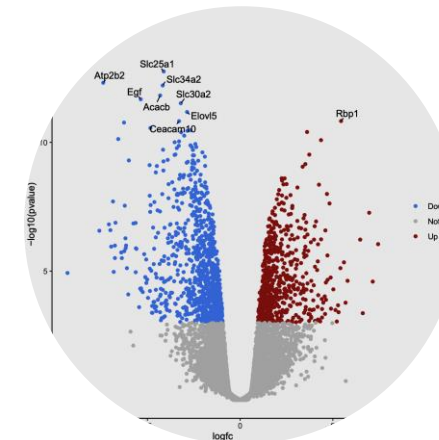
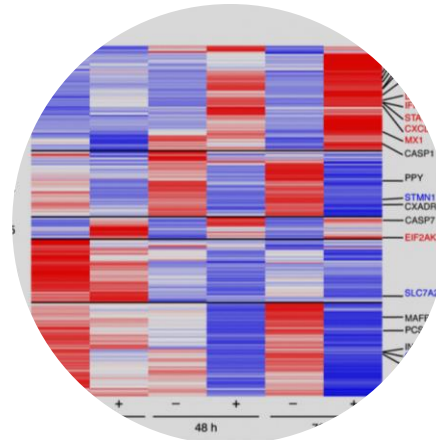
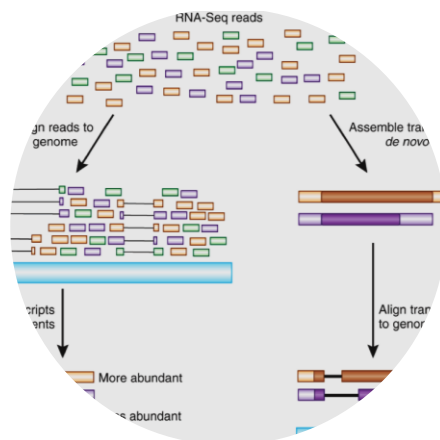


PMB2023

PATHOGEN MULTIOMICS AND BIOINFORMATICS

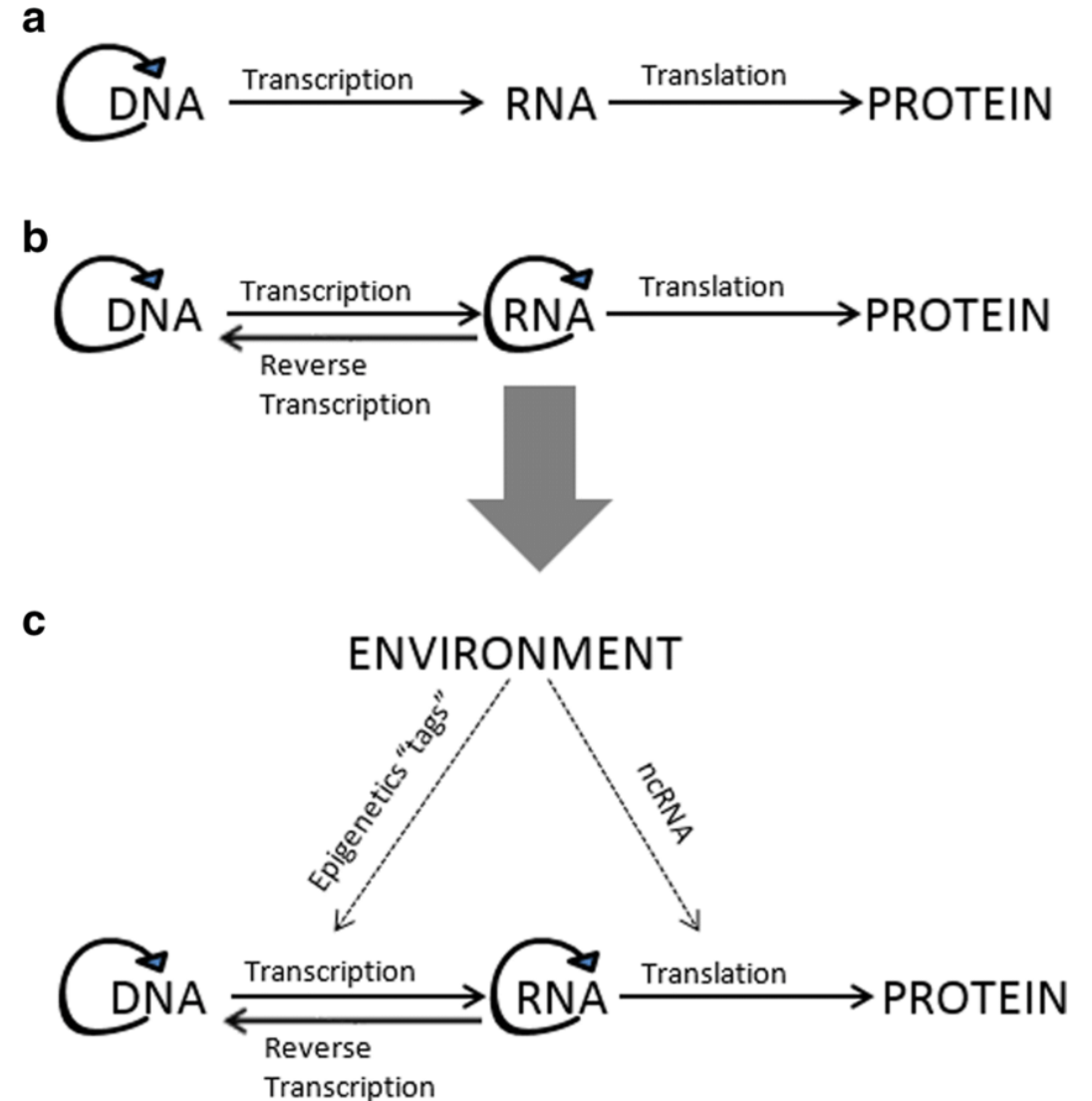
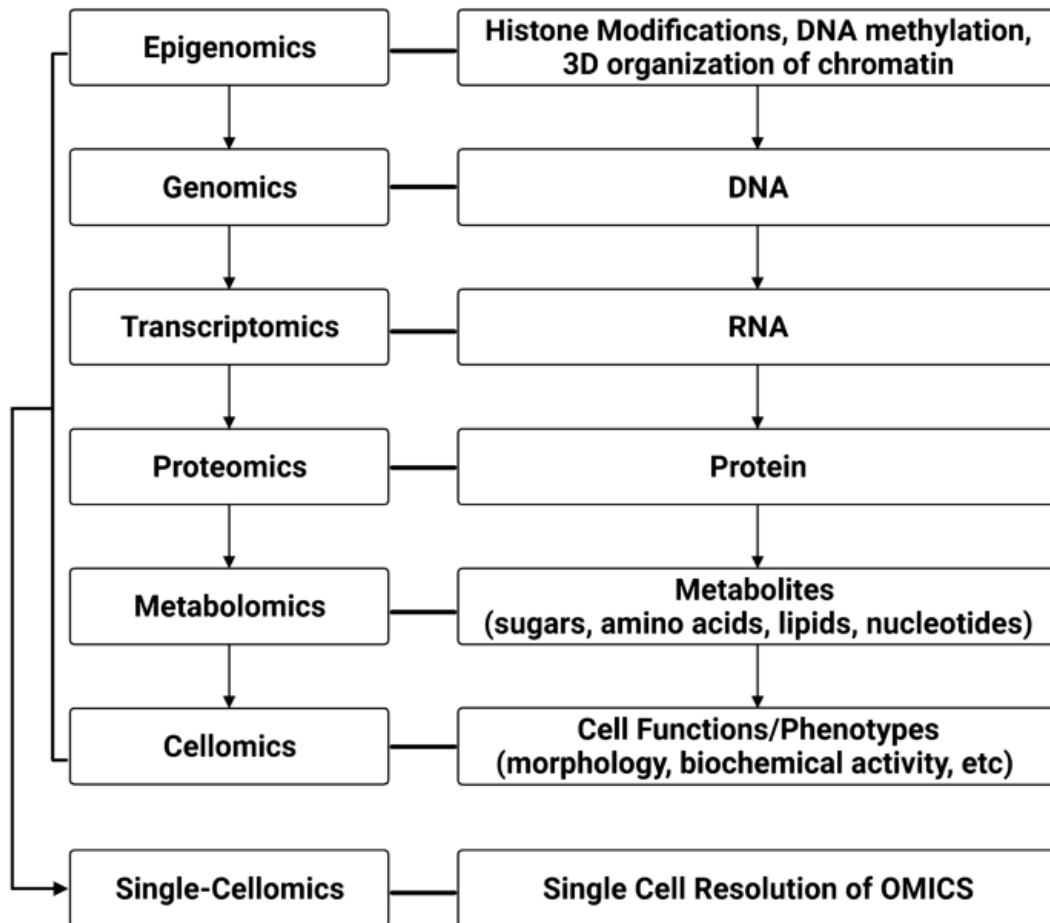
Rio Grande/RS 2023

