

Workshop about SVs detection

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Sept, 19, 2018



My group

Mapping/ Assembly reads



NextGenMap-LR
Sedlazeck et.al. (2018)

Falcon Unzip
Chin et.al. (2016)

NextGenMap
Sedlazeck et.al. (2013)

Detection of Variants



Sniffles
Sedlazeck et.al. (2018)

SURVIVOR
Jeffares et. al. (2017)

BOD-Score
Sedlazeck et.al.(2013)

Benchmarking



Teaser
Smolka et.al. (2015)

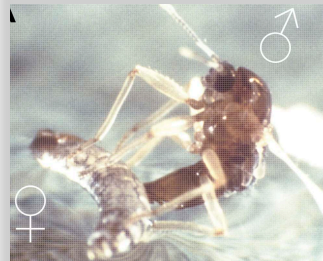
Sequencing
Jünemann et.al. (2013)

Applications



Model organisms:

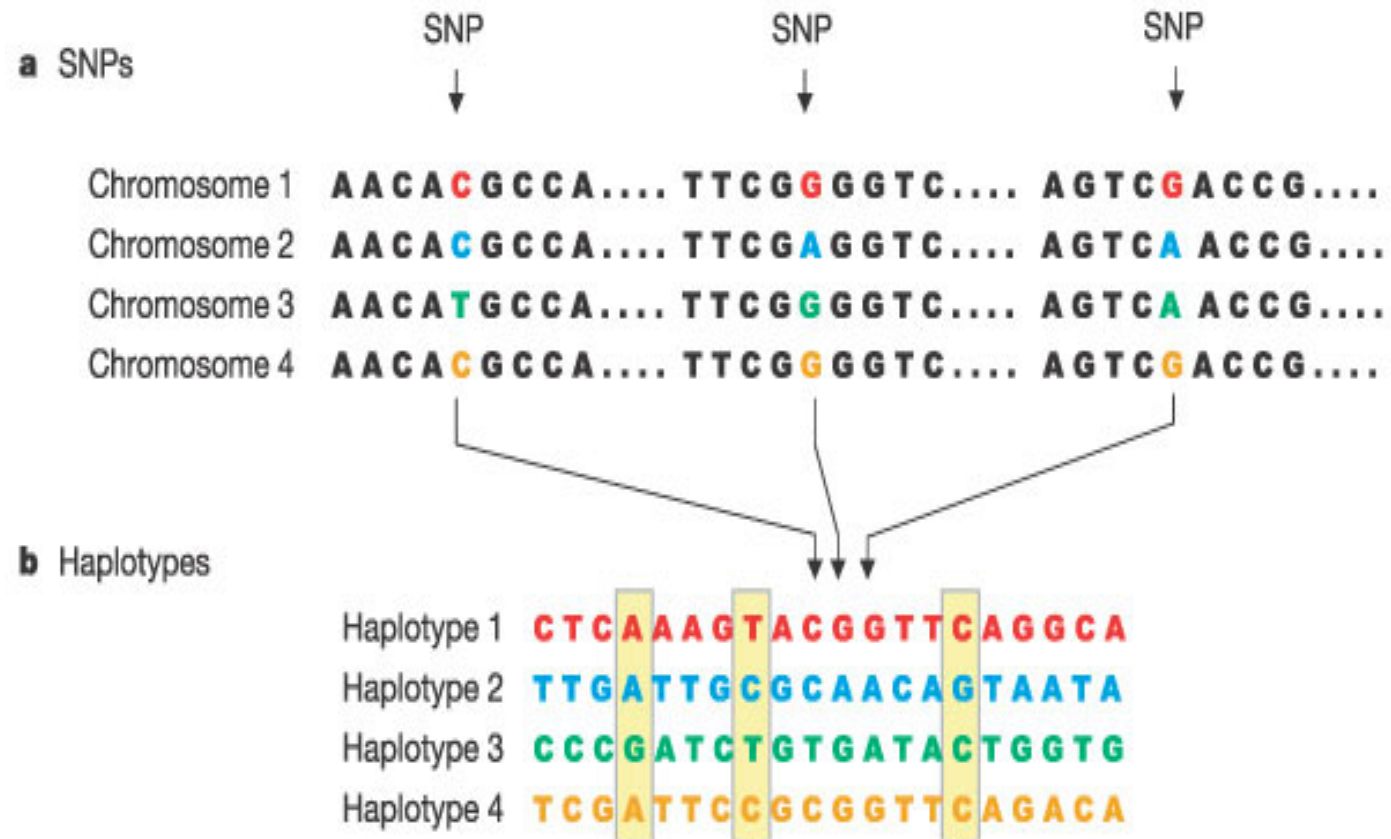
- Cancer (SKBR3) (in preparation)
- miRNA editing (Vesely et.al. 2012)



