ICQB Lecture 10: A practical guide to RNA-seq analysis

G4120

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Rapley and Walker (eds., 1998), Molecular Biomethods Handbook

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Bignell et al. (eds., 2011), Biology of Termines: A Modern Synthesis

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- Early 2000s: Microarrays become viable: The first truly quantitative method capturing the (known) transcriptome.
- 2010: Illumina HiSeq 2000 is released: Affordable RNA-seq has arrived!
- Notable developments since:
 - \circ PacBio allows for read lengths of > 1 kb.
 - o scRNA-seq allows for analysis of single-cell transcriptomics.
 - Novoseq will further reduce the price of RNA-seq, a lot.

Overview of the RNA-seq workflow



Basic principle of RNA-seq



For a snazzy, animated version of this, see <u>https://youtu.be/fCd6B5HRaZ8</u>

Kulski (ed., 2016), Next Generation Sequencing: Advances, Applications and Challenges

Key concepts for sequencing

- Typical lengths of individual sequence reads during Illumina RNA-seq:
 50, 75, 100 or 150 nt. Longer is better for alignment, but quality drops off after 100.
- Single-end (SE) vs. paired-end (PE) sequencing
 - SE: each (amplified) fragment is only sequenced once, from one direction.
 - PE: each (amplified) fragment is sequenced from *both* directions:



- Sequencing depth: the total number of reads created during RNA-seq. Should be >20 million for standard gene-expression analysis without bells and whistles.
- Phred (Q) score: each base is assigned a quality score indicating the probability P of the call being wrong. Q = -10 log₁₀ P.
 E.g., Q = 10 → P = 0.1 (poor); Q = 40 → P = 0.0001 (good)

Sequencing output: Fastq files



Line 1: ID of read.

Line 2: actual nucleotide sequence of read.

Line 3: a (+) sign, because why not. (May also be followed by repeat of read ID.)

Line 4: quality of each base call, in ASCII format. Will later be converted to Phred score.

 \rightarrow Repeat 20-50 million times.

From Fastq to differentially expressed genes



From Fastq to differentially expressed genes



Haas & Zody (2010) Nat Biotechnol

The 9-ish steps of RNA-seq analysis

1. Choose the right computational tools.

Recommended step: Clipping and trimming

- 2. Prepare the reference genome.
- 3. Align reads to the reference genome.
- 4. Quality control.
- 5. Count how many reads align to each gene.
- 6. Identify differentially expressed genes.
- 7. Visualize results.
- 8. Analyze further.
- 9. Get help.

Step 1: Choose the right computational tools

- There are many, many different tools for each step of this task. Our pipeline uses the following:
 - (Clipping adapters and quality trimming: **Trimmomatic**.)
 - Generation of genome index and alignment: **STAR**.
 - Convert SAM files to BAM files and indexing: **SAMtools**.
 - Quality control: Integrative Genomics Viewer (IGV) and QoRTs.
 - Count aligned reads: **featureCount** of the Subread package.
 - Statistical analysis and visualization: **RStudio** with various packages.
- Do <u>not</u> use Tophat or any other part of the Tuxedo suite! They are popular for historical reasons but perform very poorly compared to more modern tools.
- **Do not, under any circumstances, use Excel ever!!!!** Excel automatically converts certain gene names and other content, because it mistakes it for dates, times, currency, *etc*. This cannot be switched off. *Caveat emptor!*
- Noteworthy alternatives:
 - For the less computationally inclined: **Galaxy** (<u>usegalaxy.org</u>) is an online platform that allows full RNA-seq analysis from start to finish without any need for a command-line interface. Data is directly piped into the relevant programs.
 - Kallisto (<u>http://pachterlab.github.io/kallisto/</u>) is an alignment software that uses pseudoalignment, which requires far less computational power. Excellent alternative in the absence of a fast computer (32 GB+ RAM, multi-core CPU).