Module 6: RNA-Seq and Transcriptomics



Omics Cascade

The OMICS cascade:



Why using RNA-Seq?

Use of new sequencing technologies to capture and study the transcriptome

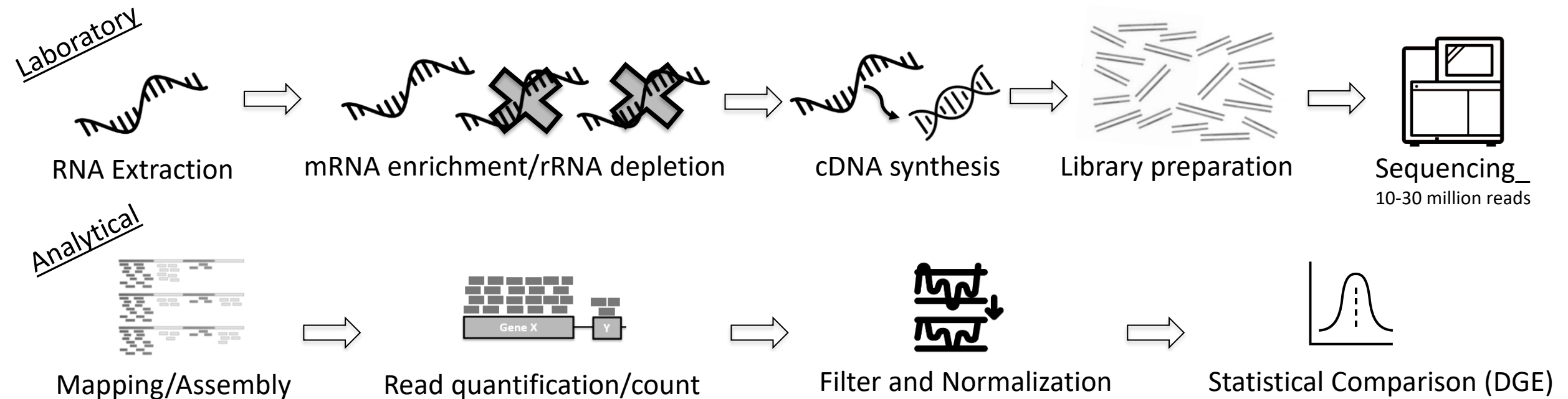
- **Identify novel transcripts**
- **Exon/transcript boundaries**
- **Splice junctions/alternative splicing**
- **Measure transcript abundance**
- **Gene expression differences across multiple samples (i.e. differential expression)**

RNA-Seq: General Workflow

What is RNA-Seq?