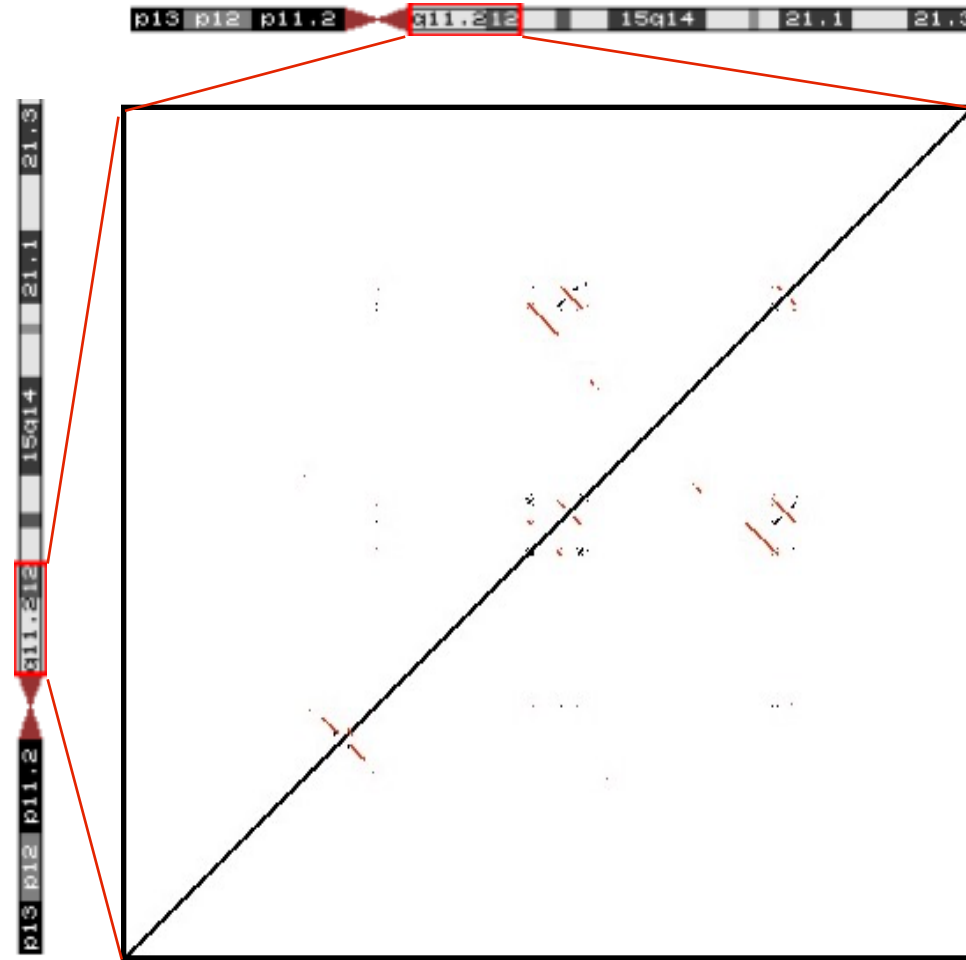
Non Model organisms:

- Cottus transposons (Dennenmoser et. al. 2017)
- Clunio (Kaiser et. al. 2016)
- Seabass (Vij et.al. 2016)
- Pineapple (Ming et.al. 2015)

Early 2000s dogma: SNPs account for most human genetic variation



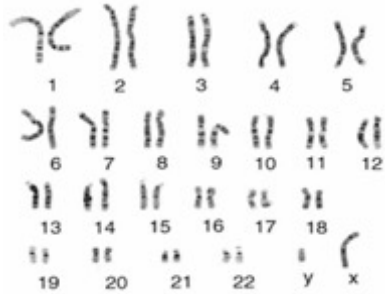
Segmental duplications (a.k.a. Low copy repeats)



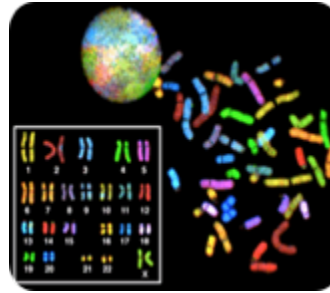
Self Dotplot:
10 megabases of Chr 15
(dot = 1 kb exact match)

~5% of the human genome is duplicated!

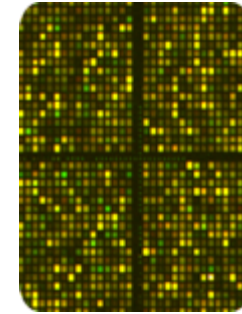
Our understanding of structural variation is driven by technology