Recommended Step: Clipping and Trimming

• Clipping:

Remove any adaptor sequences that may have been incorporated when insert is shorter than read, prior to alignment.

- Trimming: Remove low-quality bases prior to alignment.
- Modern alignment programs perform "soft-clipping", which should eliminate the need for "hard-clipping"; but "hard-clipping" still improves mapping efficiency.
- Should be applied very conservatively! Stringent parameters introduce major biases!
- *Requires sequences of the adapters used during sequencing!*
- A commonly used tool is Trimmomatic: <u>http://www.usadellab.org/cms/?page=trimmomatic</u>
- Input: .fastq file
 Output: a new .fastq file

Step 2: Prepare the reference genome

- This requires two components:
 - The full nucleotide sequence and coordinates of the reference genome.
 Usually a file designated *<name of organism>.fa*.
 - An annotation file with information about genes, transcripts and splice sites.
 Usually a file designated *<name of organism>.gtf*.
- Typical sources:
 - UCSC (<u>https://hgdownload.soe.ucsc.edu/downloads.html</u>).
 - ENSEMBL (<u>https://useast.ensembl.org/info/data/ftp/index.html</u>).
 - \circ Use different formats \rightarrow risk of compatibility issues downstream.
 - ENSEMBL more broadly compatible and less-rigorously vetted transcripts.
- Alignment programs assemble this information into a genome index for the alignment of reads.
- Input: .fa file, .gtf file.
 Output: folder with genome index files.

Step 3: Align reads to the reference genome

- Input:
 - Folder with **genome index** (just generated).
 - o (paired) .fastq files.
- Output: **.sam** file (for Sequence Alignment Map)
 - Contains 11 mandatory fields for each read with detailed information on sequencing and alignment, including genomic location and quality.
 - For details on each field: <u>https://en.wikipedia.org/wiki/SAM (file format)</u>.



• About 70-90% of reads should be mapped to the genome.

Step 4a: Quality control with IGV

- Requires conversion of .sam format to binary .bam format (condensed) and indexing, both with SAMtools.
- IGV creates a visual representation of the reads mapped to the genome:





Step 4b: Quality control with QoRTs

- Input:
 - o **.bam** format.
 - $\circ~$ Requires less computational resources when files are name-sorted \rightarrow conversion by SAMtools.
- Output: **.pdf** files.
- Performs calculations with Java but employs R to create graphical output.
- Provides graphical assessment of quality for both sequencing and alignment.



Step 5: Count how many reads align to each gene

- Input:
 - $\circ~$.bam files.
 - **.gtf** file (genome annotation).
- Output: **.txt** file.
- Consolidates information from all samples into single matrix of counts per gene.

| Geneid | S1 | S2 | S3 | S4 | S5 | S6 |
|--------------------|------|------|------|------|-----|------|
| ENSMUSG00000103090 | 0 | 0 | 0 | 0 | 0 | 0 |
| ENSMUSG0000025907 | 1710 | 1186 | 1534 | 1660 | 965 | 1525 |
| ENSMUSG0000090031 | 74 | 52 | 25 | 77 | 30 | 36 |
| ENSMUSG0000087247 | 0 | 0 | 0 | 0 | 0 | 0 |
| ENSMUSG00000103355 | 0 | 0 | 0 | 0 | 1 | 0 |
| ENSMUSG00000102706 | 0 | 0 | 0 | 0 | 0 | 0 |
| ENSMUSG00000103845 | 4 | 9 | 17 | 1 | 14 | 32 |
| ENSMUSG0000033740 | 757 | 513 | 924 | 691 | 461 | 989 |
| ENSMUSG00000103629 | 0 | 0 | 0 | 0 | 0 | 0 |
| ENSMUSG0000051285 | 1662 | 961 | 1100 | 1463 | 960 | 1228 |
| ENSMUSG0000098201 | 0 | 0 | 1 | 0 | 0 | 0 |
| ENSMUSG00000103509 | 37 | 21 | 5 | 26 | 14 | 16 |
| ENSMUSG0000048538 | 1 | 0 | 0 | 0 | 0 | 0 |
| ENSMUSG00000103709 | 0 | 0 | 0 | 0 | 0 | 0 |

