	0	alignment match (can be a sequence match or mismatch)
I	1	insertion to the reference
D	2	deletion from the reference
N	3	skipped region from the reference
S	4	soft clipping (clipped sequences present in SEQ)
H	5	hard clipping (clipped sequences NOT present in SEQ)
P	6	padding (silent deletion from padded reference)
=	7	sequence match
X	8	sequence mismatch

- Example: intron de 81 bases

flag chr pos pair

http://picard.sourceforge.net/explain-flags.html

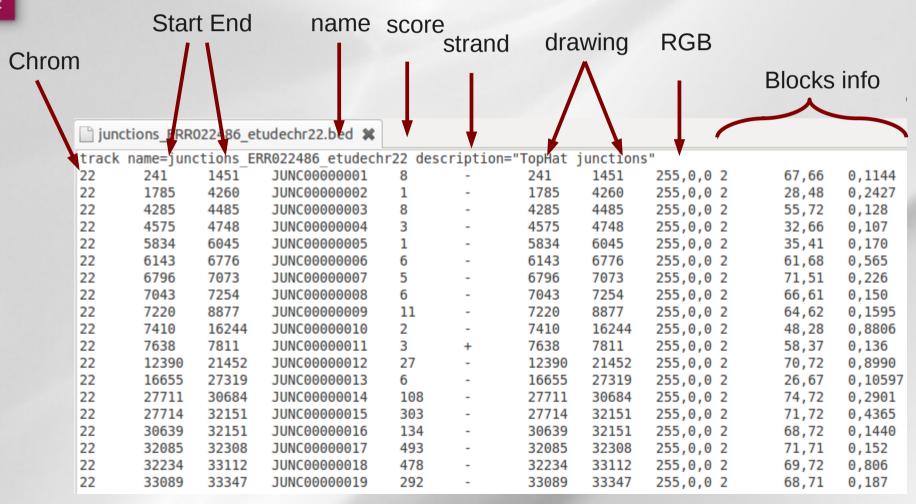


Bam & Bed

- BAM (Binary Alignment/Map) format:
 - Compressed binary representation of SAM
 - Greatly reduces storage space requirements to about 27% of original SAM
 - Bamtools: reading, writing, and manipulating BAM files
- Bed (Browser Extensible Data) format:
 - tab-delimited text file that defines a feature track
 http://genome.ucsc.edu/FAQ/FAQformat.html#format1
 - The first three required BED fields are:
 <chromosome> <start> <end>
 - 9 additional optional BED fields



Bed exemple





Tophat technical issues

- Temporary disk space
 - 100 000 000 pair-ends = 0,5 To of temporary disk space
- Number of cpus
 - 100 000 000 pair-ends = 5-7 cpu days on the local cluster
- New platform cluster:
 - 34 cluster nodes with 4*12 cores and 384 GB of ram per node: 1632 cores
 - 1 hypermem node (32 cores and 1024 GB of ram)
 - A scratch file system (157 To available, 6 Gbps bandwith)



Trans-splicing with TopHat-Fusion



- an enhanced version of TopHat with the ability to align reads across fusion points
- identify fusions due to chromosomal rearrangements whether inter- or intra-chromosomal
- suggest that reads are at least 50-bp long, where a read is split into two segments (25-bp each)
- Both single and paired-end reads can be used and the output alignments are given in a modified SAM format with a new CIGAR* operator 'F' to indicate fusion points



Mapper comparisons

Comparative Analysis of RNA-Seq Alignment Algorithms and the RNA-Seq Unified Mapper (RUM)

Gregory R. Grant^{1,2,4,*}, Michael H. Farkas³, Angel Pizarro², Nicholas Lahens⁵, Jonathan Schug⁴, Brian Brunk¹, Christian J. Stoeckert Jr^{1,4}, John B. Hogenesch^{1,2,5} and Eric A. Pierce^{3,*}

- 1 Penn Center for Bioinformatics, University of Penn 100%
- 2 Institute for Translational Medicine and Therapeuti
- 3 F.M. Kirby Center for Molecular Ophthalmology, U
- 4 Department of Genetics, University of Pennsylvani
- 5Department of Pharmacology, University of Pennsy

Associate Editor: Prof. Ivo Hofacker

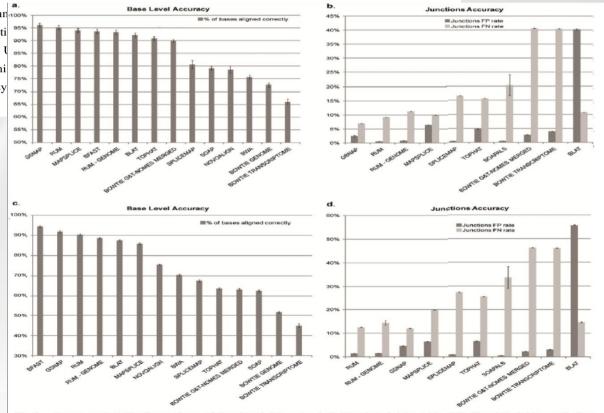


Fig. 6. Accuracy statistics for analyses of simulated data sets. A, B. Simulated data set 1. C,D. Simulated data set 2. Test 1 has low polymorphism and error rates, while Test 2 has moderate polymorphism and error rates. In A and C The dark bars show the base-wise accuracy (the percent of bases that aligned and to the right location); the light bars give the coverage plot accuracy. B and D show the accuracy of the junction calls, dark bars show the false positive (FP) rate and light bars show the false negative (FN) rate. The algorithms are sorted in A and C by accuracy and in B and D by the sum of the FP and FN rates. Results are mean +/- SEM over the three replicate simulated data sets for each test. There is a considerable dropoff in accuracy seen in Test 2 for the algorithms that do not align across indels (SpliceMap, TopHat, and Bowtie). The base-wise accuracy and the FP and FN rates on junction calls are taken in conjunction to determine the overall effectiveness of an algorithm. Based on these results, we conclude that GSPAN, MapSplice and RUM are the ones that are most viable for RNA-Seq alignment.





http://www.broadinstitute.org/igv/home

Integrative genomics viewer

James T Robinson, Helga Thorvaldsdóttir, Wendy Winckler, Mitchell Guttman, Eric S Lander, Gad Getz & Jill P Mesirov