1940s- 1980s
Cytogenetics / Karyotyping



1990s
CGH / FISH /
SKY / COBRA



2000s
Genomic microarrays
BAC-aCGH / oligo-aCGH

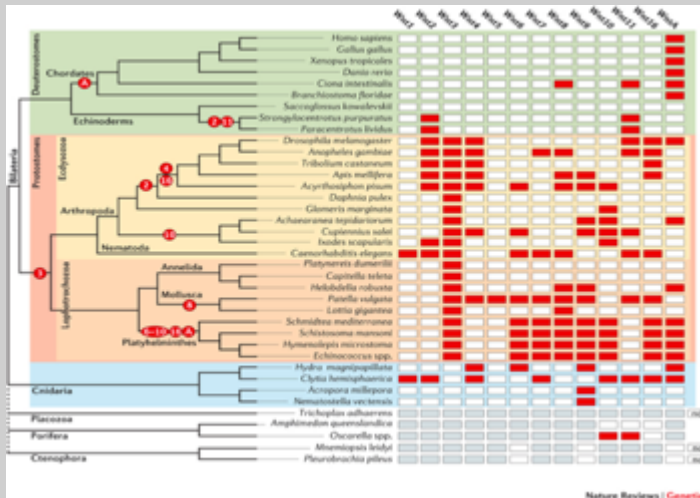
Today
High throughput
DNA sequencing



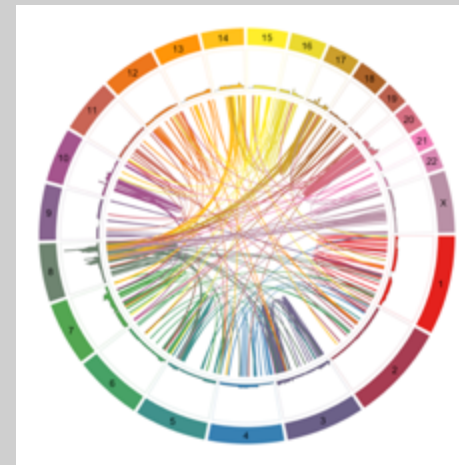
Why are structural variations relevant / important?

- They are common and affect a large fraction of the genome
- They are a major driver of genome evolution

Evolution

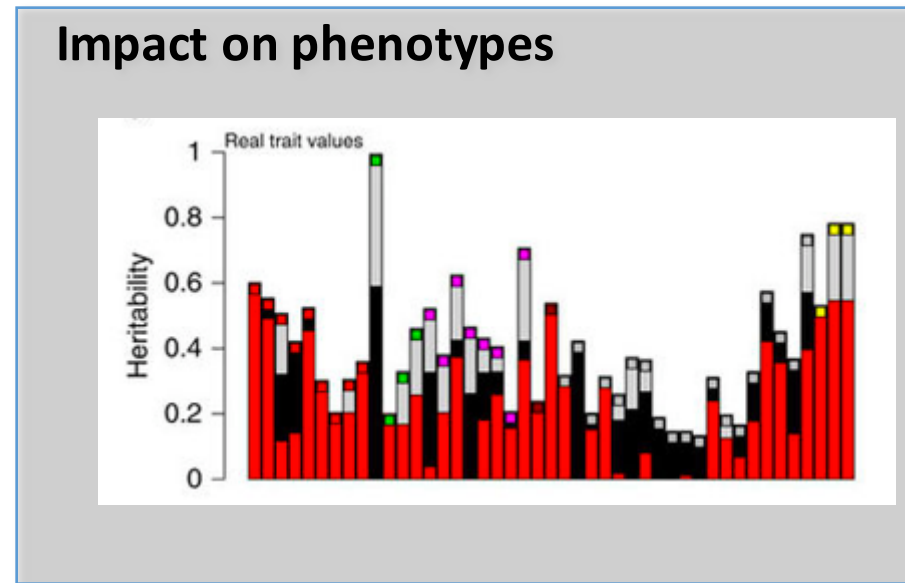
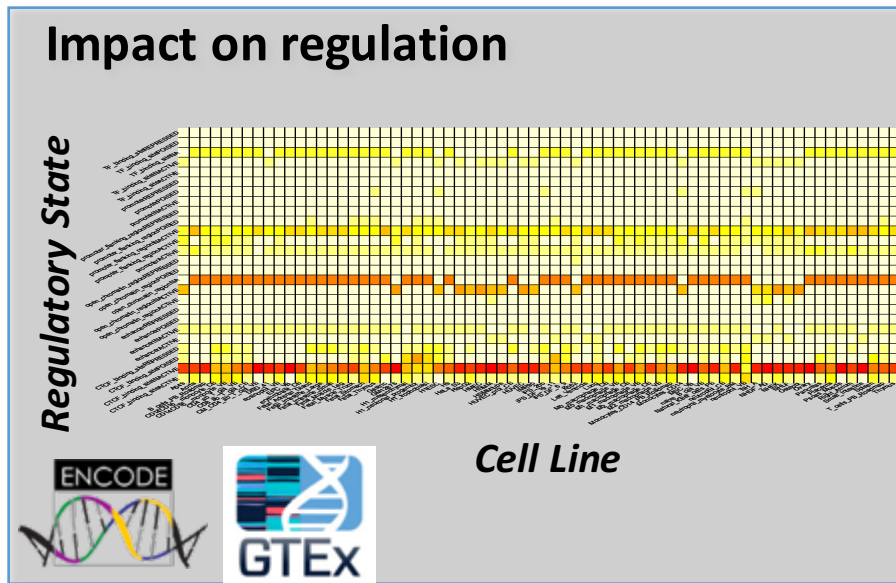


