

RNA-seq: From (good) experimental design
to (accurate) gene expression abundance.

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Narayanan Raghupathy

The Jackson Laboratory
Short Course on The Genetics of Addiction 2015

Next Generation Genome Sequencers

Illumina NextSeq, HiSeq and MiSeq



454 GS FLX



Ion Torrent Proton



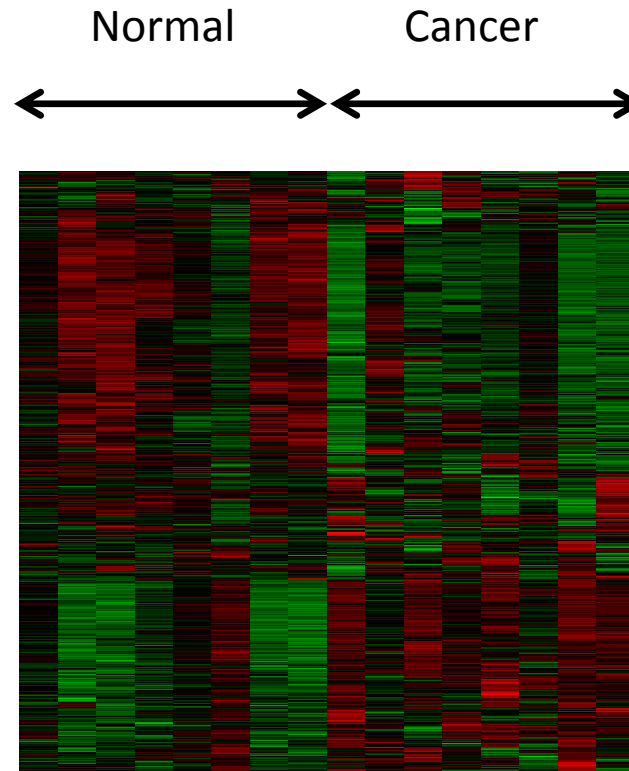
Oxford Nanopore



RNA-seq: Sequencing Transcriptomes

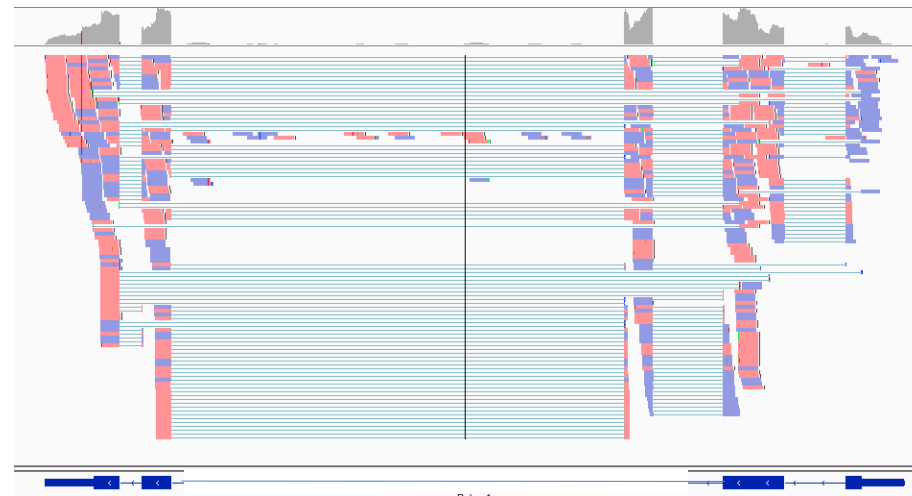


Applications of RNA-seq Technology



Differential Gene expression analysis

Applications of RNA-seq Technology

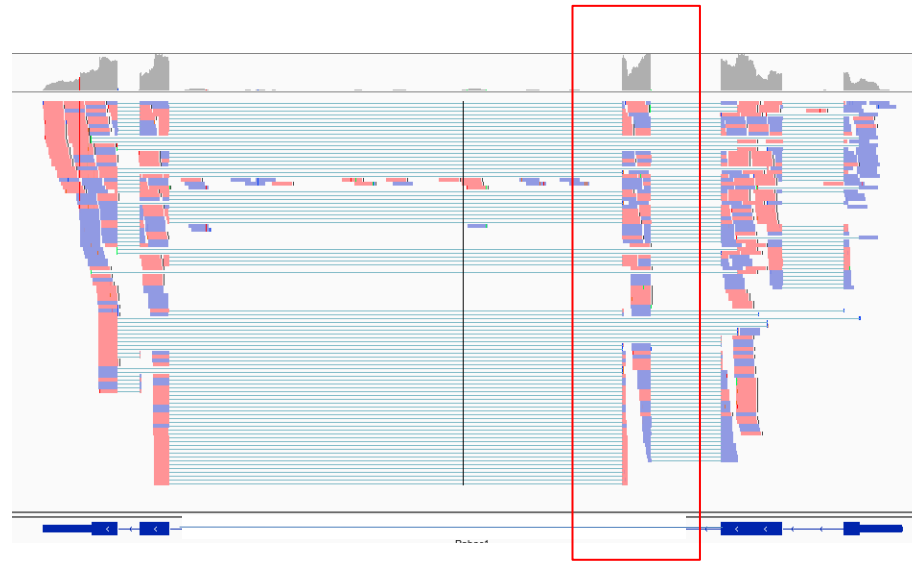


← Evidence from
RNA-seq

↘ Annotated gene

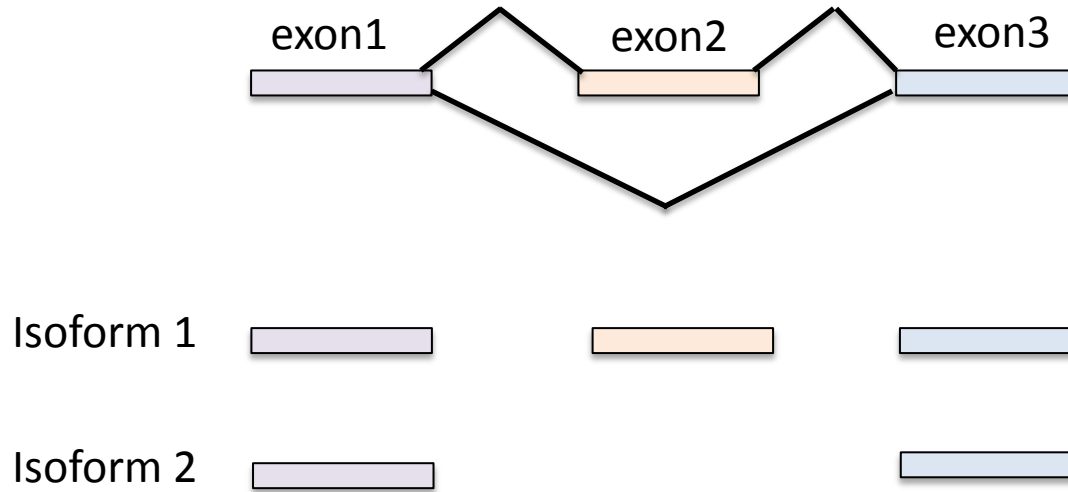
Novel exon discovery

Applications of RNA-seq Technology



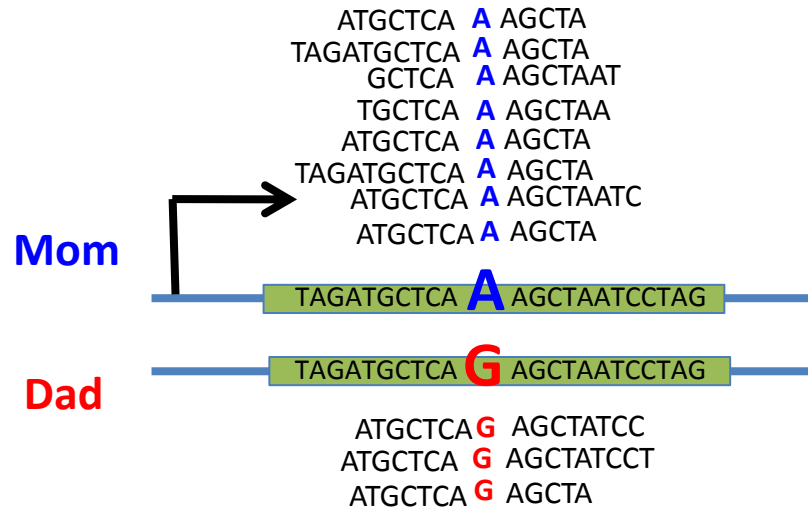
Novel exon discovery

Applications of RNA-seq Technology