Step 6: Identify differentially expressed genes

- Input: counts table (.txt).
- Output: data table (.txt or .csv) with fold changes and adjusted p-values.
- Most popular tools are DESeq2 and EdgeR (both R-based).
- Need at least 2 replicates; 3 are better; more are best.
- Can include batch correction.

| baseMean log2 | FoldChange | lfcSE | stat | pvalue | padj |
|---------------|---|---|--|--|---|
| 0 N A | | NA | NA | NA | NA |
| 0.195636 | 1.986700116 | 4.993 | 0.398 | 0.691 | NA |
| 0 N A | | NA | NA | NA | NA |
| 0 N A | | NA | NA | NA | NA |
| 0 N A | | NA | NA | NA | NA |
| 0 N A | | NA | NA | NA | NA |
| 1.103537 | -0.097401599 | 2.444 | -0.04 | 0.968 | NA |
| 0.650705 | 0.579256789 | 3.35 | 0.173 | 0.863 | NA |
| 0 N A | | NA | NA | NA | NA |
| 0 N A | | NA | NA | NA | NA |
| 0.874765 | 1.552357216 | 2.86 | 0.543 | 0.587 | NA |
| 572.9266 | 0.179076205 | 0.111 | 1.618 | 0.106 | 0.181 |
| 3.412223 | -0.492101491 | 1.471 | -0.33 | 0.738 | 0.827 |
| 1070.492 | 0.168258337 | 0.084 | 2.004 | 0.045 | 0.086 |
| | baseMean log2 0 NA 0.195636 VA 0 NA 0 NA 0 NA 0.650705 VA 0.650705 ST2.9266 3.412223 1070.492 | baseMean log2FoldChange 0 NA 0.195636 1.986700116 0 NA 0 NA 0 NA 0 NA 1.103537 -0.097401599 0.650705 0.579256789 0 NA 0.874765 1.552357216 572.9266 0.179076205 3.412223 -0.492101491 1070.492 0.168258337 | baseMean log2FoldChange lfcSE 0 NA NA 0.195636 1.986700116 4.993 0 NA NA NA 1.103537 -0.097401599 2.444 0.650705 0.579256789 3.35 0 NA NA NA 0.874765 1.552357216 2.866 572.9266 0.179076205 0.111 3.412223 -0.492101491 1.471 1070.492 0.168258337 0.084 | baseMean log2FoldChange lfcSE stat 0 NA NA NA NA 0.195636 1.986700116 4.993 0.398 0 NA NA NA 1.103537 -0.097401599 2.444 -0.04 0.650705 0.579256789 3.35 0.173 0 NA NA NA NA 0.874765 1.552357216 2.86 0.543 572.9266 0.179076205 0.111 1.618 3.412223 -0.492101491 1.471 -0.33 1070.492 0.168258337 0.084 2.004 | baseMean log2FoldChange lfcSE stat pvalue 0 NA NA NA NA NA 0.195636 1.986700116 4.993 0.398 0.691 0 NA NA NA NA NA 1.103537 -0.097401599 2.444 -0.04 0.968 0.650705 0.579256789 3.35 0.173 0.868 0.650705 0.579256789 3.35 0.173 0.868 0.650705 0.579256789 3.45 0.543 0.587 0.874765 1.552357216 2.86 0.543 0.587 572.9266 0.179076205 0.111 1.618 0.106 3.412223 -0.492101491 1.471 -0.33 0.738 1070.492 0.168258337 |

Step 7: Visualize results

• Common initial visualizations include:



• Can all be done in R(Studio).