Genomic Disorders

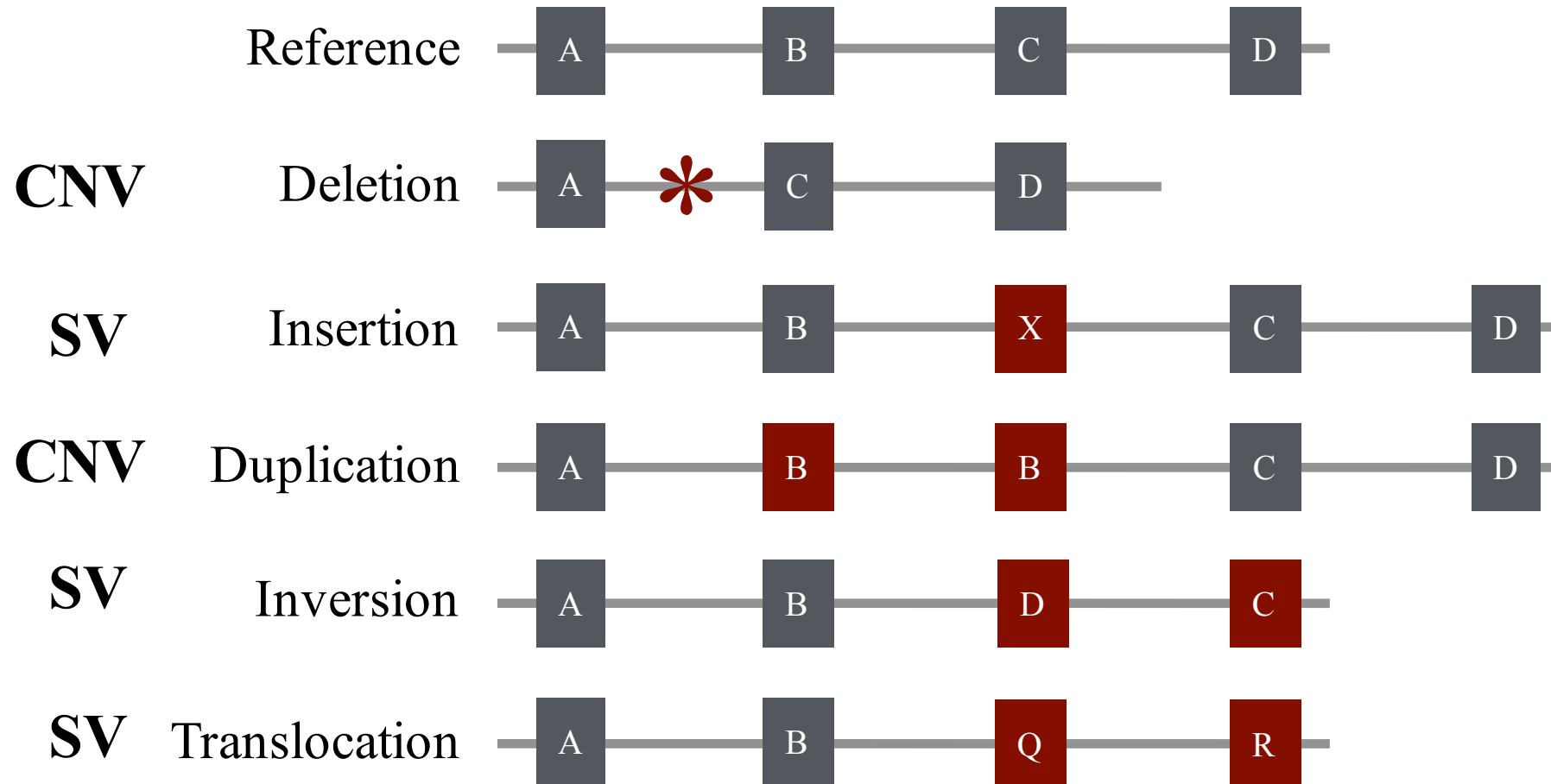


Why are structural variations relevant / important?

- Genetic basis of traits



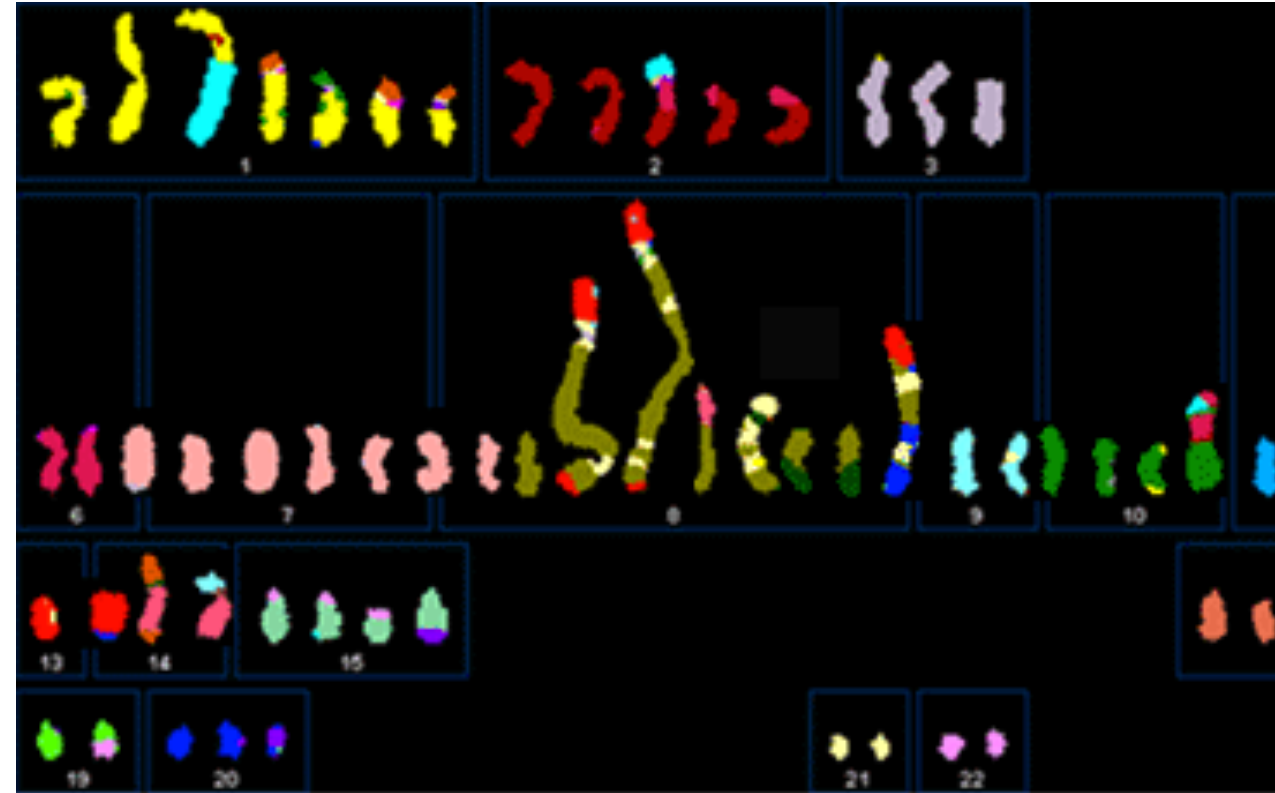
Variation in genome structure. So-called "structural variation" (SV)