Alternative splicing

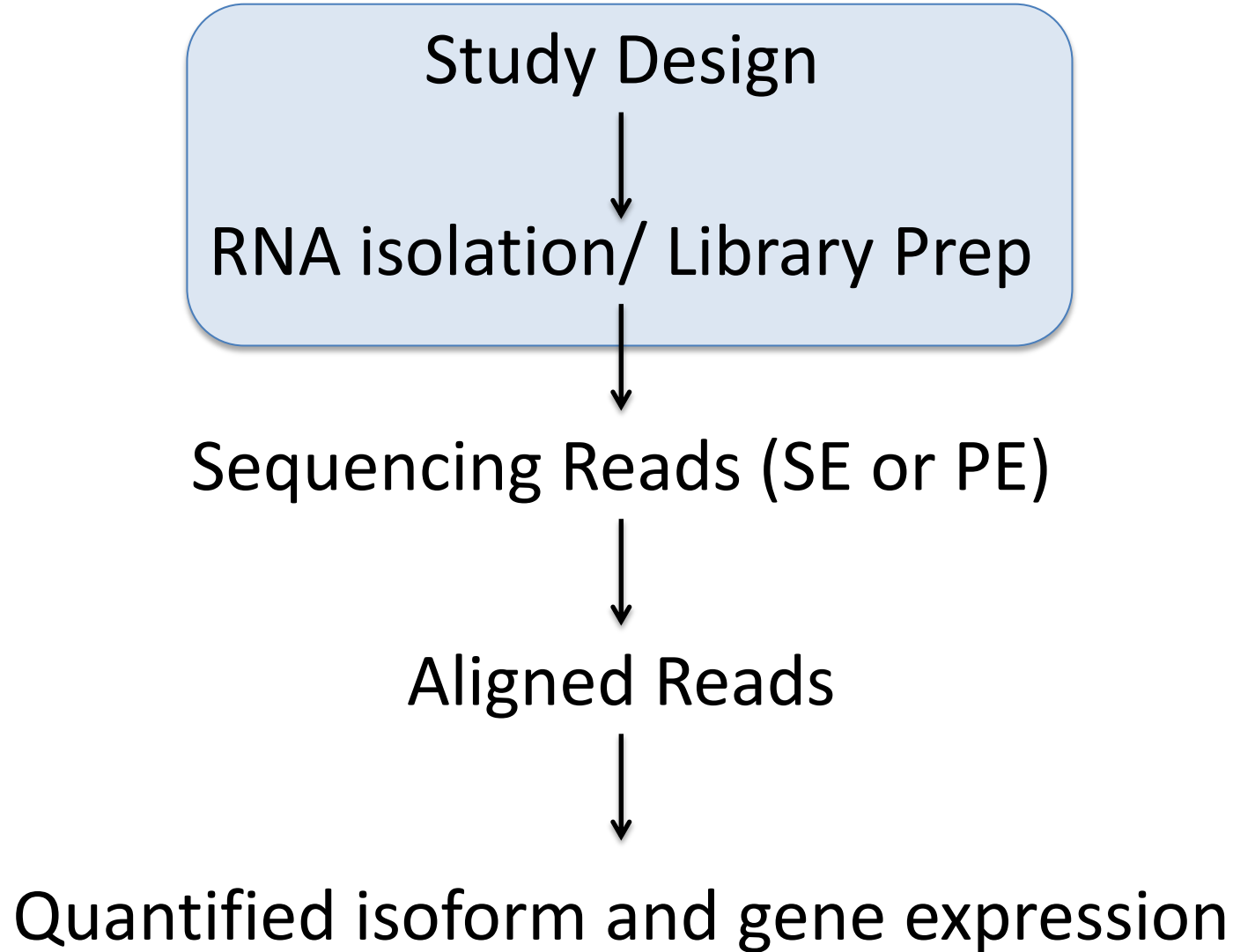
Applications of RNA-seq Technology



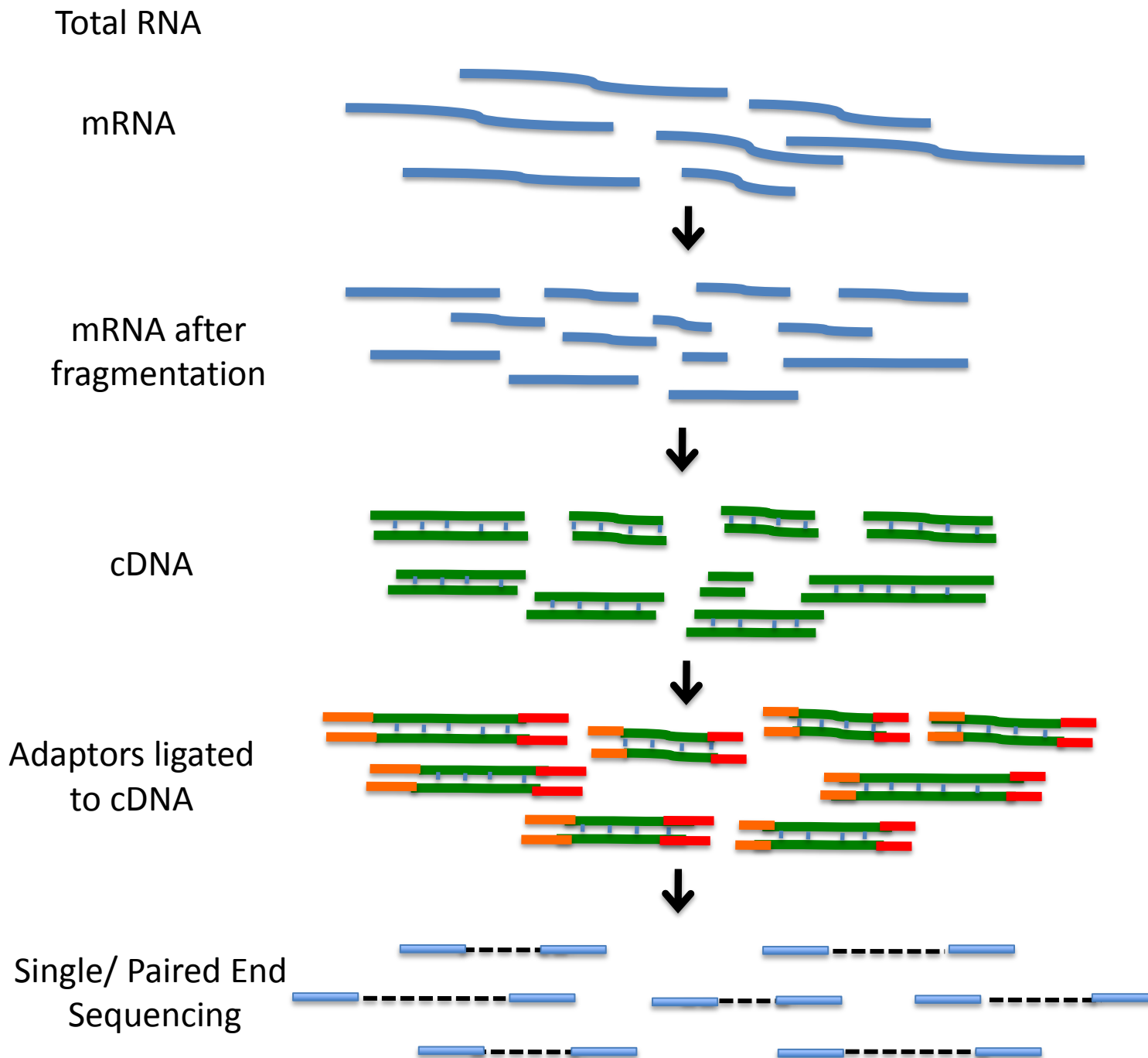
Allele-Specific gene Expression (ASE)

Preferential expression of one allele over the other.

RNA-seq Work Flow



RNA-Seq



Know your application – Design your experiment accordingly

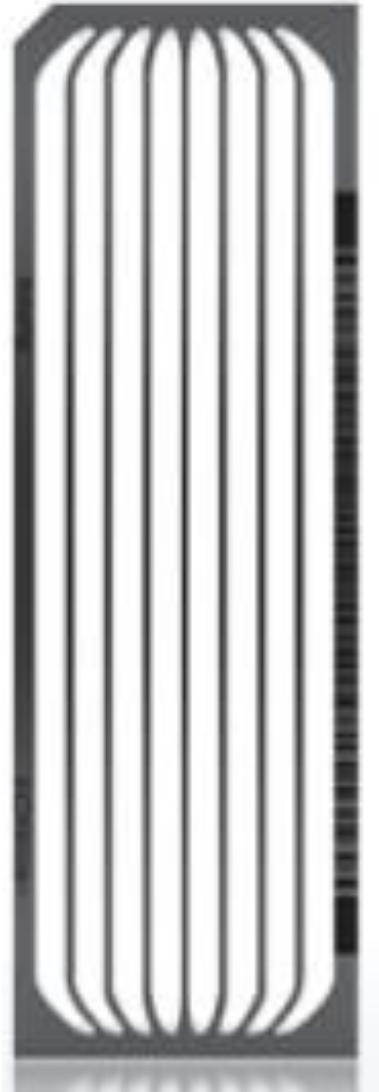
- How many reads? Read depth
- Single-end or Paired-end sequencing?
- Read length?
- How many samples?

RNA-seq Experimental design

- Differential expression of highly expressed and well annotated genes?
 - Smaller sample depth; more biological replicates
 - No need for paired end reads; shorter reads (50bp) may be sufficient.
 - Better to have 20 million 50bp reads than 10 million 100bp reads.
- Looking for novel genes/splicing/isoforms?
 - More read depth, paired-end reads from longer fragments.