Affiliations | Corresponding authors

Nature Biotechnology 29, 24–26 (2011) | doi:10.1038/nbt.1754

Published online 10 January 2011

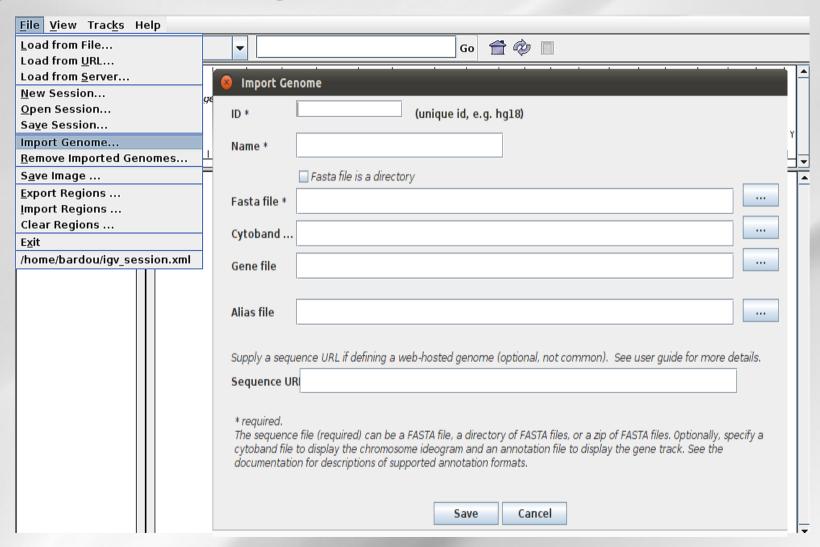


- High-performance visualization tool
- Interactive exploration of large datasets
- Supports a wide variety of data types
- Documentations available
- Developed at the Broad Institute of MIT and Harvard

- File Extension Identifies Format
- Recommended File Formats
- BAN
- BED
- BedGraph
- bigBed
- bigWig
- Birdsuite Files
- CBS
- CN
- Cufflinks Files
- Custom File Formats
- Cytoband
- FASTA
- GCT
- genePred
- GFF
- GISTIC
- Goby
- GWAS
- IGV
- LOH
- MAF
- Merged BAM File (.bam.list)
- MUT
- PSL PEC
- RES
- Sample Information
- SEG
- SNP
- <u>TAB</u>
- TDF
- Track Line
- Type Line
- VCF
- WIG

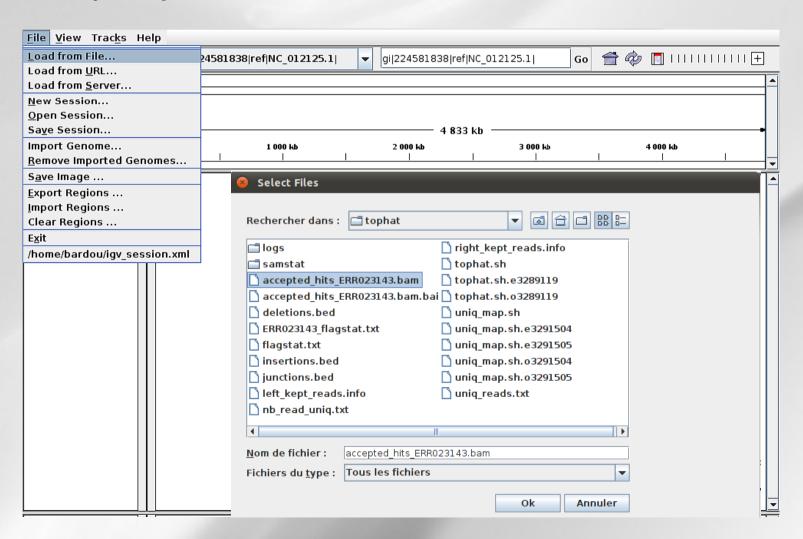


Import a reference genome



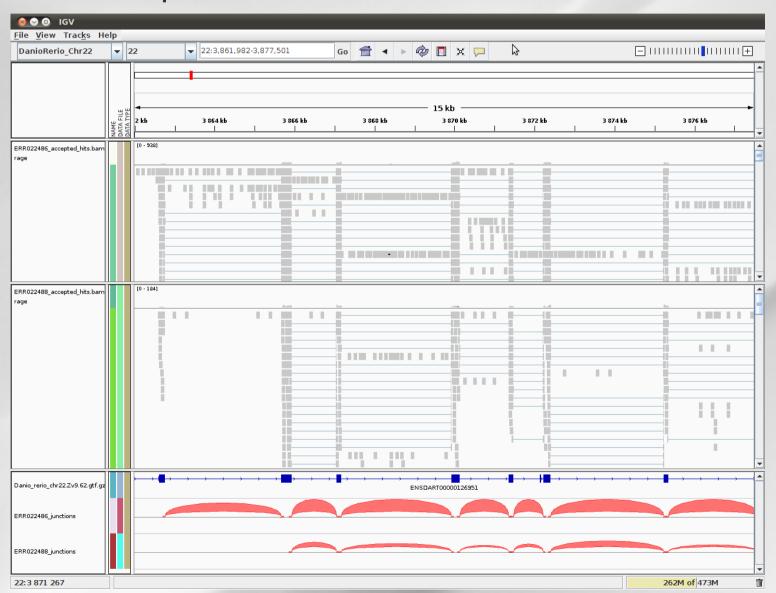


Import your BAM Files





- Exemple of bam and bed files visualisation





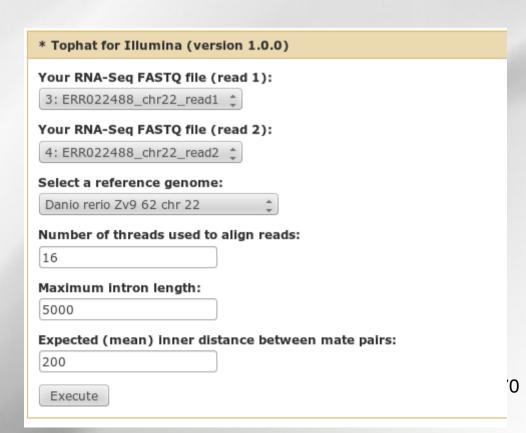
hands-on: tophat

Tophat location: 8 – *Trainings*

- RNA-Seq
 - Step 2 : Alignement and statistics
 - * Tophat for Illumina Find splice junctions using RNA-seq data

Indexation: * Samtools index

Samtools flagstat





Analysis workflow

Data quality control

Spliced mapping

Quantification

Gene and transcript discovery



What do we want to build?