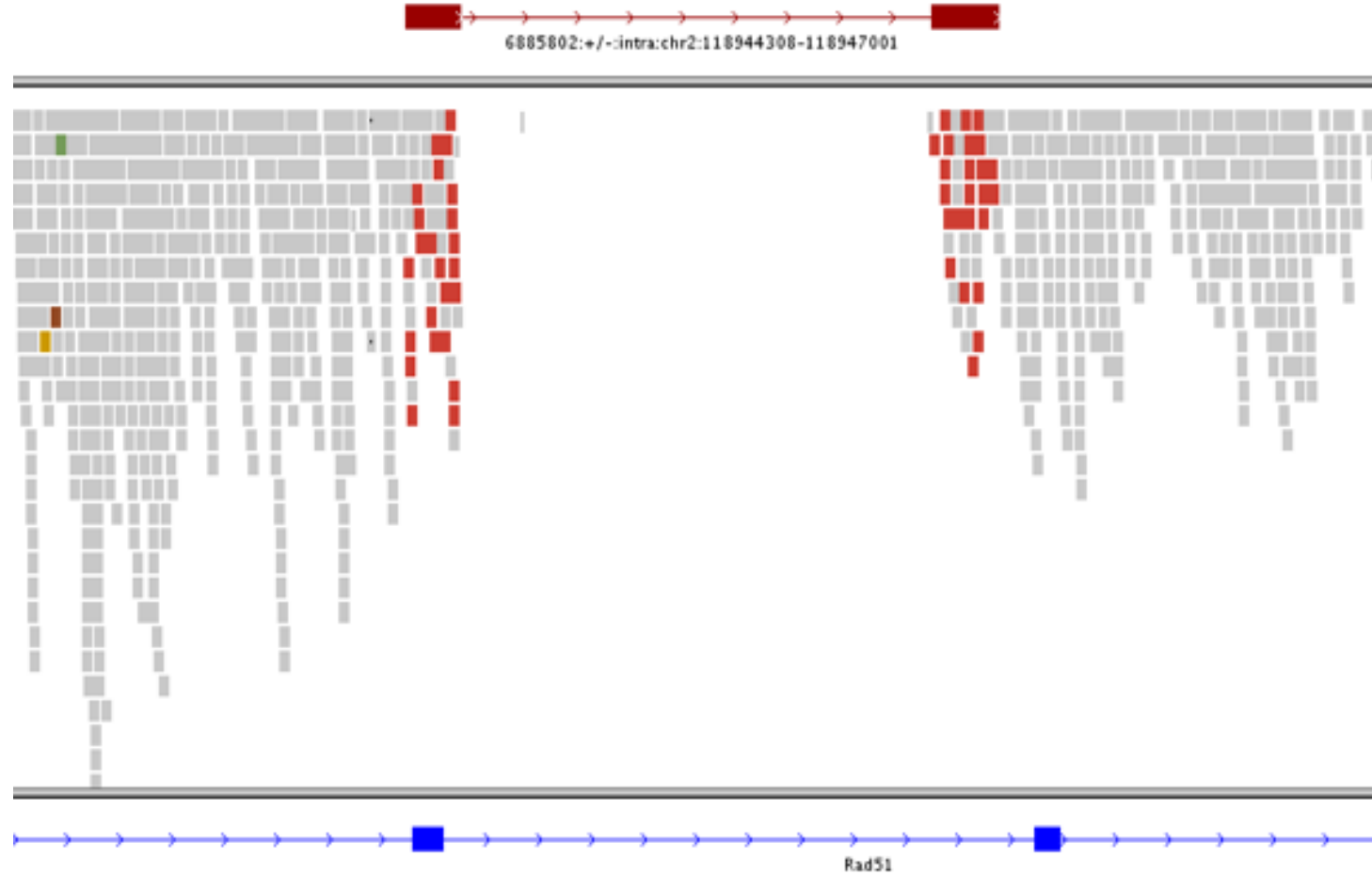
SV is a superset of copy number variation (CNV). Not all structural changes affect copy number (e.g., inversions)!