Good Experimental Design

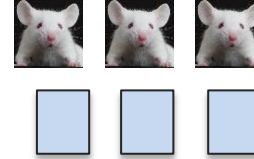
Multiplexing
Replication
Randomization



RNA-Seq Experimental Design: Randomization

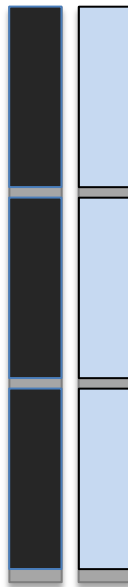


Experimental Group 1



Experimental Group 2

Two Illumina Lanes



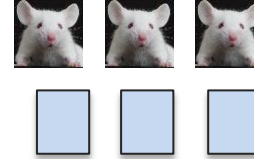
Bad Design

Random.org

RNA-Seq Experimental Design: Randomization

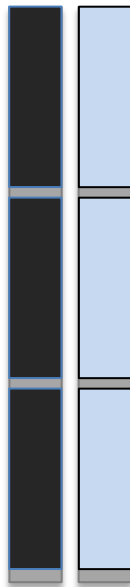


Experimental Group 1



Experimental Group 2

Two Illumina Lanes



Bad Design



Better Design

Random.org

RNA-seq Work Flow

Study Design



RNA isolation/ Library Prep



Sequencing Reads (SE or PE)

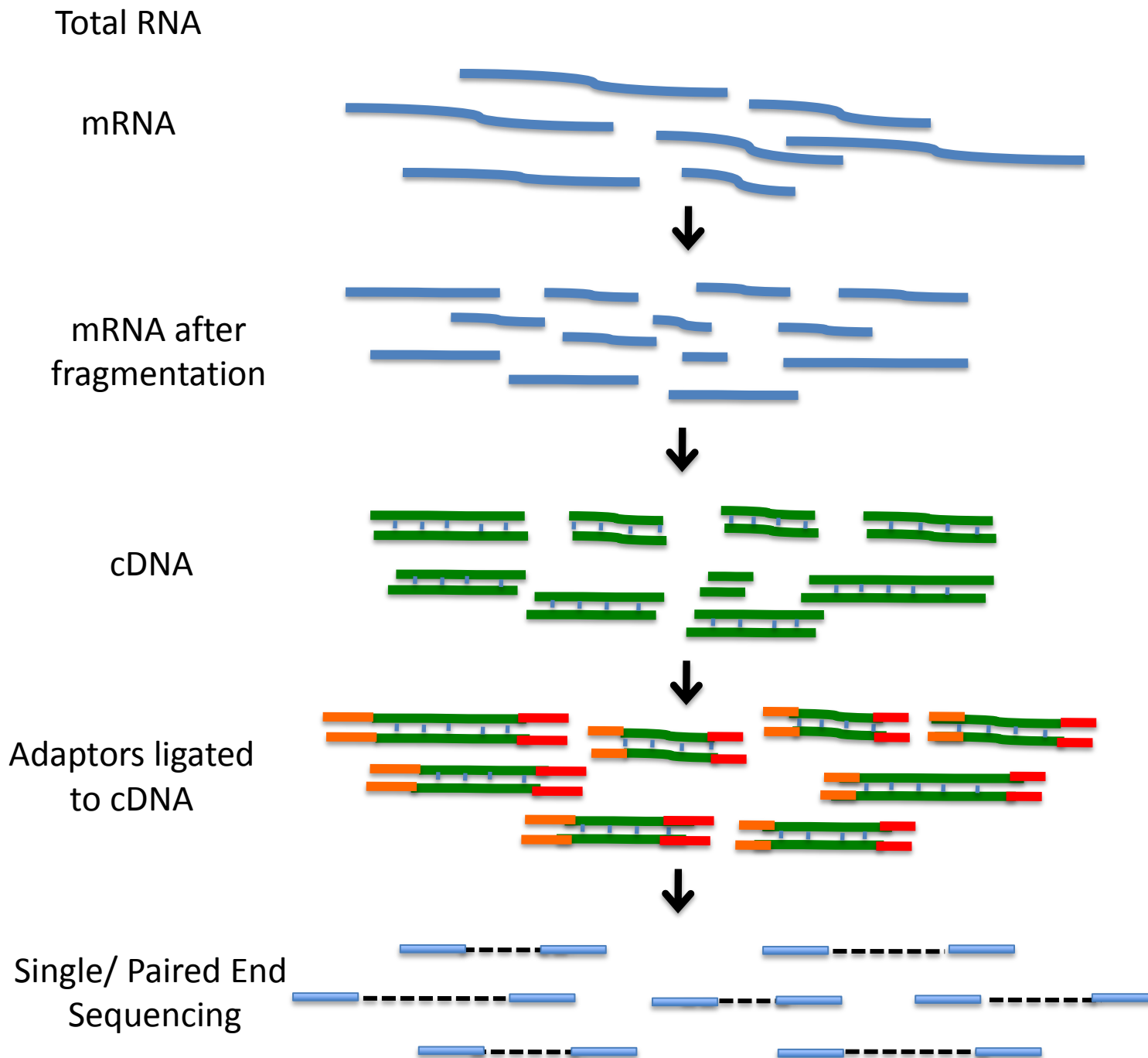


Aligned Reads



Quantified isoform and gene expression

RNA-Seq



Millions and millions of reads...

```
@HISEQ2000_0074:8:1101:7544:2225#TAGCTT/1
TCACCCGTAAGGTAACAAACCGAAAGTATCCAAAGCTAAAAGAAGTGGACGACGTGCTTGGTGGAGCAGCTGCATG
+
CCCCFFFFHHHHDHHJJJJJJJJJJ?FGIIJJJJJJJJJJFHIJJJJHHHFFFFD>AC?B??C?ACCAC>BB<<<>C@CCCACCCDCCIJ
```

@HISEQ2000_0074:8:1101:7544:2225#TAGCTT/1

Instrument: run/flowcell id

Flowcell lane and tile number

X-Y Coordinate in flowcell

The member of a pair

Index Sequence

Phred Score:

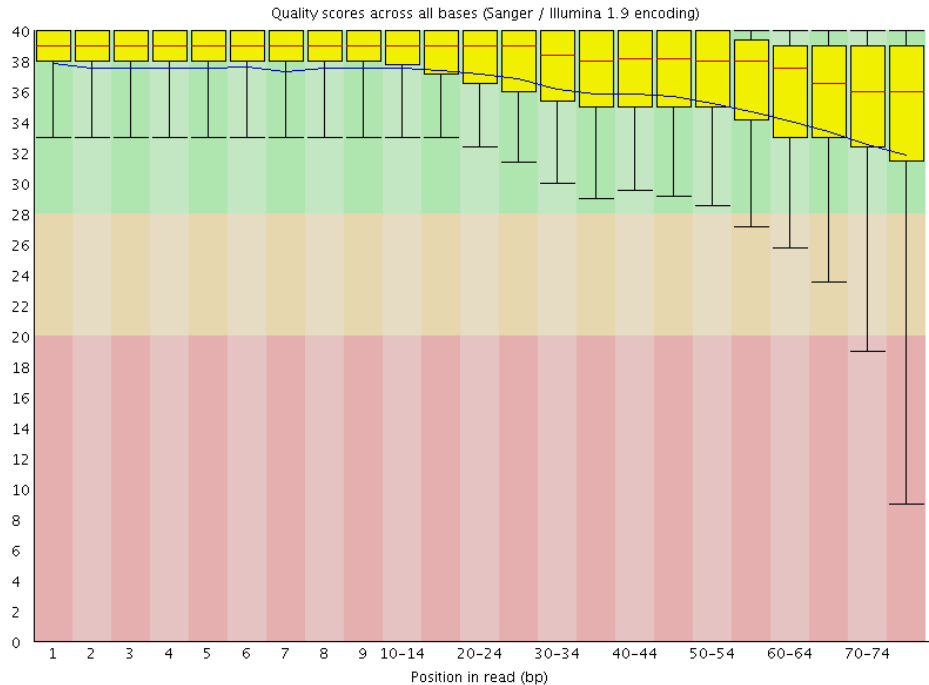
$$Q = -10 \log_{10} P$$

10 indicates 1 in 10 chance of error

20 indicates 1 in 100,

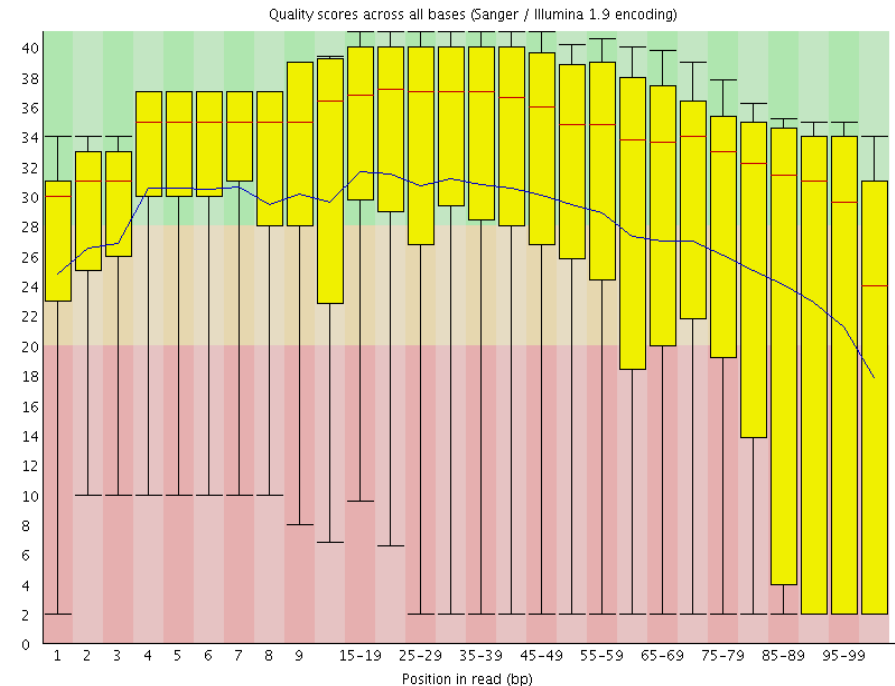
30 indicates 1 in 1000,

Quality Control: How to tell if your data is clean



Good data

- Consistent
- High Quality Along the reads



Bad data

- High Variance
- Quality Decrease with Length

RNA-seq Work Flow

Study Design



RNA isolation/ Library Prep



Sequencing Reads (SE or PE)