RNA-Seq consists of a method to analyze the transcriptomics of thousands of features in a single assay and, hence, evaluate and compare gene expression in a genome-wide manner.

Two main stages:



RNA-Seq vs cDNA/EST Seq vs Microarrays

| Technology | Tiling microarray | cDNA or EST sequencing | RNA-Seq |
|--|-------------------------|-----------------------------|----------------------------|
| <i>Technology specifications</i> | | | |
| Principle | Hybridization | Sanger sequencing | High-throughput sequencing |
| Resolution | From several to 100 bp | Single base | Single base |
| Throughput | High | Low | High |
| Reliance on genomic sequence | Yes | No | In some cases |
| Background noise | High | Low | Low |
| <i>Application</i> | | | |
| Simultaneously map transcribed regions and gene expression | Yes | Limited for gene expression | Yes |
| Dynamic range to quantify gene expression level | Up to a few-hundredfold | Not practical | >8,000-fold |
| Ability to distinguish different isoforms | Limited | Yes | Yes |
| Ability to distinguish allelic expression | Limited | Yes | Yes |
| <i>Practical issues</i> | | | |
| Required amount of RNA | High | High | Low |
| Cost for mapping transcriptomes of large genomes | High | High | Relatively low |

Wang *et al* 2009

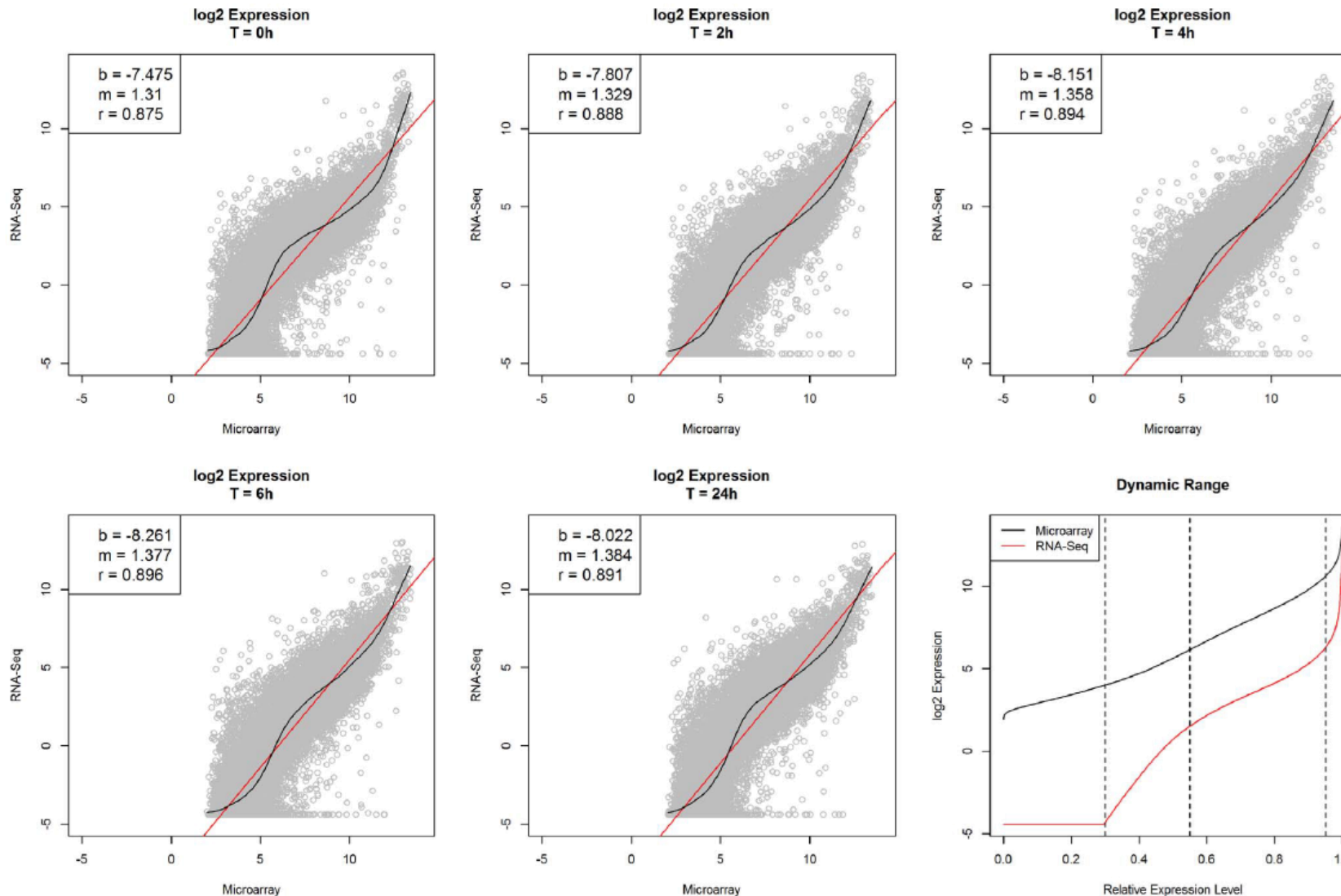
Ability to detect novel transcripts

Wider dynamic range

Higher specificity and sensitivity

Simple detection of rare and low-abundance transcripts

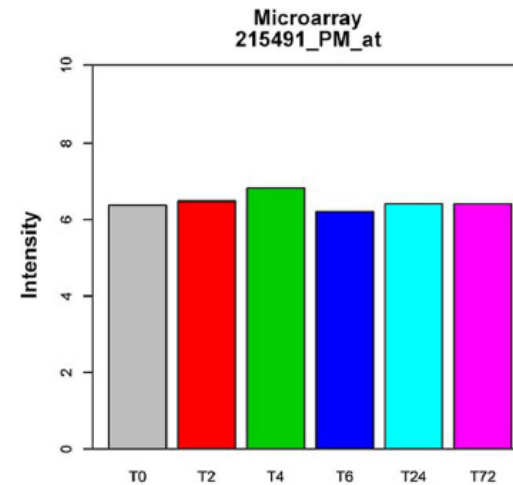
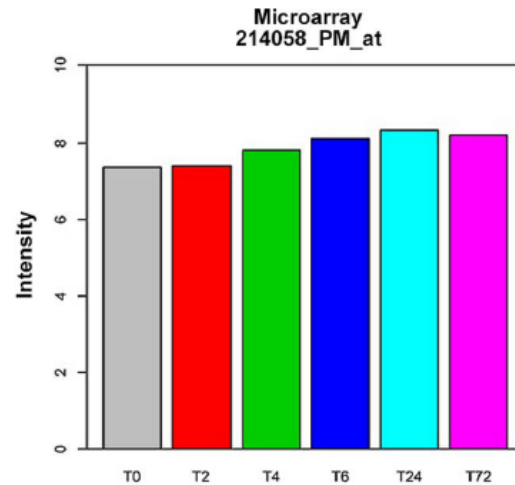
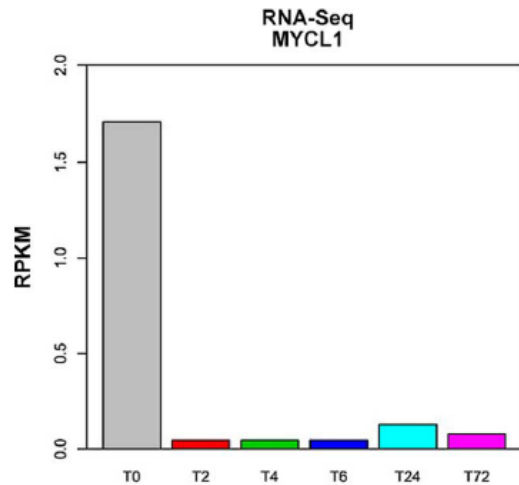
RNA-Seq vs Microarrays



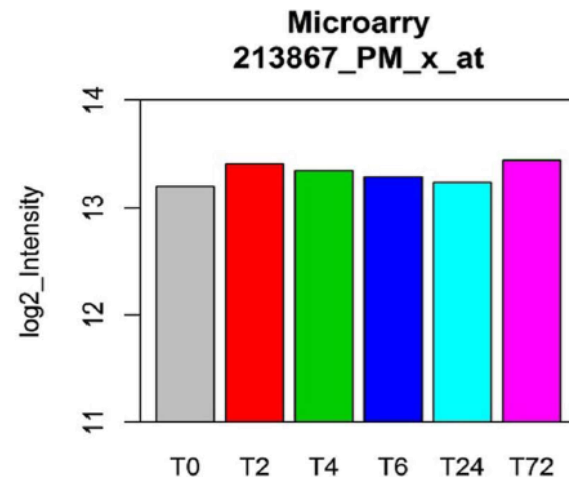
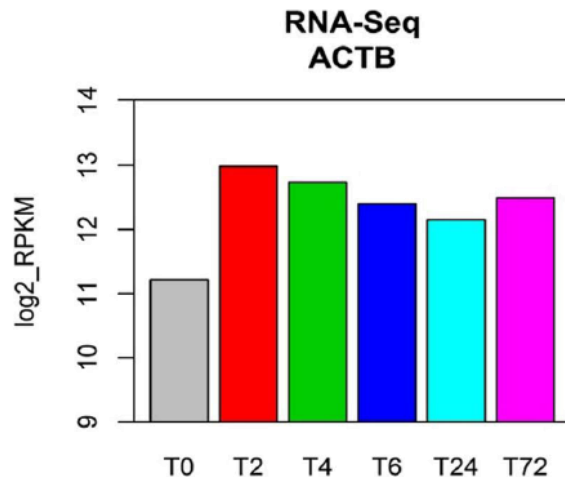
The plots show that the overall dynamic range of the 18,306 common genes generated by the two platforms is much broader in RNA-Seq (2.66105) than in microarray (3.66103).

RNA-Seq vs Microarrays

RNA-Seq is able to detect subtle changes to the level of genes with low expression levels whereas microarrays are not