Outline

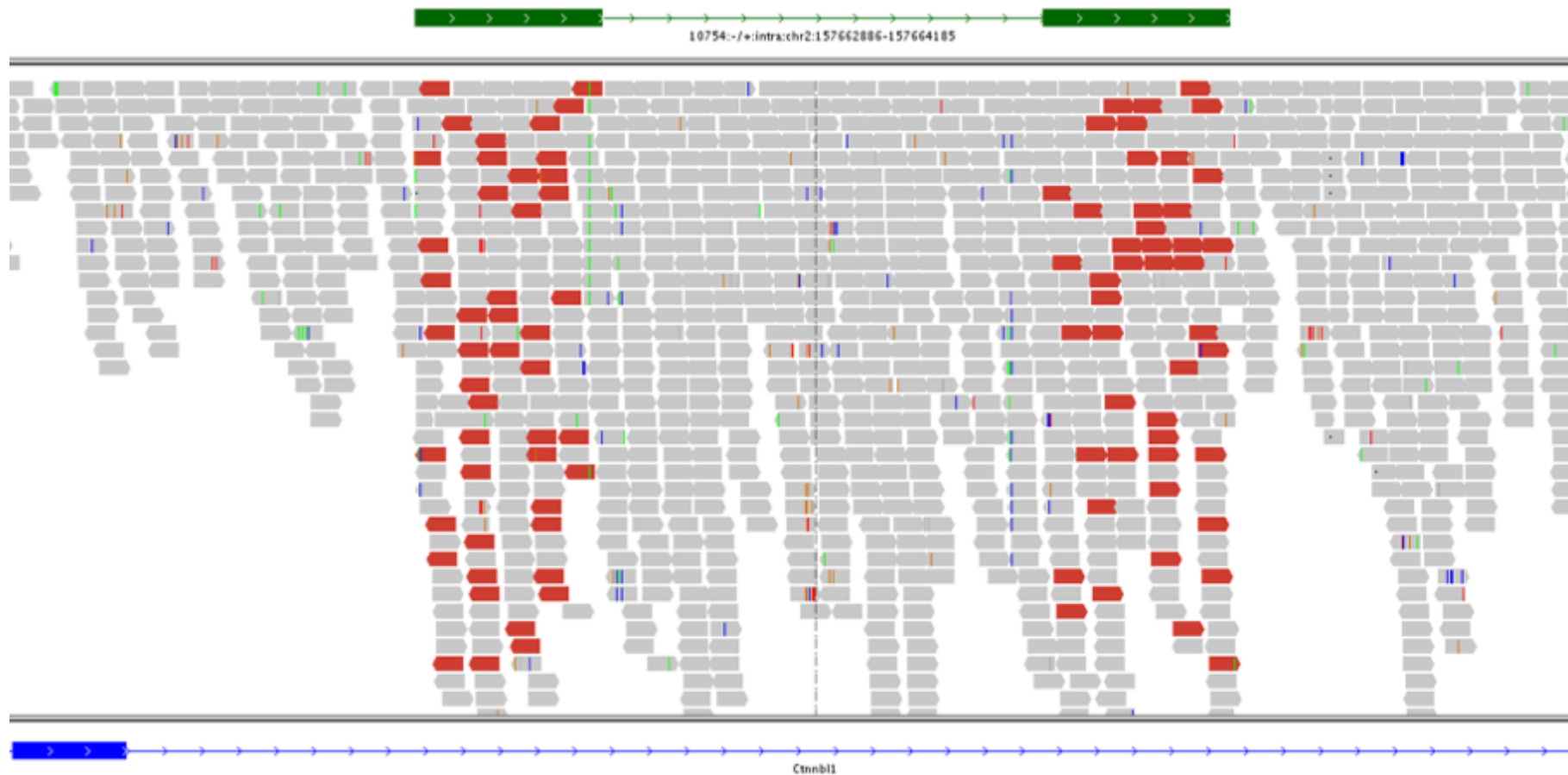
1. CNV analysis
2. SVs analysis and their impact
 1. Assembly based
 2. Short reads
 3. Long reads
3. Comparing + annotation of SVs