Aligned Reads



Quantified isoform and gene expression

Alignment 101

100bp Read

ACATGCTGCGGA



Chr 1



Chr 2

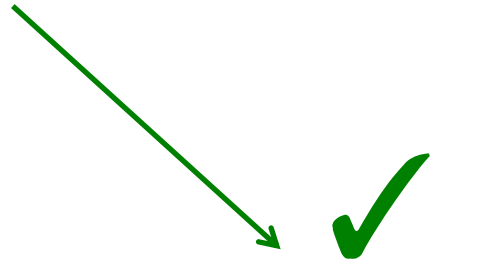


Chr 3

The perfect read: 1 read = 1 unique alignment.

100bp Read

ACATGCTGCGGA



ACATGCTGCGGA

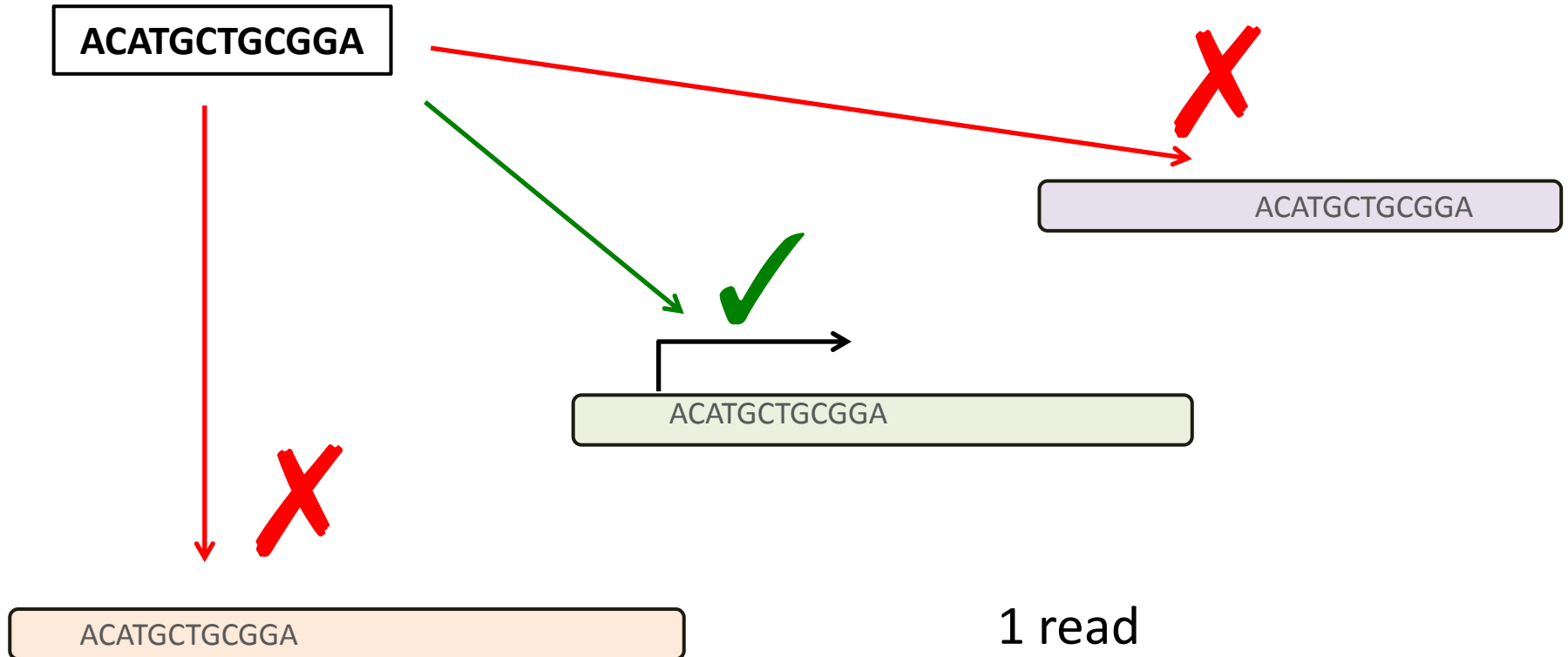
Chr 2

Chr 3

Chr 1

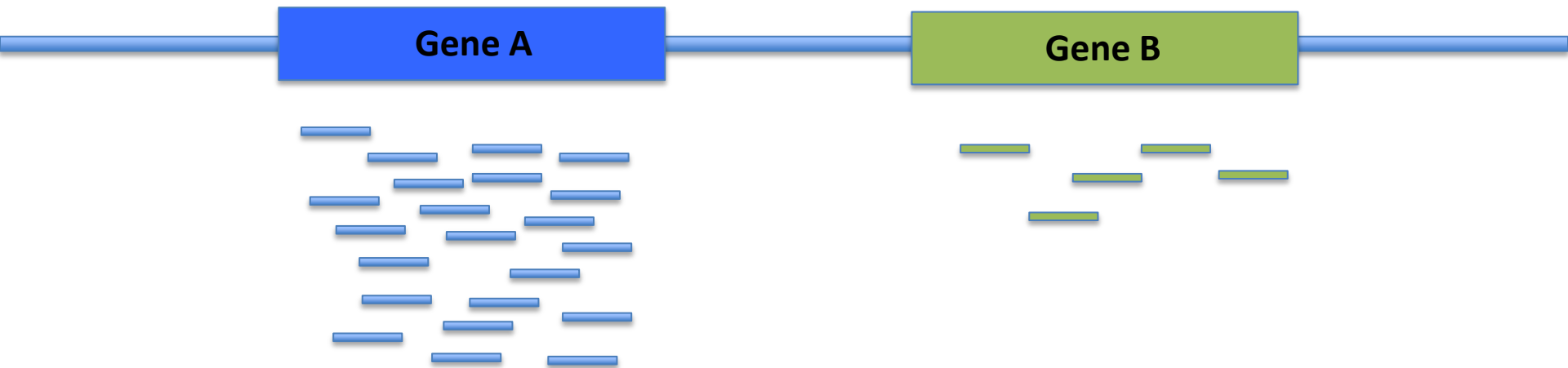
Some reads will align equally well to multiple locations. “Multireads”

100bp Read



1 read
3 valid alignments
Only 1 alignment is correct

Aligning Millions of Short Sequence Reads



Aligners: Bowtie, GSNAP, STAR, BWA, BLAT, HISAT, Bowtie2, Bowtie10000

Designed to align the short reads fast, but not accurate

Align to Genome or Transcriptome?

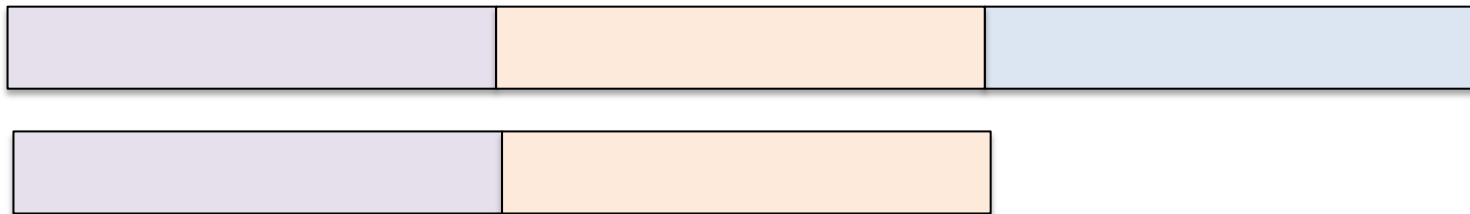
Genome



Advantages: Can align novel isoforms.

Disadvantages: Difficult, Spurious alignments, spliced alignment, gene families, pseudo genes

Transcriptome



Align to Genome or Transcriptome?

Genome



Advantages: Can align novel isoforms.

Disadvantages: Difficult, Spurious alignments, spliced alignment, gene families, pseudo genes

Transcriptome



Advantages: Easy, Focused to the part of the genome that is known to be transcribed.

Disadvantages: Reads that come from novel isoforms may not align at all or may be misattributed to a known isoform.