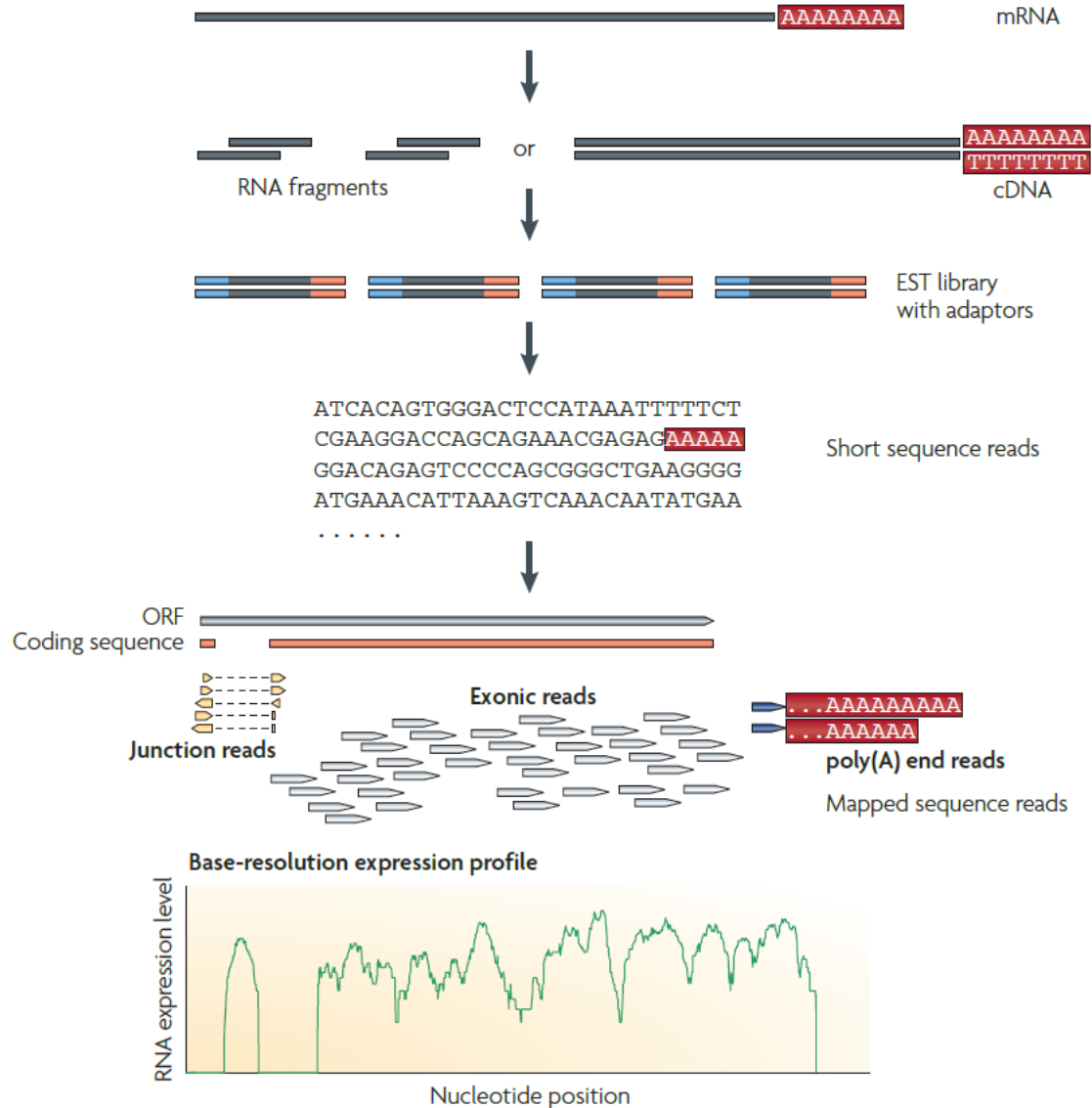
Zhao et al 2014



Zhao et al 2014

... Similarly RNA-Seq is able to detect expression level changes to highly expressed genes and microarrays are not (saturation).

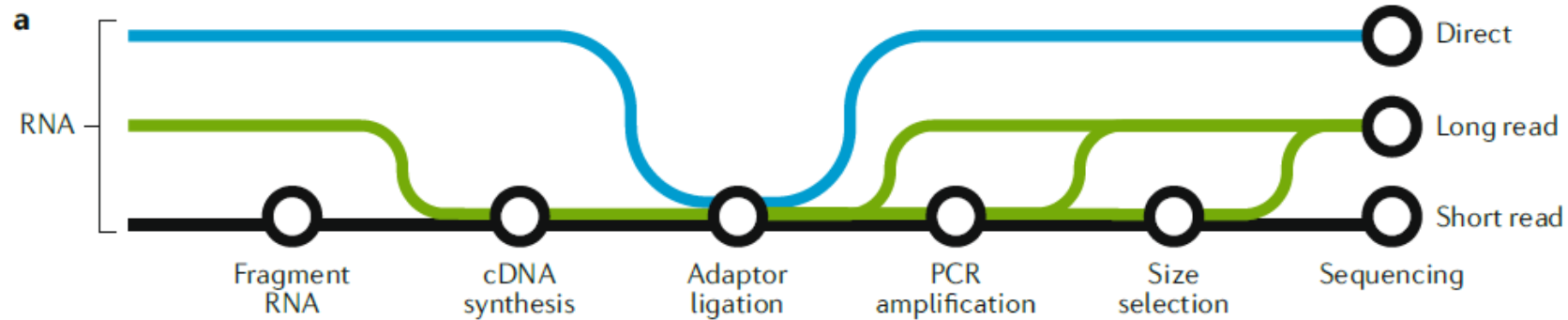
Library Preparation



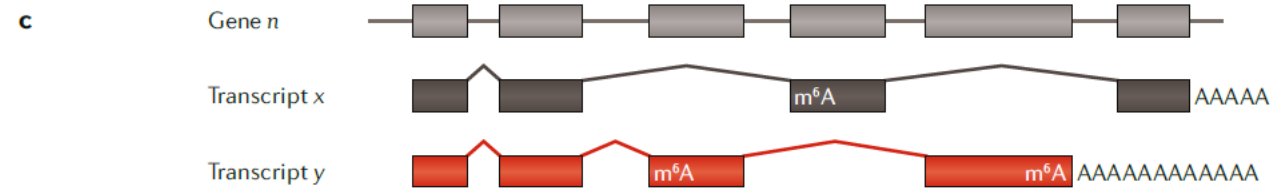
Aspects and factors to consider:

- RNA Source: Total RNA, mRNA, depletion of rRNA?
- Strand specific?
- Replicates?
 - Technical (multiple libraries from the same sample)
 - Biological (multiple samples from the same condition)
- Which platform?
- Multiple samples/multiplexing