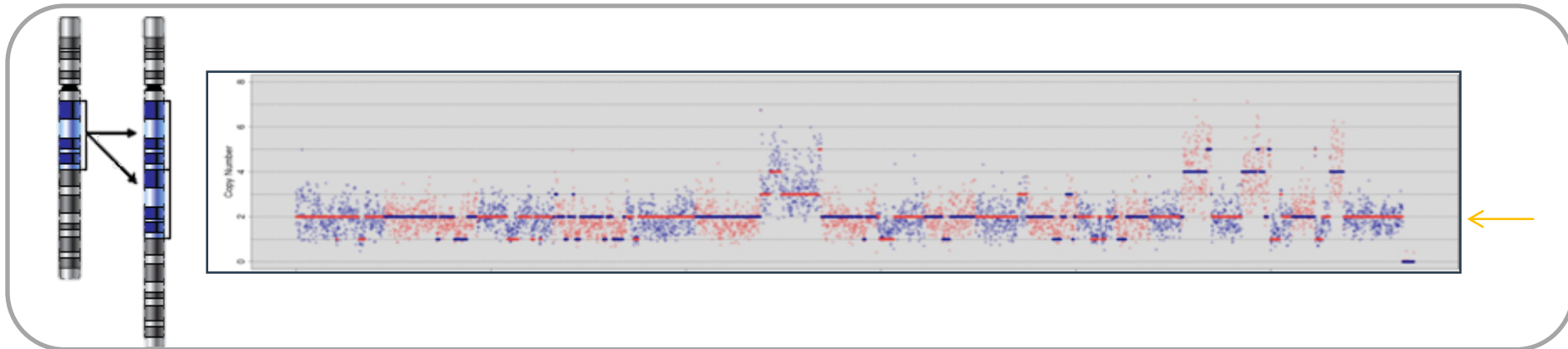
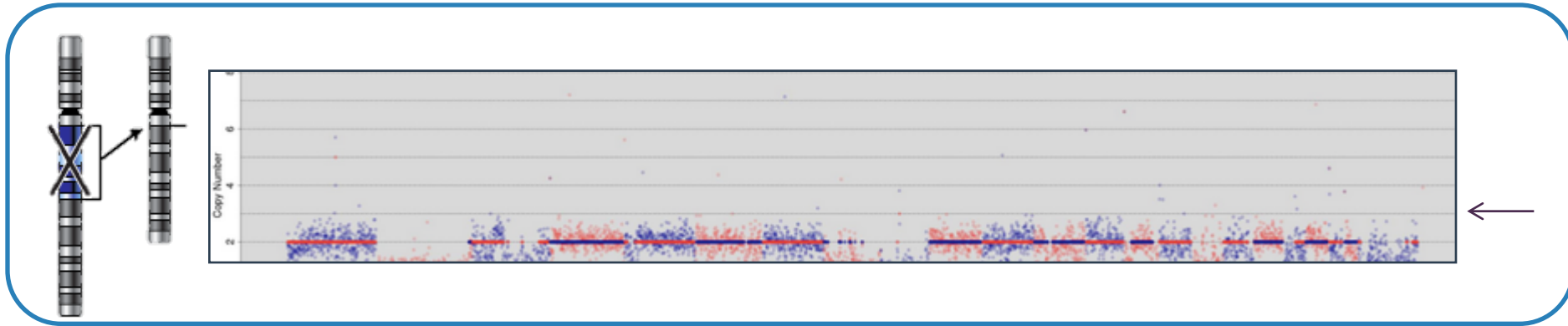
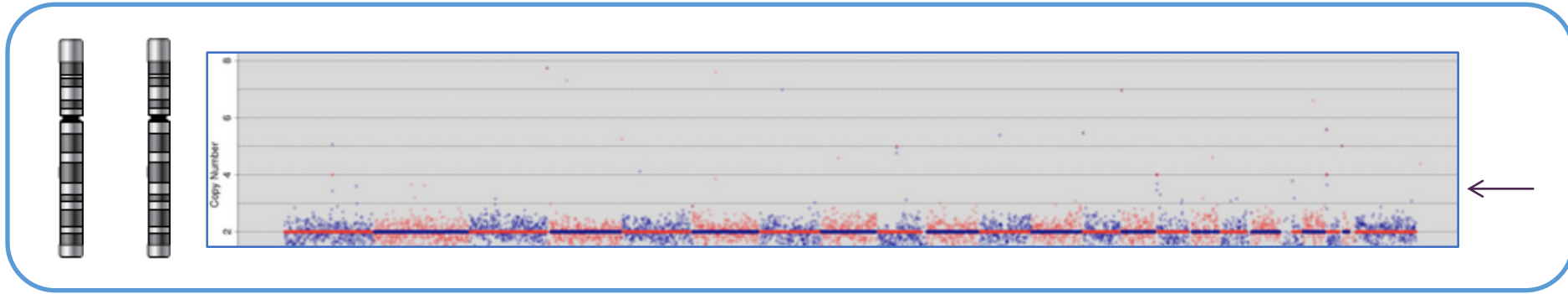
Humans differ by roughly 3,000 deletions
($\geq 500\text{bp}$)



Humans differ by a few hundred duplications

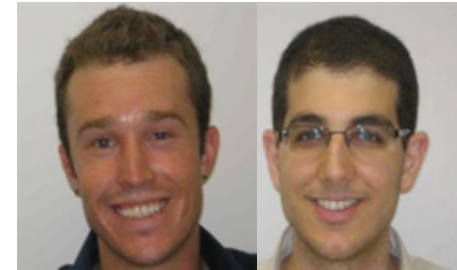


Copy-number Profiles



Ginkgo

<http://qb.cshl.edu/ginkgo>



Interactive Single Cell CNV analysis & clustering

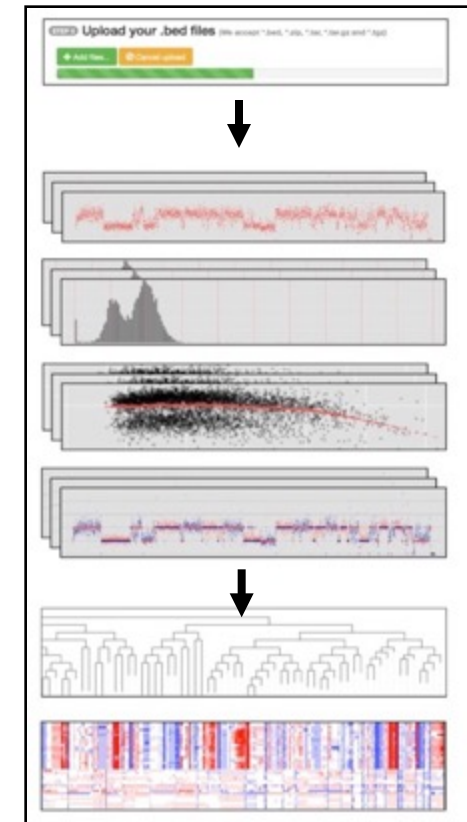
- Easy-to-use, web interface, parameterized for binning, segmentation, clustering, etc
- Per cell through project-wide analysis in any species