Output of most aligners: Bam/Sam file
of reads and genome positions

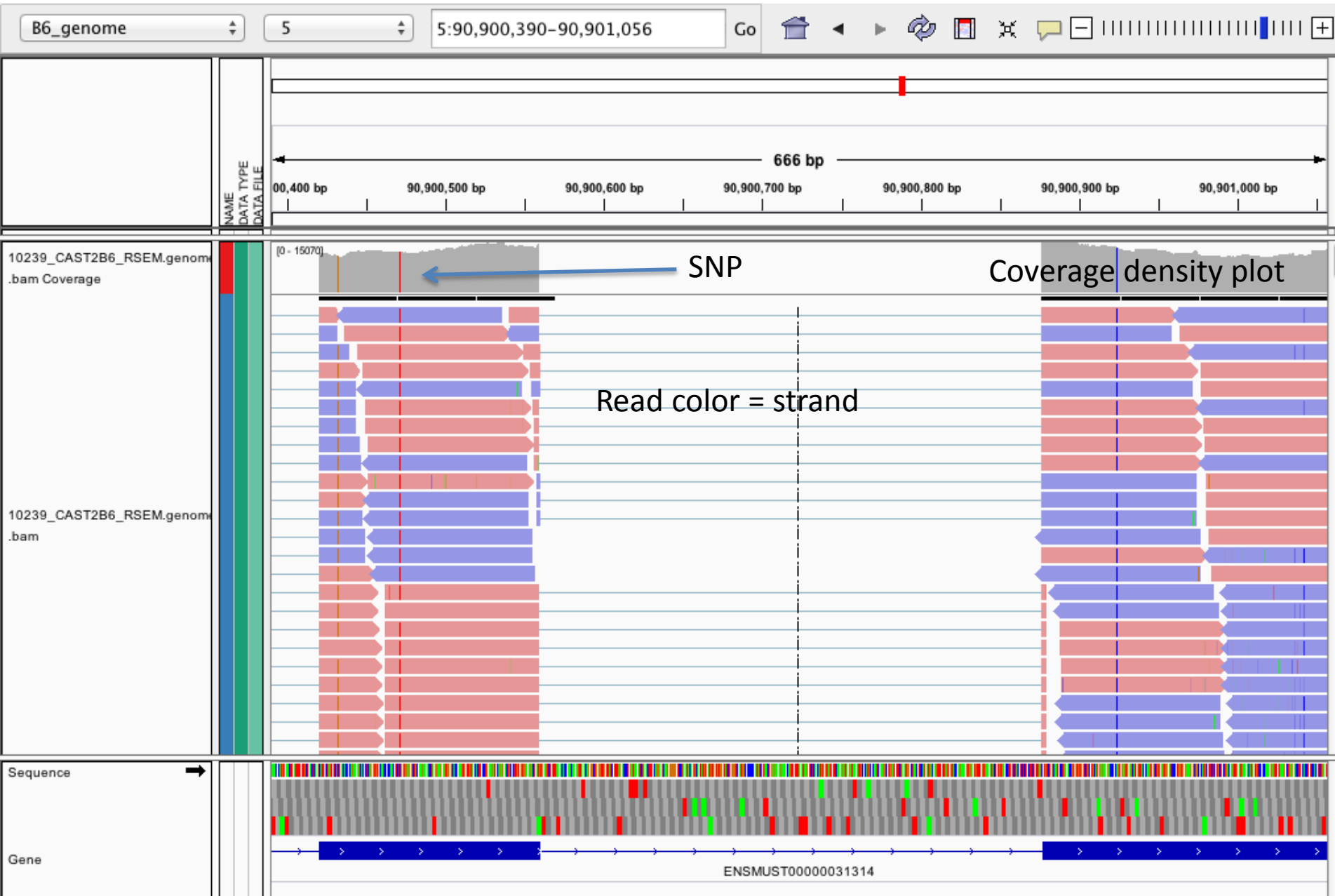
[illegible]

Visualization of alignment data (BAM/SAM)

- Genome browsers – UCSC, IGV, etc.



IGV is your friend.



Aligned Reads to Gene Abundance

Total RNA



100bp Reads



Aligned Reads



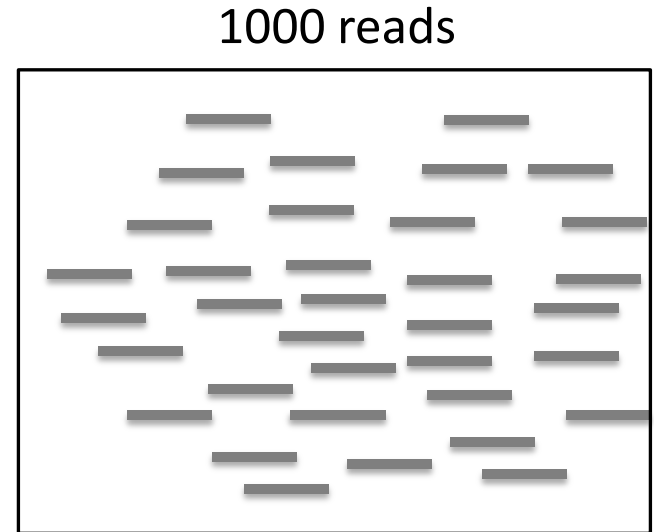
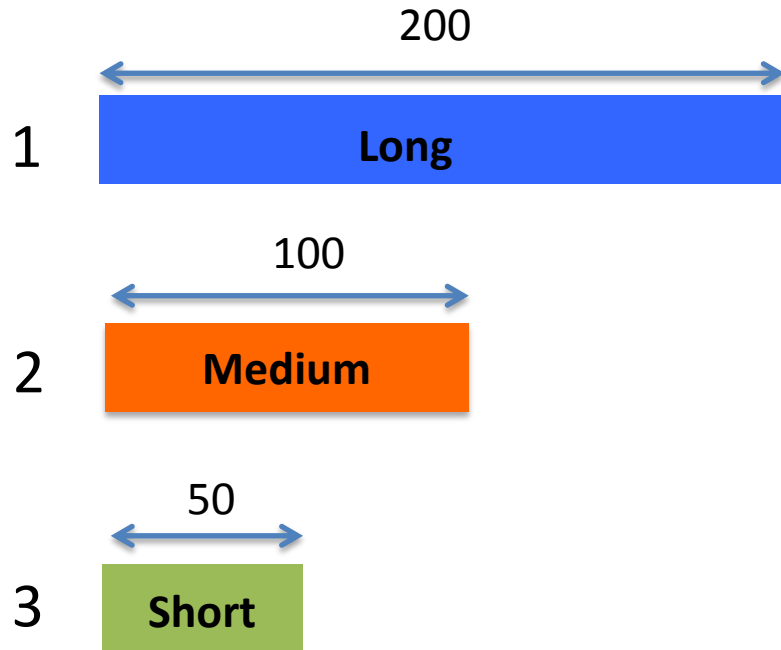
Quantified isoform and gene expression

Aligned Reads to Gene Abundance: Challenges



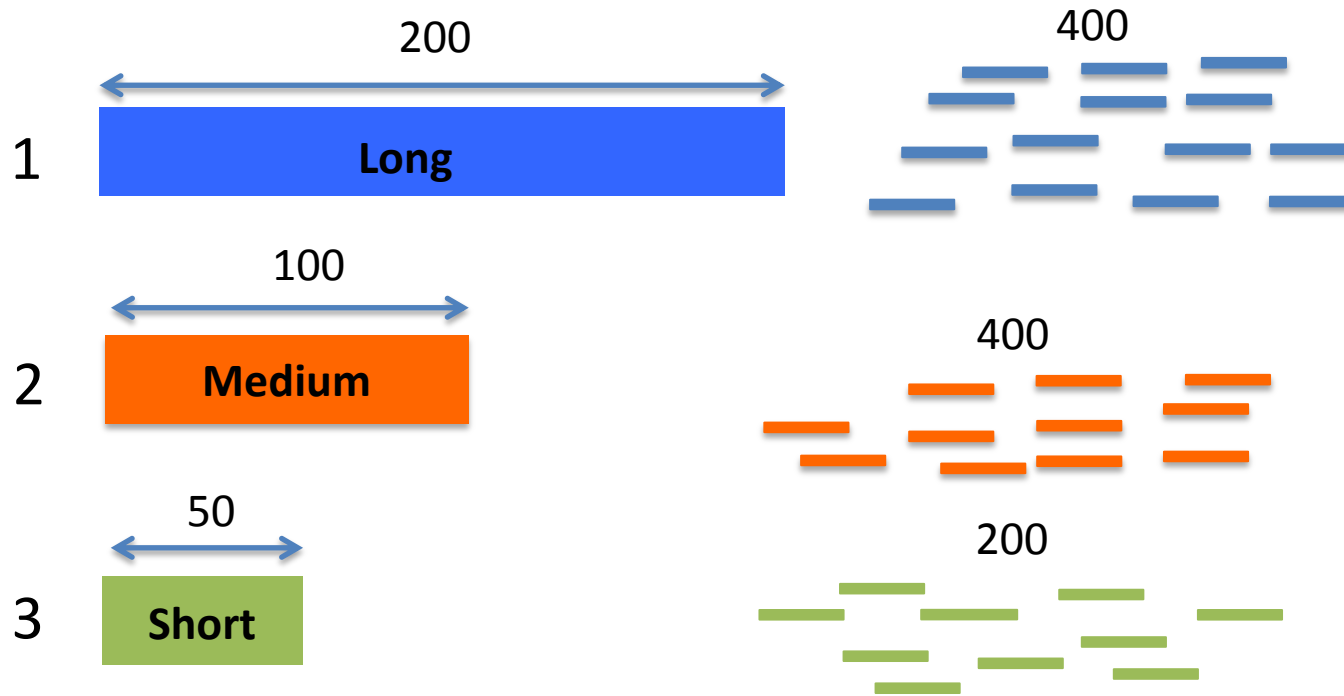
Many approaches to quantify expression abundance