The gene / transcript description file (and corresponding fasta)

```
protein coding exon
                                                               gene id "ENSDARGO0000075709"; transcript id "ENSDART00000144625"; exon number "1"
protein coding exon
                       696518 696600
                                                               gene id "ENSDARGO0000075709"; transcript id "ENSDART00000144625"; exon number "2"
                       694364 694502 .
                                                               gene id "ENSDARG00000075709"; transcript id "ENSDART00000144625"; exon number "3"
protein coding exon
protein coding CDS
                       694364 694497 .
                                                               gene id "ENSDARG00000075709"; transcript id "ENSDART00000144625"; exon number "3"
protein coding start codon
                               694495 694497
                                                                       gene id "ENSDARG00000075709"; transcript id "ENSDART00000144625"; exon number "3"
protein coding exon
                       693528 693822 .
                                                               gene id "ENSDARG00000075709"; transcript id "ENSDART00000144625"; exon number "4"
                                                               gene id "ENSDARG00000075709"; transcript id "ENSDART00000144625"; exon number "4"
protein coding CDS
                       693675 693822
protein_coding stop_codon
                               693672 693674
                                                                       gene id "ENSDARGO0000075709"; transcript id "ENSDART00000144625"; exon number "4"
                                                               gene id "ENSDARGO0000075709"; transcript id "ENSDART00000112112"; exon number "1"
protein coding exon
                       694364 694497
protein coding CDS
                                                               gene id "ENSDARG00000075709"; transcript id "ENSDART00000112112"; exon number "1"
protein_coding start_codon
                               694495 694497
                                                                       gene_id "ENSDARG00000075709"; transcript_id "ENSDART00000112112"; exon_number "1"
protein_coding exon
                       693672 693822
                                                               gene_id "ENSDARG00000075709"; transcript_id "ENSDART00000112112"; exon_number "2"
protein coding CDS
                       693675 693822
                                                               gene id "ENSDARG00000075709"; transcript id "ENSDART00000112112"; exon number "2"
protein coding stop codon
                               693672 693674
                                                                       gene id "ENSDARGO0000075709"; transcript id "ENSDART00000112112"; exon number "2"
protein coding exon
                       697453 697832 .
                                                               gene id "ENSDARG00000011999"; transcript id "ENSDART00000136627"; exon number "1"
protein_coding CDS
                       697623 697832 .
                                                               gene_id "ENSDARG00000011999"; transcript_id "ENSDART00000136627"; exon_number "1"
protein coding start codon
                                                                       gene id "ENSDARG00000011999": transcript id "ENSDART00000136627": exon number "1"
protein coding exon
                                                               gene id "ENSDARG00000011999"; transcript id "ENSDART00000136627"; exon number "2"
                       698442 698573 .
                                                               gene_id "ENSDARG00000011999"; transcript_id "ENSDART00000136627"; exon_number "2"
protein coding CDS
                       699401 699469 .
                                                               gene_id "ENSDARG00000011999"; transcript_id "ENSDART00000136627"; exon_number "3"
protein coding exon
                                                               gene id "ENSDARG00000011999"; transcript id "ENSDART00000136627"; exon number "3"
protein codina CDS
                       699401 699469 .
                                                               gene id "ENSDARG00000011999"; transcript id "ENSDART00000136627"; exon number "4"
protein coding exon
                       700666 700876
                                                               gene_id "ENSDARGO0000011999"; transcript_id "ENSDART00000136627"; exon_number "4"
protein_coding CDS
                       700666 700725
```

The count file

	row.names	SRR519727	SRR519728	SRR519729	SRR519730	SRR519731	SRR519747	SRR519748	SRR519749	SRR519750	SRR51975
1	mira_cl	1855	4095	4693	4407	3826	1749	4355	3679	4396	4066
2	mira_c2	358	616	929	834	854	393	769	644	1015	732
3	mira_c3	1874	1392	2583	1333	1245	2890	5104	4052	12012	4150
4	mira_rep_c4	697	789	1044	1100	1363	657	1001	836	1289	1313
5	mira_rep_c5	5765	12517	17170	16120	15121	6042	16388	14329	18505	16999
6	mira_rep_c6	2165	4727	6457	5312	4960	2399	7010	5196	8063	6718
7	mira_rep_c7	260	436	637	627	694	247	689	522	928	940
8	mira_rep_c8	616	1425	1906	1897	2050	691	1537	1551	1667	1552
9	mira_rep_c9	786	1885	2739	2493	2573	735	2345	2012	3308	2645
10	mira_rep_c10	311	517	684	886	895	346	659	581	1041	1030
11	mira_rep_cll	51	212	234	210	175	68	192	261	209	299
12	mira_rep_c12	1129	2191	2833	3128	3088	1139	2983	2575	4384	3811
13	mira_rep_c13	536	913	944	1256	1275	515	1029	913	1407	1444
14	mira_rep_c15	4678	13751	18095	16722	16476	4962	16867	14581	17733	18771
15	mira_rep_c16	7209	22856	32768	28699	27176	8532	28567	25091	35040	30702
16	mira_rep_c17	945	1566	2066	2530	3372	860	1704	1451	3327	3498
17	mira_rep_c18	4419	5668	7750	8570	9559	3954	6610	6180	8273	8728
18	mira_rep_c19	1765	2941	4757	4265	4062	1652	4604	3568	4983	4202
19	mira_rep_c20	1236	2314	3180	2903	2605	818	2196	1843	2478	2410
20	mira_rep_c22	2315	4329	5360	5760	5582	2471	5163	5061	5906	6482
21	mira_rep_c24	4488	7523	11333	10104	9537	4409	8676	9297	9060	10178
22	mira_rep_c25	448	702	944	1155	1245	338	885	740	1680	1599
23	mira_rep_c26	1307	2569	3436	3231	3009	1310	2907	2785	2989	3267
24	mira_c27	766	889	1283	1364	1577	820	1224	1100	1530	1436