Library Preparation: comparison between technologies and limitations



All long-read and short-read approaches require adaptor ligation



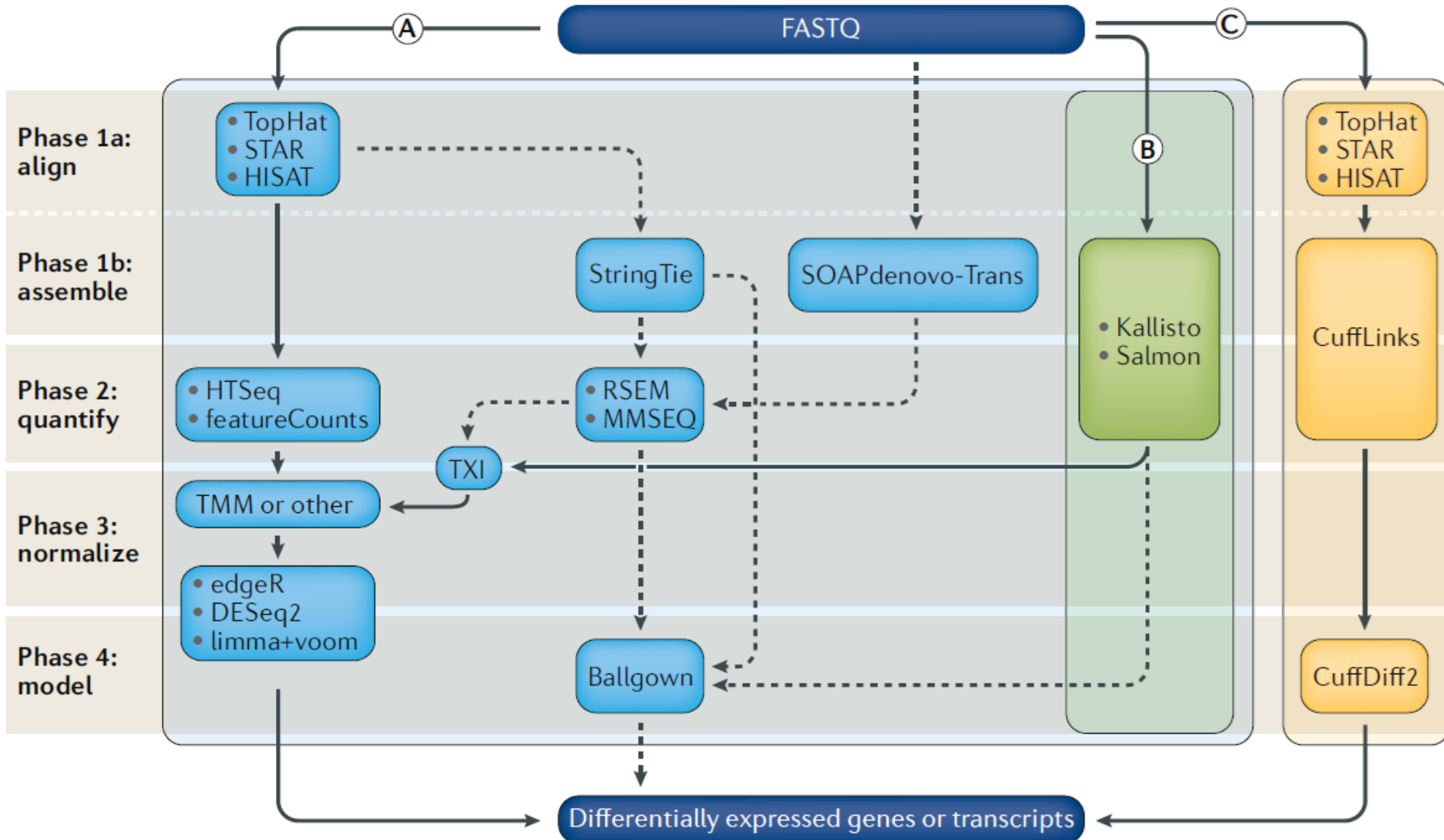
| | | |
|-----------------|------------------------|--|
| Short-read cDNA | Ambiguous to exon | |
| | Unambiguous to exon | |
| | Ambiguous to isoform | |
| | Unambiguous to isoform | |
| Long-read cDNA | Unambiguous to isoform | |
| Direct RNA-Seq | Unambiguous to isoform | |