Aligned Reads to Gene Abundance: Challenges



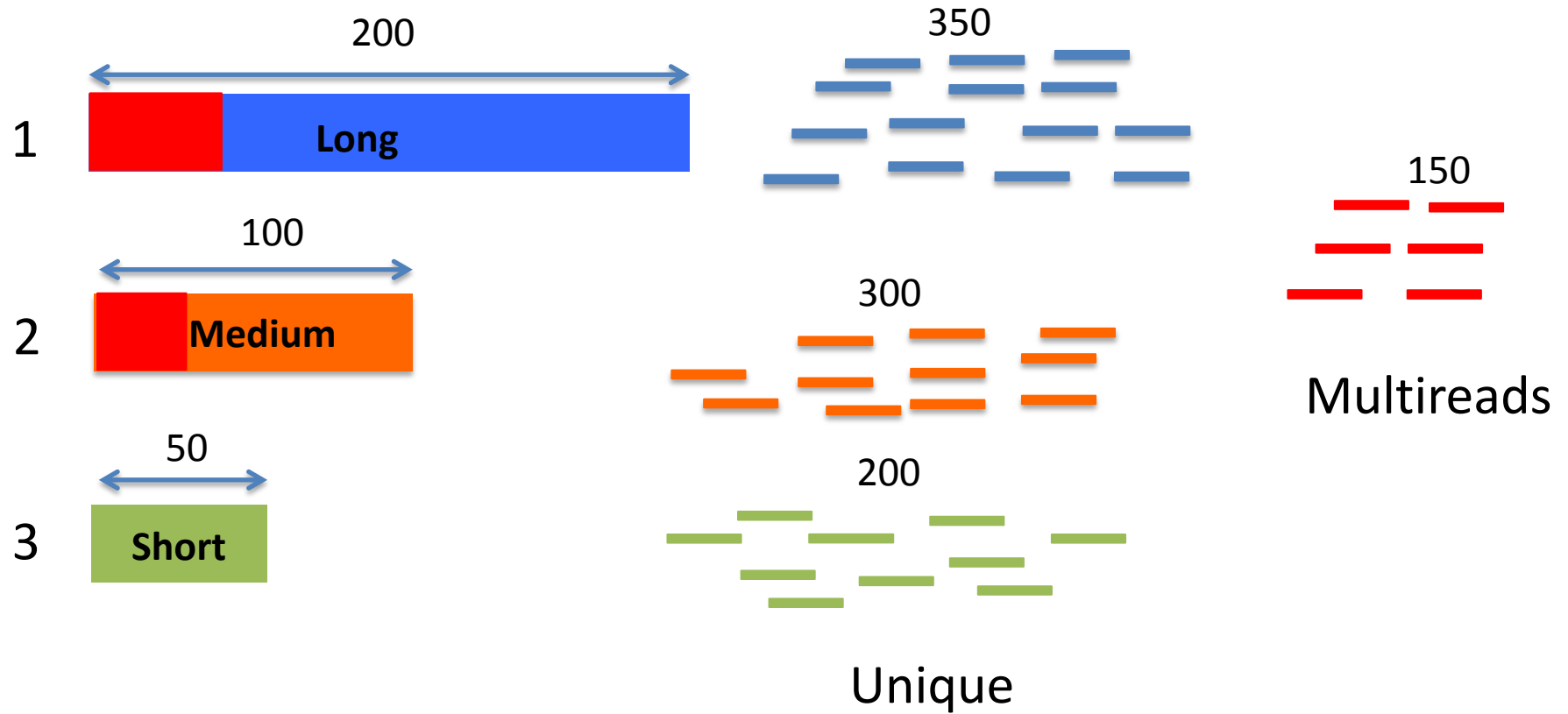
Relative abundance for these genes, f_1 , f_2 , f_3

Aligned Reads to Gene Abundance: Challenges



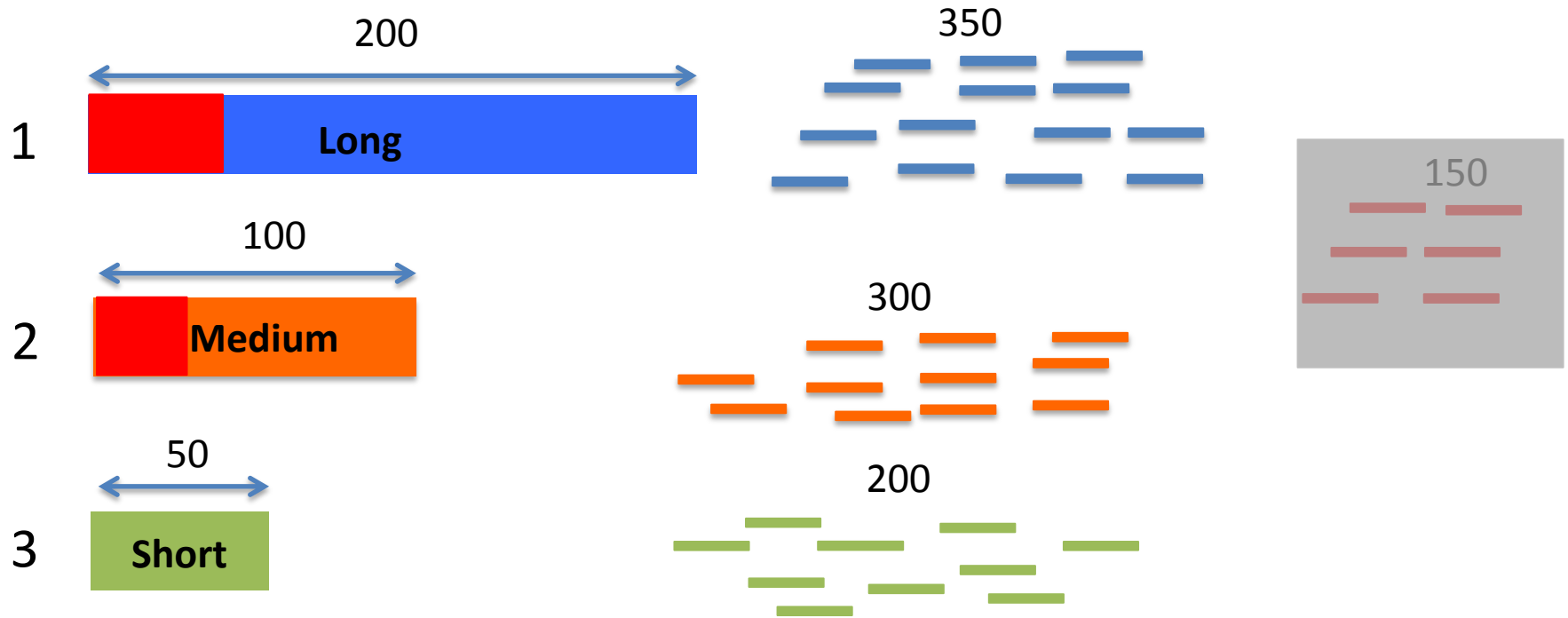
Relative abundance for these genes, f_1 , f_2 , f_3