If you have the model file

The model is presented in the GTF file (Gene Transfer Format)
Two approaches

- Gene level
- Transcript level

Tools for each approach

- htseq-count
- cufflinks (sigcufflinks)



HTSeq-count

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

- Process the output from short read aligners in various formats
- Count how many reads map to each feature (in RNA-Seq, the features are typically genes)
 - counting reads by genes
 - or consider each exon as a feature to check for alternative splicing
- Inputs:
 - file with aligned sequencing reads: bam (or sam) file
 - list of genomic feature; gtf file



HTSeq-count

- Command line:
 - htseq-count [options] <sam_file> <gtf_file>
 - samtools view accepted_hits.bam | htseq-count --stranded=no -m intersection-nonempty - file.gtf -q > output.htseq-count.txt &

	union	intersection _strict	intersection _nonempty					
read gene_A	gene_A	gene_A	gene_A					
gene_A	gene_A	no_feature	gene_A					
gene_A gene_A	gene_A	no_feature	gene_A					
gene_A read gene_A	gene_A	gene_A	gene_A					
gene_A	gene_A	gene_A	gene_A					
gene_A gene_B	ambiguous	gene_A	gene_A					
gene_A gene_B	ambiguous	ambiguous	ambiguous					

Some options:

-m <mode> : intersection-strict or intersection-nonempty (default union)

--stranded =<yes, no, or reverse>
(default yes)

-t <feature type> : 3rd column in GTF file

-q : quiet

-h: help



HTSeq-count

 Output: a table with counts for each feature and a summary of reads not counted for any feature:

ENSDARG00000095643 967 ENSDARG00000095659 36 ENSDARG00000095667 ENSDARG00000095677 98 ENSDARG00000095760 no feature 362748 ambiquous 9937 too low aQual not aligned alignment not unique 239465

- no_feature: reads which couldn't be assigned to any feature
- ambiguous: reads which could have been assigned to more than one feature and hence were not counted for any of these
- not_aligned: reads in the SAM file without alignment
- alignment_not_unique: reads with more than one reported alignment. These reads are recognized from the NH optional SAM field tag. (If the aligner does not set this field, multiply aligned reads will be counted multiple times.)



Cufflinks in general

NATURE BIOTECHNOLOGY | RESEARCH | LETTER

Transcript assembly and quantification by RNA-Seq reveals unannotated transcripts and isoform switching during cell differentiation

Cole Trapnell, Brian A Williams, Geo Pertea, Ali Mortazavi, Gordon Kwan, Marijke J van Baren, Steven L Salzberg, Barbara J Wold & Lior Pachter

Affiliations | Contributions | Corresponding author

Nature Biotechnology 28, 511–515 (2010) | doi:10.1038/nbt.1621

Received 02 February 2010 | Accepted 22 March 2010 | Published online 02 May 2010

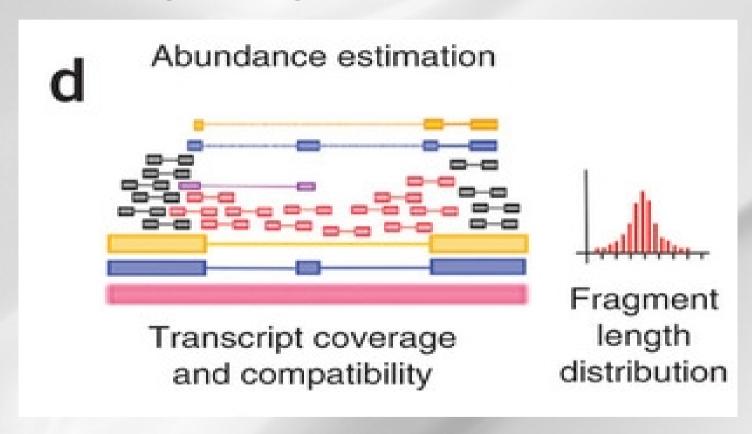
http://cufflinks.cbcb.umd.edu/

- assembles transcripts
- estimates their abundances : based on how many reads support each one
- tests for differential expression in RNA-Seq samples



Cufflinks read attribution

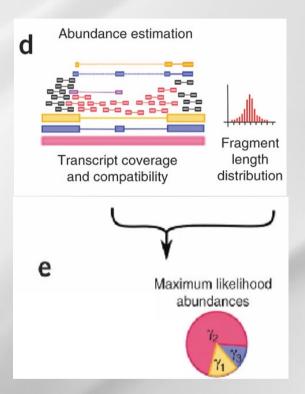
- Violet fragment: from which transcript?
 - Use of Fragment length distribution





Cufflinks expression measurement

- Fragments attribution
- Isoforms abundances estimation:
 - RPKM for single reads
 - FPKM for paired-end reads





RPKM / FPKM

- Transcript length bias
- **RPKM**: Reads per kilobase of exon per million mapped reads
 - 1kb transcript with 1000 alignments in a sample of 10 million reads (out of which 8 million reads can be mapped) will have:

$$RPKM = 1000/(1 * 8) = 125$$

- the transcript length depends on isoform inference
- **FPKM**: for paired-end sequencing
 - A pair of reads constitute one fragment



Cufflinks inputs and options

- Command line:
 - cufflinks [options]* <aligned_reads.(sam/bam)>
- Some options:
 - -h/--help
 - -o/--output-dir
 - -p/--num-threads
 - -G/--GTF <reference_annotation.(gtf/gff)> : estimate isoform expression, no assembly novel transcripts