Short-reads can be ambiguously mapped to diferente isoforms

Library Preparation: comparison between technologies and limitations

| Sequencing technology | Platform | Advantages | Disadvantages | Key applications |
|-----------------------|-----------------------|---|---|--|
| Short-read cDNA | Illumina, Ion Torrent | <ul style="list-style-type: none"> • Technology features very high throughput: currently 100–1,000 times more reads per run than long-read platforms • Biases and error profiles are well understood (homopolymers are still an issue for Ion Torrent) • A huge catalogue of compatible methods and computational workflows are available • Analysis works with degraded RNA | <ul style="list-style-type: none"> • Sample preparation includes reverse transcription, PCR and size selection adding biases to all methods • Isoform detection and quantitation can be limited • Transcript discovery methods require a de novo transcriptome alignment and/or assembly step | Nearly all RNA-seq methods have been developed for short-read cDNA sequencing: DGE, WTA, small RNA, single-cell, spatialomics, nascent RNA, translatoe, structural and RNA–protein interaction analysis, and more are all possible |
| Long-read cDNA | PacBio, ONT | <ul style="list-style-type: none"> • Long reads of 1–50 kb capture many full-length transcripts • Computational methods for de novo transcriptome analysis are simplified | <ul style="list-style-type: none"> • Technology features low-to-medium throughput: currently only 500,000 to 10 million reads per run • Sample preparation includes reverse transcription, PCR and size selection (for some protocols), adding biases to many methods • Degraded RNA analysis is not recommended | Sequencing is particularly suited to isoform discovery, de novo transcriptome analysis, fusion transcript discovery, and MHC, HLA or other complex transcript analysis |
| Long-read RNA | ONT | <ul style="list-style-type: none"> • Long reads of 1–50 kb capture many full-length transcripts • Computational methods for de novo transcriptome analysis are simplified • Sample preparation does not require reverse transcription or PCR-reducing biases • RNA base modifications can be detected • Poly(A) tail lengths can be directly estimated from single-molecule sequencing | <ul style="list-style-type: none"> • Technology features low throughput: currently only 500,000 to 1 million reads per run • Sample preparation and sequencing biases are not well understood • Degraded RNA analysis is not recommended | <ul style="list-style-type: none"> • Sequencing is particularly suited to isoform discovery, de novo transcriptome analysis, fusion transcript discovery, and MHC, HLA or other complex transcript analysis • Ribonucleotide modifications can be detected |

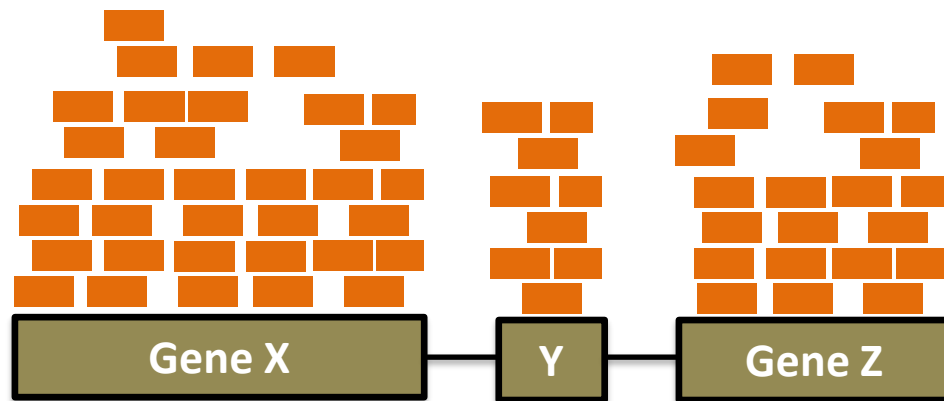
Analytical Pipeline Overview



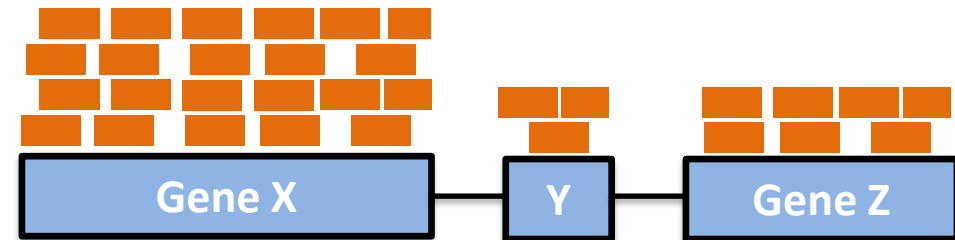
Searching for Differentially Expressed Genes

For differential expression the number of reads mapping to each gene (read count) is used to evaluate expression levels...

In which sample is Gene X overexpressed?



Sample A



Sample B

Raw counts cannot be used to evaluate or compare expression between samples! And within a sample?

Factors to consider:

- *Sequencing Depth*
- *Gene Length*
- *RNA Composition*

Normalizing Raw Read Counts: CPM/RPM, RPKM/FKPM and TPM

The answer: Normalization - this is required for differential expression analysis vizualization, etc.

Some Normalization Methods:

CPM/RPM – Counts/Reads per million

$$CPM = \frac{\text{No. reads mapped to gene} \times 10^6}{\text{Total number of mapped reads}}$$

RPKM/FPKM – Reads/fragments per kilobase million

$$\text{Scaling Factor (SF)} = \frac{\text{Total number of mapped reads}}{10^6}$$

$$RPM = \frac{\text{No. reads mapped to gene}}{SF}$$

$$RPMK = \frac{RPM}{\text{gene length(Kbp)}}$$

$$RPMK = \frac{\text{No. reads mapped to gene} \times 10^3 \times 10^6}{\text{Total number of mapped reads} \times \text{gene length(bp)}}$$

TPM – Transcripts per kilobase million

$$RPK = \frac{\text{No. reads mapped to gene}}{\text{gene length(Kbp)}}$$

$$\text{Scaling Factor (SF)} = \frac{\sum RPK}{10^6}$$

$$TPM = \frac{RPK}{SF}$$

Normalizing Raw Read Counts: Median of Ratios (DESeq2)

DESeq2 – Median of Ratios Method Normalization

Accounts for sequencing depth and RNA composition... but not gene length

1. Starting on raw counts, calculate the geometric mean for each gene across all sample – pseudo-reference;



2. Calculate the ratio of each sample to the pseudo-reference;



3. Calculate the normalization factor for each sample (**size factor**) by taking the median of all ratios;



4. Normalized counts are obtained by dividing the raw count of each gene by the normalization factor;

Anders and Huber Genome Biology 2010, 11:R106
<http://genomebiology.com/2010/11/10/R106>