Multireads: Reads Mapping to Multiple Genes/Transcripts



Relative abundance for these genes, f_1 , f_2 , f_3

Approach 1: Ignore Multireads

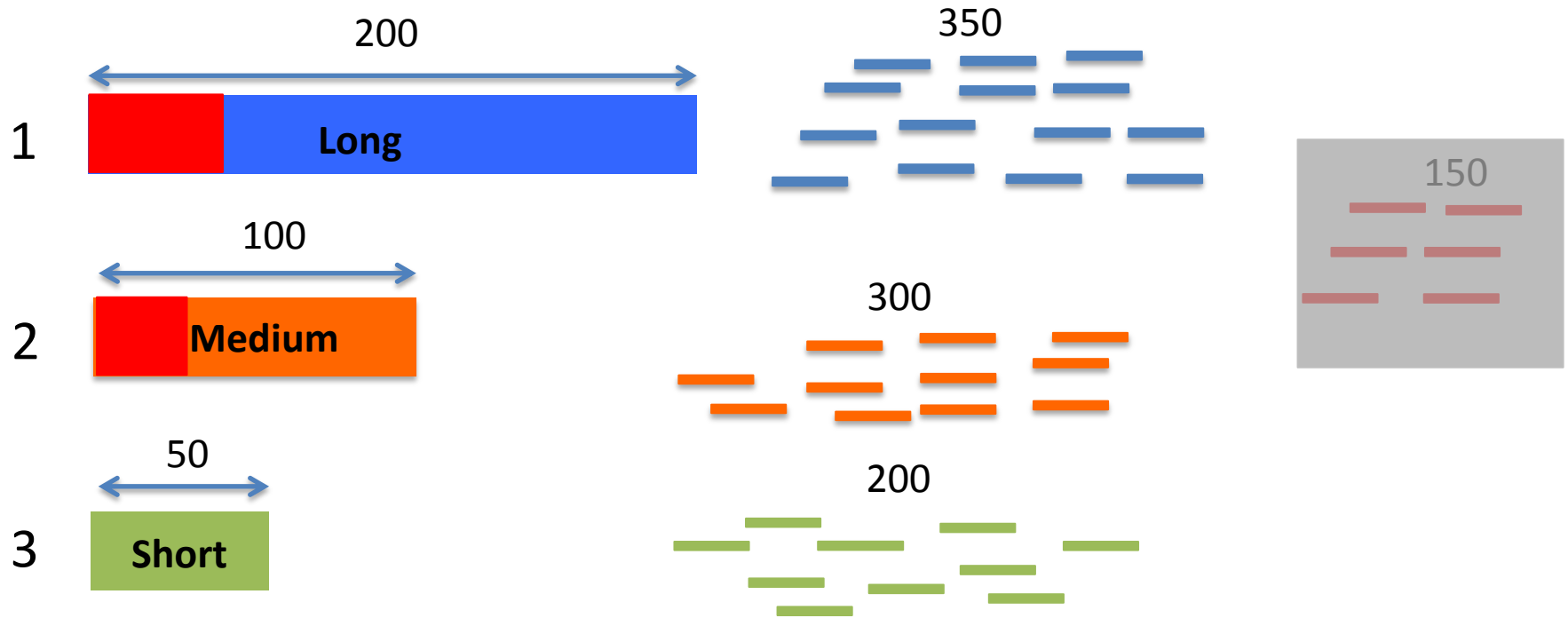


Relative abundance for these genes, f_1 , f_2 , f_3

Nagalakshmi et. al. Science. 2008

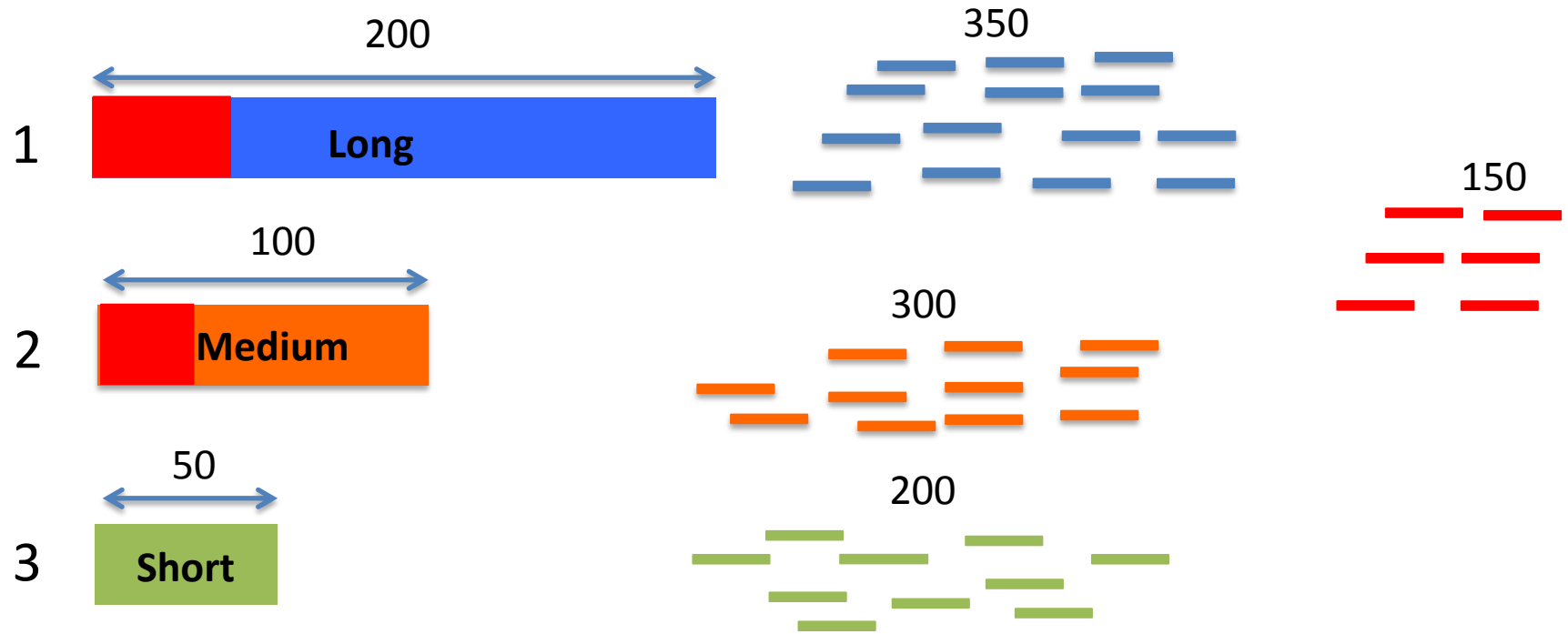
Marioni, et. al. Genome Research 2008

Approach 1: Ignore Multireads



- Over-estimates the abundance of genes with unique reads
- Under-estimates the abundance of genes with multireads
- Not an option at all, if interested in isoform expression

Approach 2: EM algorithm based allocation of Multireads



Relative abundance for these genes, f_1 , f_2 , f_3

Sailfish, Salmon, and Kallisto: The rise of Pseudo-alignment a.k.a alignment-free methods

100bp Read

ACATGCTGCGGA

K-mers

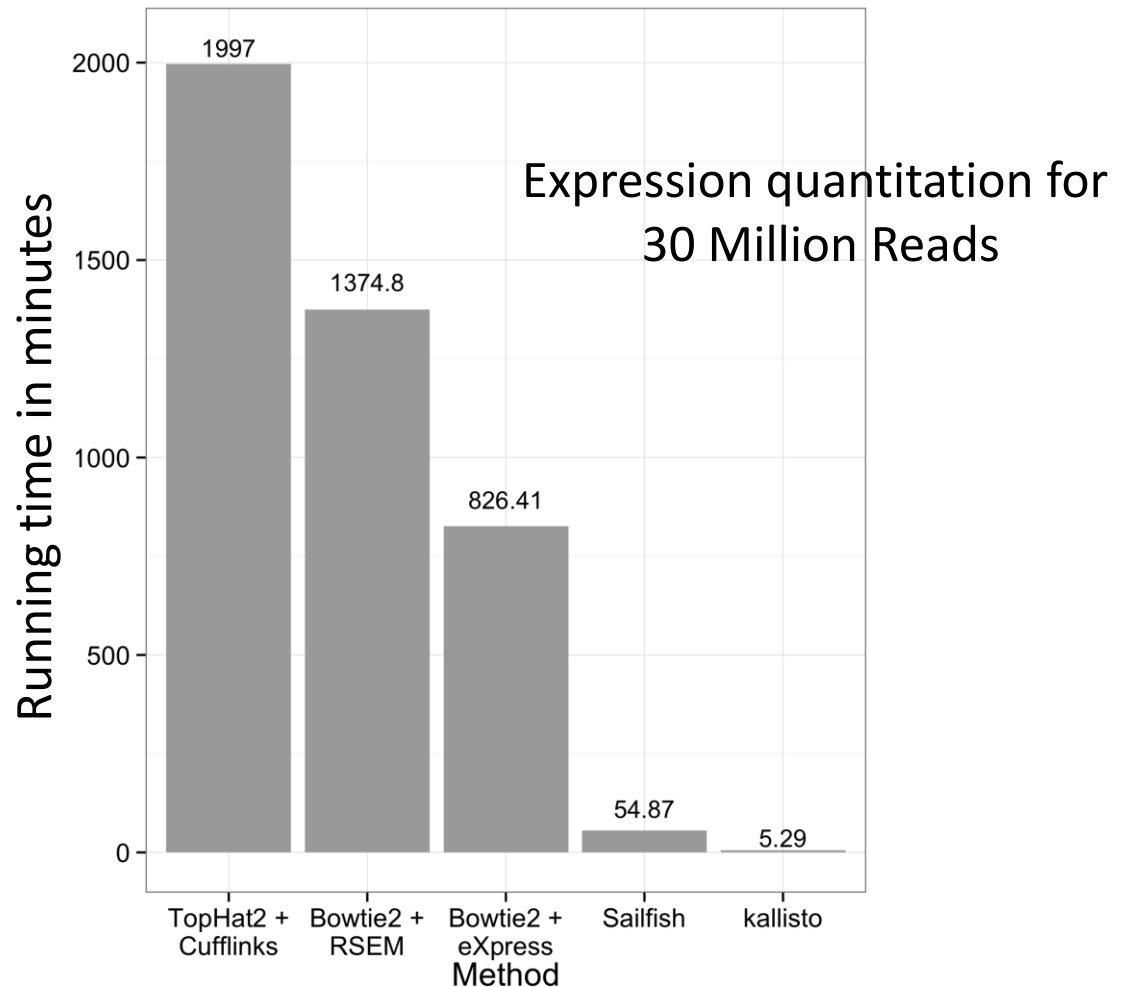
Transcriptome



Kallisto: K-mer based pseudo-alignment

100bp Read

ACATGCTGCGGA



Conclusions for quantitation

- EM approaches are currently the best option.
- Isoform-level estimates are still challenging and will become easier as read length increases.
- K-mer counting methods (Salmon, Kallisto) are very fast – they can be run easily on your own PC – and are reasonably accurate.