Sigcufflinks

- Cufflinks code has been modified by the Sigenae Team of Toulouse in order to obtain raw count of reads: use sigcufflinks on genotoul
- Run cufflinks, cufflinks outputs + raw_transcripts.tsv:

```
      gene_id
      transcript_id
      pairs
      forward
      reverse

      CUFF.6
      CUFF.6.1
      4873
      4873
      3431

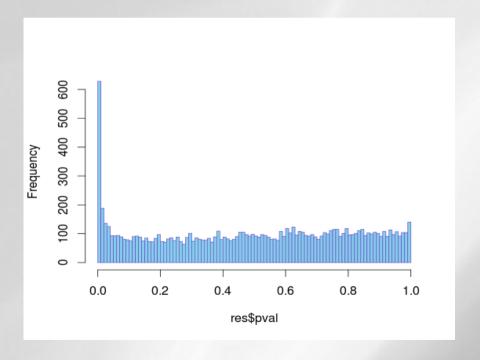
      CUFF.6 CUFF.6.2
      5222
      5222
      3769

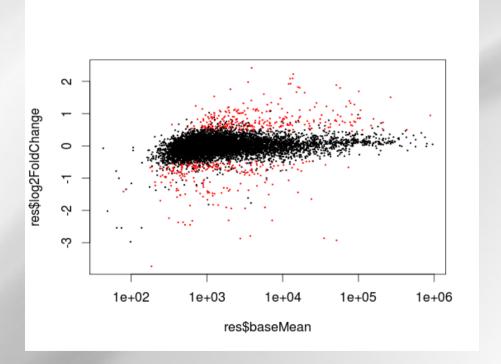
      CUFF.6 ENSDART00000067635
      4819
      4819
      3580
```



In R with DEseq

```
> head(res)
                                      baseMeanB foldChange log2FoldChange
           id
                 baseMean
                           baseMeanA
                                                                                   pval
                                                                                               padi
               3549.2301
                                      3753.1228
      mira c1
                           3345.3374
                                                  1.1218967
                                                                0.165939787 0.375560007 0.97718309
      mira_c2
                 685.7651
                            662.2140
                                       709.3163
                                                  1.0711284
                                                                0.099131456 0.521137290 1.00000000
      mira c3
               3530.8670
                           5096.4370
                                      1965.2970
                                                  0.3856218
                                                               -1.374741648 0.001403322 0.03732238
4 mira rep c4 1012.5217
                            975.4453
                                      1049.5981
                                                  1.0760194
                                                               0.105704140 0.795193064 1.00000000
5 mira rep c5 12946.1199 12949.4349 12942.8048
                                                  0.9994880
                                                               -0.000738847 0.985437095 1.00000000
6 mira rep c6 4924.7817 5224.1292 4625.4341 0.8853981
                                                               -0.175601809 0.290161543 0.92152339
> hist(res$pval, breaks=100, col="skyblue", border="slateblue", main="")
> plotDE <- function( res ) { plot( res$baseMean, res$log2FoldChange, log="x", pch=20, cex=.3, col = ifelse( res$padj < .1,
"red", "black" ) ) }
> plotDE(res)
```







Hands-on: quantification

- 1/ Quantify the genes of chromosome 22 using htseq-count and the Ensembl GTF file for both samples.
- 2/ Quantify the genes and transcripts of chromosome 22 using sigcufflinks and the Ensembl GTF file for both samples.
- 3/ In each case merge the files to produce the count tables.



Hands-on: hints

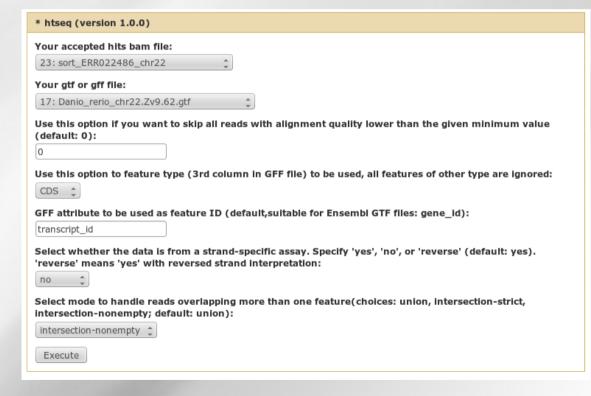
samtools sort by read names

htseq-count on sorted bam file and strand-specific assay specify 'no', select mode to handle reads overlapping more than one feature(choice:intersection-

nonempty)

Sigcufflinks with accepted-hit.bam

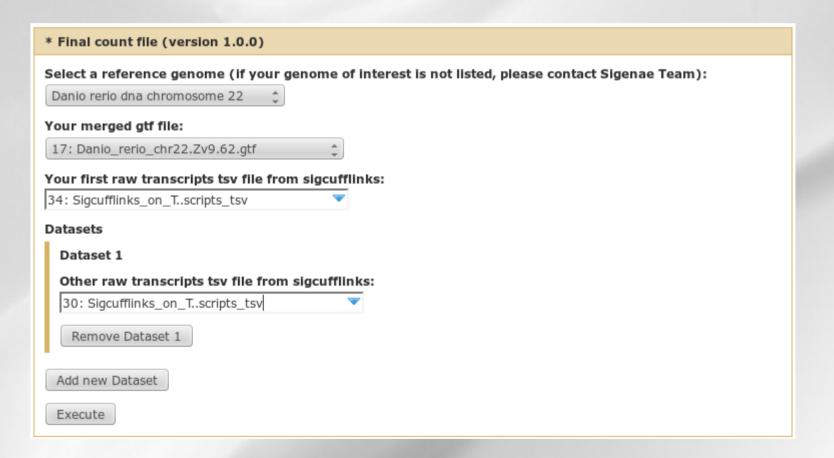
* Sigcufflinks (version 1.0.0)
Your accepted hits bam file:
9: Tophat_ERR022486ed_hits_bam 💠
Your gtf file:
17: Danio_rerio_chr22.Zv9.62.gtf 💠
G or g ?:
quantitate against reference transcript annota 💠
Execute





Hands-on: file merging

Merge sigcufflinks





Analysis workflow

Data quality control

Spliced mapping

Quantification

Gene and transcript discovery



Transcript reconstruction

The different paths:

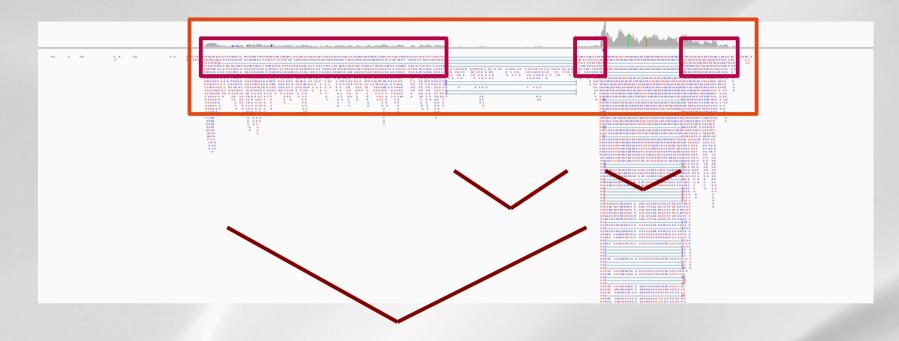
- Finding the gene locations
- Finding the exons
- Finding the junctions :
 - Between pairs junctions
 - · Within sequences junction

Defining the model building strategy

- Number of built models
- Intronic reads



The elements of the model



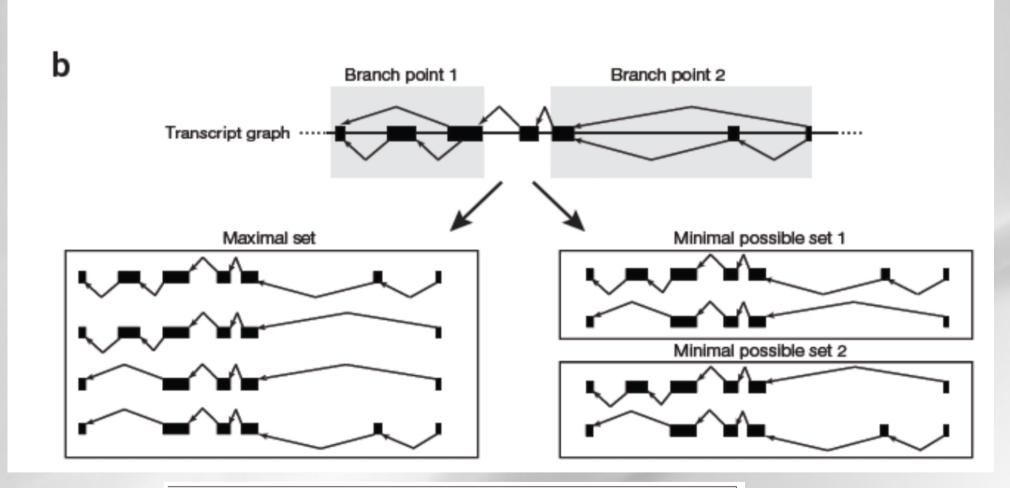
gene location Exon location Junctions:

- Between read pair junction
- Within read junction





Model building strategies



REVIEW

Computational methods for transcriptome annotation and quantification using RNA-seq

 $Manuel\ Garber^1, Manfred\ G\ Grabherr^1, Mitchell\ Guttman^{1,2}\ \&\ Cole\ Trapnell^{1,3}$



Cufflinks

NATURE BIOTECHNOLOGY | RESEARCH | LETTER

Transcript assembly and quantification by RNA-Seq reveals unannotated transcripts and isoform switching during cell differentiation

Cole Trapnell, Brian A Williams, Geo Pertea, Ali Mortazavi, Gordon Kwan, Marijke J van Baren, Steven L Salzberg, Barbara J Wold & Lior Pachter

Affiliations | Contributions | Corresponding author

Nature Biotechnology 28, 511–515 (2010) | doi:10.1038/nbt.1621

Received 02 February 2010 | Accepted 22 March 2010 | Published online 02 May 2010

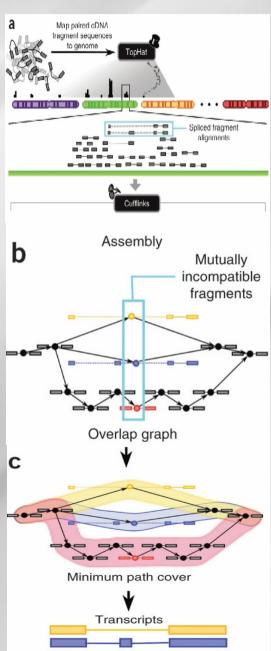
http://cufflinks.cbcb.umd.edu/

- assembles transcripts
- estimates their abundances : based on how many reads support each one
- tests for differential expression in RNA-Seq samples



Cufflinks transcript assembly

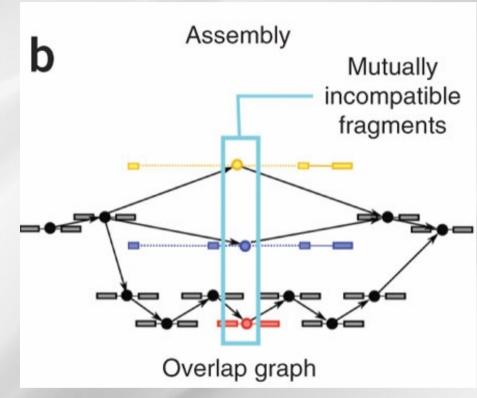
- Transcripts assembly :
 - Fragments are divided into nonoverlapping loci
 - each locus is assembled independently :
- Cufflinks assembler
 - find the mini nb of transcripts that explain the reads
 - find a minimum path cover (Dilworth's theorem):
 - nb incompatible read = mini nb of transcripts needed
 - each path = set of mutually compatible fragments overlapping each other



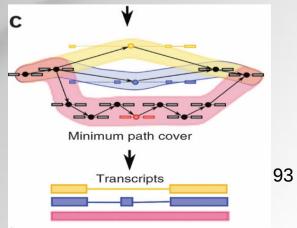


Cufflinks transcript assembly

- Transcripts assembly :
 - Identification incompatibles
 fragments: distinct isoforms



Compatibles fragments
 are connected: graphe construction





Some videos of examples

- Chromosome 3 of the bovine genome, UMD3
- 3 locations
- 3 tracks:
 - Ensembl reference gene
 - Cufflinks model
 - Reads alignment