METHOD

Open Access

Differential expression analysis for sequence count data

Simon Anders*, Wolfgang Huber

| Gene | Sample A | Sample B | Pseudo-reference |
|-------------|----------|----------|--------------------------------------|
| <i>rpoB</i> | 1100 | 750 | $\sqrt[2]{1100 \times 750} = 908,30$ |
| <i>eis</i> | 15 | 10 | $\sqrt[2]{15 \times 10} = 12,25$ |

| Gene | Ratio Sample A | Ratio Sample B |
|-------------|----------------------|---------------------|
| <i>rpoB</i> | $1100/908,30 = 1,21$ | $750/908,30 = 0,83$ |
| <i>eis</i> | $15/12,25 = 1,22$ | $10/12,25 = 0,82$ |

Normalization Factors:

Sample A – Median(1,21; 1,22) = 1,215

Sample B - Median(0,83; 0,82) = 0,825

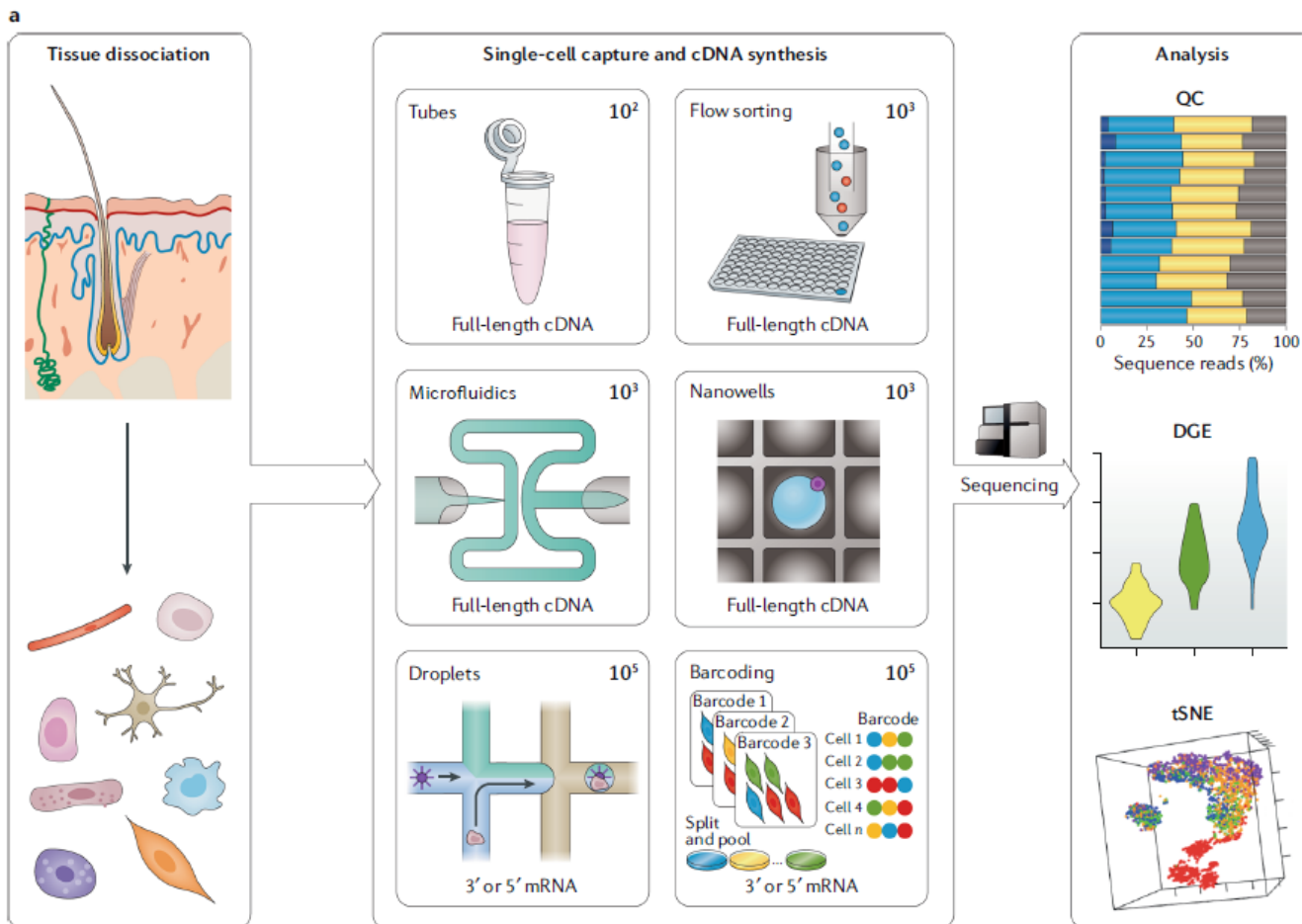
| Gene | Normalized Count A | Normalized Count B |
|-------------|-----------------------|----------------------|
| <i>rpoB</i> | $1100/1,215 = 905,35$ | $750/0,825 = 909,09$ |
| <i>eis</i> | $15/1,215 = 12,35$ | $10/0,825 = 12,12$ |

Comparison of Normalization Methods

| Method | Factors Accounted | | | Applications | | |
|---|-------------------|-------------|-----------------|---------------|-----------------------------|-------------|
| | Sequencing Depth | Gene Length | RNA Composition | Within sample | Comparisons between samples | DE Analysis |
| CPM | ✓ | ✗ | ✗ | ✗ | ✓ | ✗ |
| RPKM/FPKM | ✓ | ✓ | ✗ | ✓ | ✗ | ✗ |
| TPM | ✓ | ✓ | ✗ | ✓ | ✓ | ✗ |
| Median of Ratios (<i>DESeq2</i>) | ✓ | ✗ | ✓ | ✗ | ✓ | ✓ |
| Trimmed Mean of M Values (<i>EdgeR</i>) | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Other than bulk RNA-Seq ...

Single-cell RNA-Seq



Spatialomics