Expression Abundance: Counts, RPKM/FPKM, TPM

Sample 1

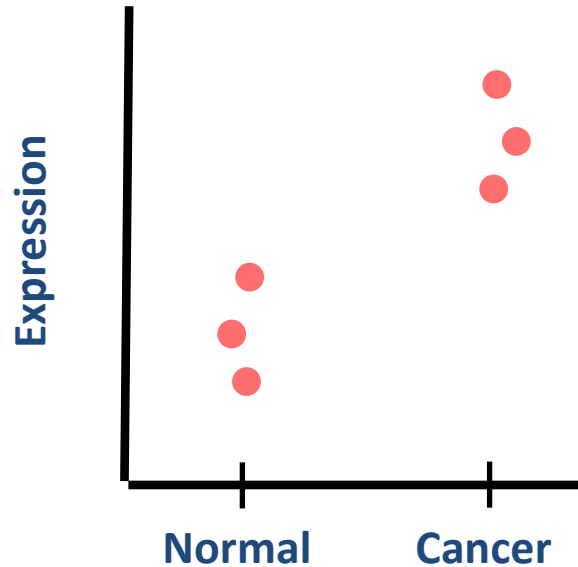


Sample 2



$$\text{FPKM} = \frac{\text{Number of Fragments Matched to a Gene} / \text{Kilo base}}{\text{Total matched reads in Millions}}$$

Differential Expression Analysis



T-test

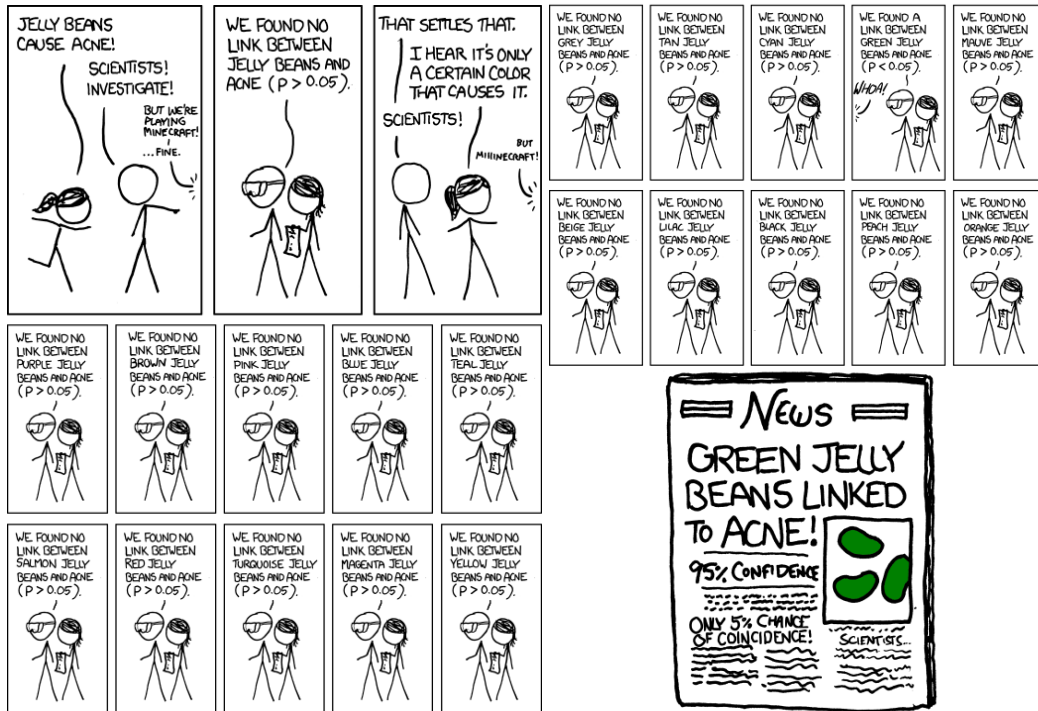
$$t_g = \frac{\hat{\mu}_{g,1} - \hat{\mu}_{g,2}}{\sqrt{\frac{\hat{\sigma}_{g,1}^2}{N_1} + \frac{\hat{\sigma}_{g,2}^2}{N_2}}}$$

Over-estimation of $\hat{\sigma}_g^2 \longrightarrow$ Too conservative

Under-estimation of $\hat{\sigma}_g^2 \longrightarrow$ Too sensitive
(Many false positives)

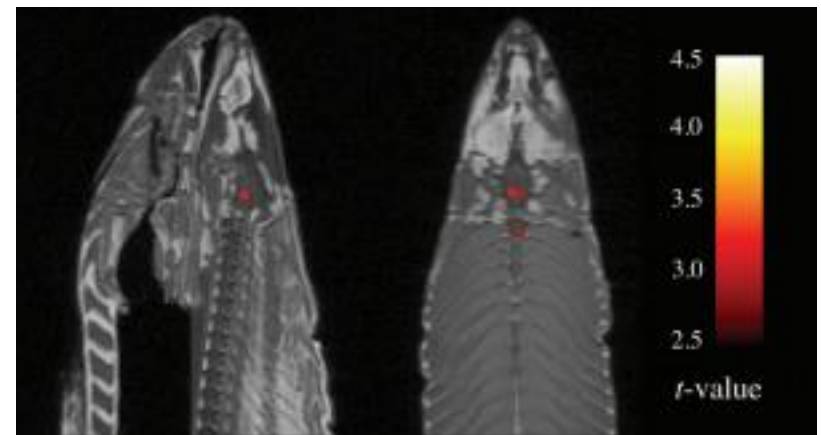
DESEQ2, edgeR, Voom, & CuffDiff

Multiple Testing Correction and False Discovery rate



XKCD Significant

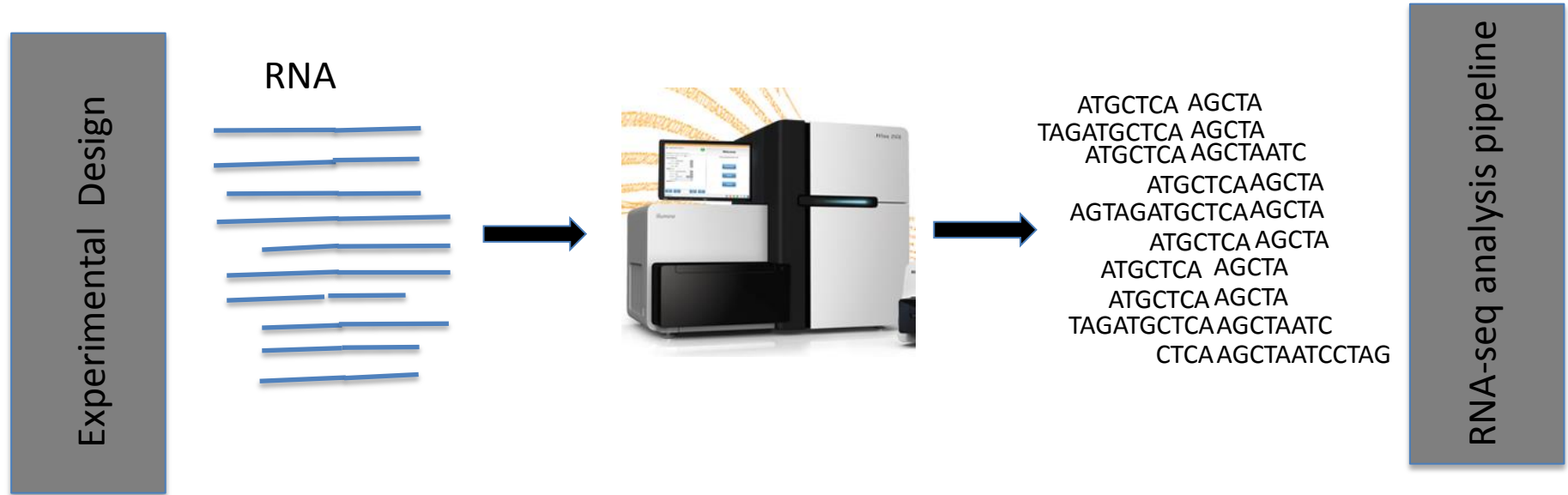
2012 IgNobel prize in
Neuroscience for “finding
Brain activity signal in dead salmon using fMRI”



Summary



Summary



As sequences get longer, alignment and isoform quantitation becomes easier!

Resources

Aligner

- Bowtie 2 <http://bowtie-bio.sourceforge.net/bowtie2/index.shtml>
- GSNAP <http://research-pub.gene.com/gmap/>

Transcript Discovery/Annotation

- STAR <https://github.com/alexdobin/STAR/releases>
- Tophat <http://tophat.cbcb.umd.edu/>

Transcript Abundance

- Kallisto <http://pachterlab.github.io/kallisto/>
- RSEM <http://deweylab.biostat.wisc.edu/rsem/>
- EMASE <https://github.com/churchill-lab/emase>

Differential Expression

- DESeq <http://www-huber.embl.de/users/anders/DESeq/>
- edgeR <http://bioconductor.org/packages/release/bioc/html/edgeR.html>
- EBSeq <https://www.biostat.wisc.edu/~kendzior/EBSEQ/>

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- Gene Expression Technologies group at JAX