Cufflinks inputs and options

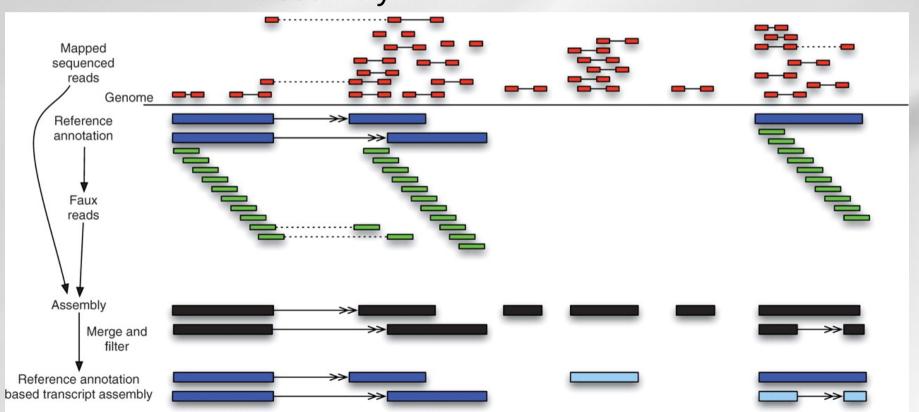
- Command line:
 - cufflinks [options]* <aligned_reads.(sam/bam)>
- Some options:
 - -h/--help
 - -o/--output-dir
 - -p/--num-threads
 - -G/--GTF <reference_annotation.(gtf/gff)> : estimate isoform expression, no assembly novel transcripts
 - -g/--GTF-guide <reference_annotation.(gtf/gff)> : guide RABT (Reference Annotation Based Transcript) assembly



Cufflinks RABT assembly option

- Some options:

-g/--GTF-guide <reference_annotation.(gtf/gff)> : guide RABT assembly





Cufflinks outputs

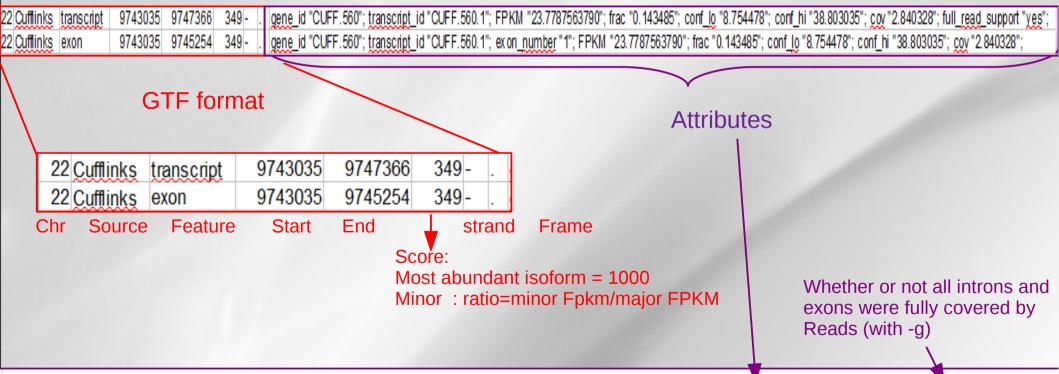
 transcripts.gtf: contains assembled isoforms (coordinates and abundances)

- genes.fpkm_tracking: contains the genes FPKM
- isoforms.fpkm_tracking: contains the isoforms
 FPKM



Cufflinks GTF description

- transcripts.gtf (coordinates and abundances): contains assembled isoforms: can be visualized with a genome viewer
 - GTF format + attributes (ids, FPKM, confidence inteval bounds, depth or read coverage, all introns and exons covered)



gene_id "CUFF.560"; transcript_id "CUFF.560.1"; FPKM "23.7787563790"; frac "0.143485"; conf_lo "8.754478"; conf_hi "38.803035"; cov "2.840328"; full_read_support "yes"; gene_id "CUFF.560"; transcript_id "CUFF.560.1"; exon_number "1"; FPKM "23.7787563790"; frac "0.143485"; conf_lo "8.754478"; conf_hi "38.803035"; cov "2.840328";



Cufflinks GTF description

- transcripts.gtf (coordinates and abundances): contains assembled isoforms: can be visualized with a genome viewer
 - Exemple VISUALISATION IGV





Cufflinks tracking description

- genes.fpkm_tracking:

 contains the estimated gene-level expression values in the generic FPKM Tracking Format
 Quantification status

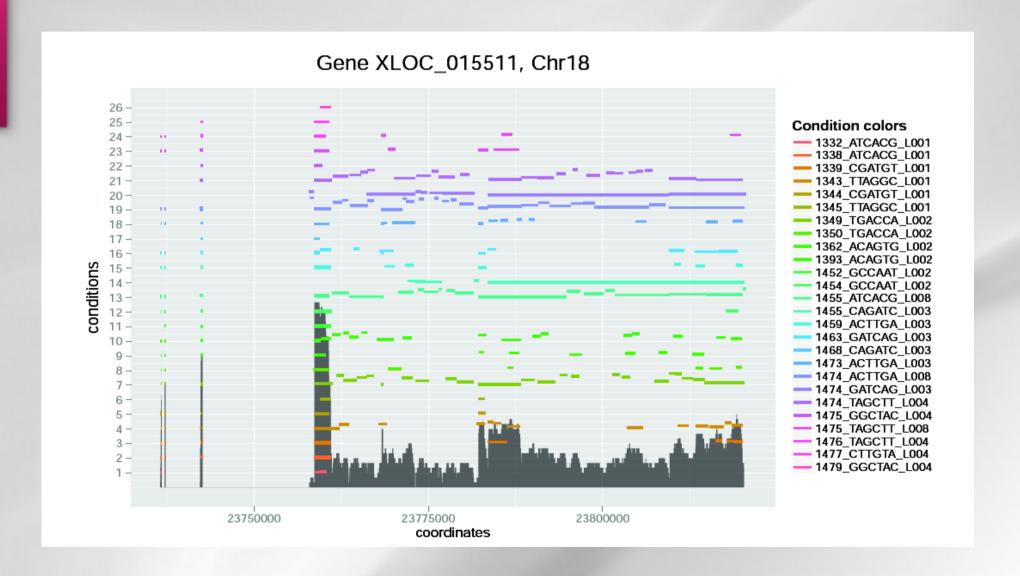
tracking_id	class_code	nearest_ref_id	gene_id	gene_short_name	tss_id	locus	length	coverage	status	FPKM	FPKM_conf_lo	FPKM_conf_hi
CUFF.560	-	-	CUFF.560	-	-	22:9743034-9762309	-	-	0K	105.69	77.9404	133.439