Step 8: Analyze further

 Gene Set Enrichment Analysis (<u>https://www.gsea-msigdb.org/gsea/index.jsp</u>) and Gene Ontology (<u>https://biit.cs.ut.ee/gprofiler/gost</u>): Search for pathways and functions enriched for DEGs.



 HOMER (<u>http://homer.ucsd.edu/homer/motif/</u>): Searches for DNA motifs enriched in the promoters of DEGs.

| Ran | k Motif | Name | P-value | log P-pvalue | q-value (Benjamini) | # Target Sequences with Motif | % of Targets Sequences with Motif | # Background Sequences with Motif | % of Background Sequences with Motif |
|-----|----------------------------|--|---------|-----------------|------------------------|--|---|--|---|
| 1 | GAAA<u>EIG</u>AAAEI | IRF1(IRF)/PBMC-IRF1-ChIP- Seq(GSE43036)/Homer | 1e-7 | -1.625e+01 | 0.0000 | 21.0 | 7.29% | 521.9 | 1.77% |
| 2 | AGTITCASTTTC | ISRE(IRF)/ThioMac-LPS- Expression(GSE23622)/Homer | 1e-6 | -1.519e+01 | 0.0001 | 14.0 | 4.86% | 244.4 | 0.83% |
| 3 | <u>AGTTTCASTTTC</u> | IRF3(IRF)/BMDM-Irf3-ChIP- Seq(GSE67343)/Homer | 1e-6 | -1.471e+01 | 0.0001 | 29.0 | 10.07% | 1017.5 | 3.44% |
| | ΑΛΟΛΓΔΤΤΤΛΛΛ | NFkR-n65(RHD)/GM12787-n65-ChIP- | | | | | | | |

Step 9: Get help.

- If you get stuck, which you almost certainly will, you're probably not the first one who has encountered this problem. Use a search engine like DuckDuckGo or directly look at these places for help:
 - Stackoverflow:
 - https://stackoverflow.com/questions
 - Geared towards programming in general.
 - o **biostarS**:
 - https://www.biostars.org/
 - Specializes in questions about bioinformatics.
 - R for Dummies:
 - https://rfordummies.com/
 - Swallow your pride. It's worth it.
- Affordable, local training courses:
 - New York Academy of Sciences: Introductory Coding for Researchers (1 weekend).
 - New York Genome Center: Sequencing Informatics Workshop (1 week).

A shameless plug

L-RAPiT: A Cloud-Computing Pipeline for the Analysis of Long-Read RNA Sequencing Data

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ABSTRACT

Long-read sequencing (LRS) has been adopted to meet a wide variety of research needs, ranging from the construction of novel transcriptome annotations to the rapid identification of emerging virus variants. Amongst other advantages, LRS preserves more information about RNA at the transcript level than conventional high-throughput sequencing, including far more accurate and quantitative records of splicing patterns. New studies with LRS datasets are being published at an exponential rate, generating a vast reservoir of information that can be leveraged to address a host of different research questions. However, mining such publicly available data in a tailored fashion is currently not trivial, as the available software tools typically require familiarity with the command-line interface, which constitutes a significant obstacle to many researchers. Additionally, different research groups utilize different software packages to perform LRS analysis, which often prevents a direct comparison of published results across different studies. To address these challenges, we have developed the Long-Read Analysis Pipeline for Transcriptomics (L-RAPiT), a user-friendly, free pipeline requiring no dedicated computational resources or bioinformatics expertise (https://github.com/Theo-Nelson/long-read-sequencing-pipeline). L-RAPiT can be implemented directly through Google Colaboratory, a system based on the open-source Jupyter notebook environment, and allows for the direct analysis of transcriptomic reads from Oxford Nanopore and PacBio LRS machines. This new pipeline enables the rapid, convenient and standardized analysis of publicly available or newly generated LRS datasets.



Practice Run

- Demonstration with practice data set:
 - Computationally generated reads
 - \rightarrow trimming not necessary.
 - Limited to chromosome X of *Drosophila melanogaster* \rightarrow can be run on standard laptop.