 isoforms.fpkm_tracking: contains the estimated isoform-level expression values in the generic FPKM Tracking Format

class_code	nearest ref id	gene_id	gene_short_name	tss_id	locus	length	coverage	status	FPKM	FPKM_conf_lo	FPKM_conf_hi
•	-	CUFF.560	-	-	22:9743034-9747366	2466	2.84033	OK	23.7788	8.75448	38.803
	-	CUFF.560	-	-	22:9743034-9762309	4020	8.11967	OK	67.9765	50.3804	85.5727
	-	CUFF.560	-	-	22:9743034-9762309	3846	1.66444	OK	13.9344	(29.2533
	lass_code	-	- CUFF.560 - CUFF.560	lass_code nearest_ref_id gene_id gene_short_name - CUFF.560 CUFF.560 -	- CUFF.560 CUFF.560	- CUFF.560 22:9743034-9747366 - CUFF.560 22:9743034-9762309	- CUFF.560 22:9743034-9747366 2466 - CUFF.560 22:9743034-9762309 4020	- CUFF.560 22:9743034-9747366 2466 2.84033 - CUFF.560 22:9743034-9762309 4020 8.11967	- CUFF.560 22:9743034-9747366 2466 2.84033 OK - CUFF.560 22:9743034-9762309 4020 8.11967 OK	- CUFF.560 22:9743034-9747366 2466 2.84033 OK 23.7788 - CUFF.560 22:9743034-9762309 4020 8.11967 OK 67.9765	- CUFF.560 22:9743034-9747366 2466 2.84033 OK 23.7788 8.75448 - CUFF.560 22:9743034-9762309 4020 8.11967 OK 67.9765 50.3804

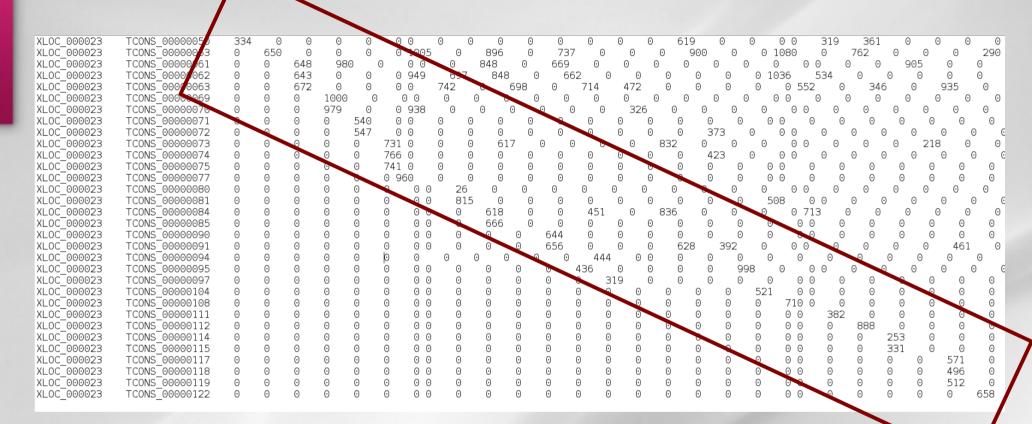


Cufflink transcript models





Cufflink transcript models





Gene discovery pipeline

Alignment (Tophat)

Bam merge (samtools)

Discovery of novels features (cufflinks)

Quantification at a transcript level (sigcufflinks)

Quantification file merging (shell script)



Quantification strategy

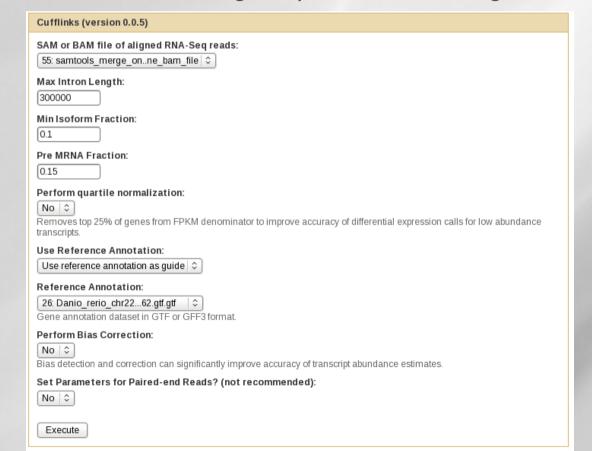
- First set your gene and transcript model = build a reference
 GTF file
- Then use option -G to quantify the same set of elements on all your samples with sigcufflinks
- Then sort your raw_transcript.tsv files
- cut the second or third column of the sorted file
- Paste all the column in the count file

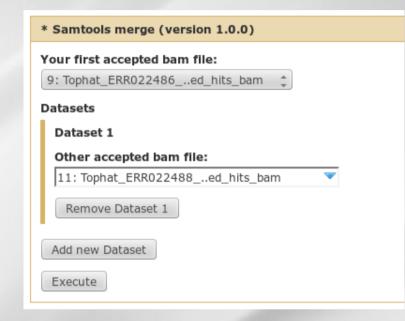


Hands-on: cufflinks

Merge all bam : Step 5 : RNAseq De Novo

Cufflinks on merge file with -g option (reference annotation as guide) and the Danio gtf file :







Hands-on: file merging

Sigcufflinks with the new gtf file (transcript.gtf of previously step) with -G option

Final count:





Quality for Bioinfo Plateform!

Exam:

http://bioinfo.genotoul.fr/index.php?id=93

Satisfaction form:

http://bioinfo.genotoul.fr/index.php?id=79



Useful links

Seqanswer: http://seqanswers.com/

RNAseq blog: http://rna-seqblog.com/

Illumina: http://www.illumina.com/