Compare MDA, DOP-PCR, and MALBAC

- DOP-PCR shows superior resolution and consistency

Available for collaboration

- Analyzing CNVs with respect to different clinical outcomes
- Extending clustering methods, prototyping scRNA

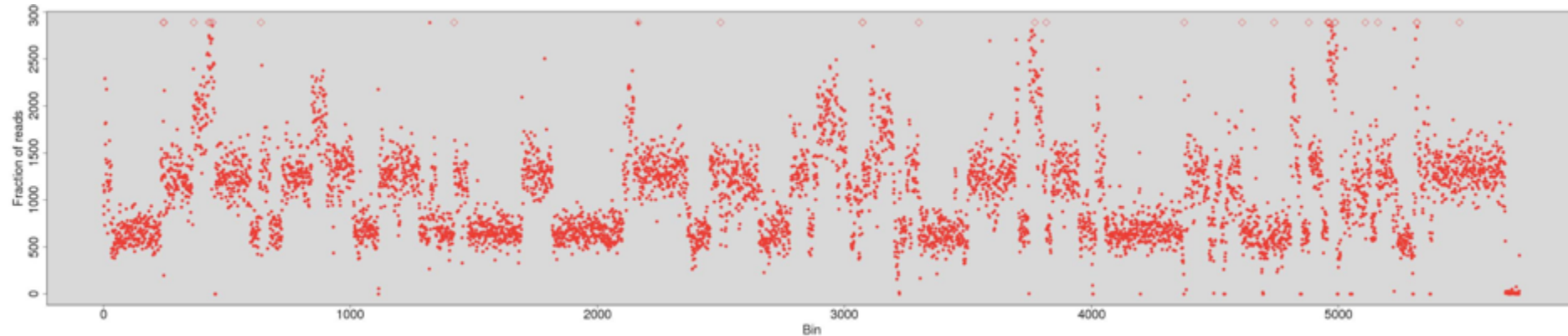


Interactive analysis and assessment of single-cell copy-number variations.

Garvin T, Aboukhalil R, Kendall J, Baslan T, Atwal GS, Hicks J, Wigler M, Schatz MC

(2015) Nature Methods doi:10.1038/nmeth.3578

Data are noisy



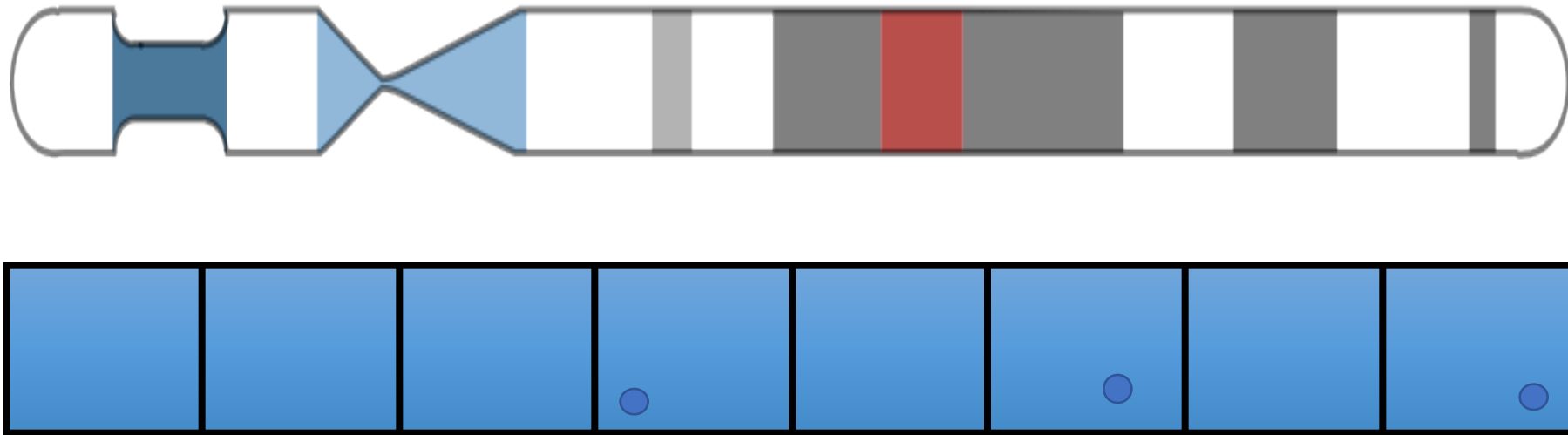
Potential for biases at every step

- WGA: Non-uniform amplification
- Library Preparation: Low complexity, read duplications, barcoding
- Sequencing: GC artifacts, short reads
- Computation: mappability, GC correction, segmentation, tree building

Coverage is too sparse and noisy for SNP analysis

-> Requires special processing

1. Binning

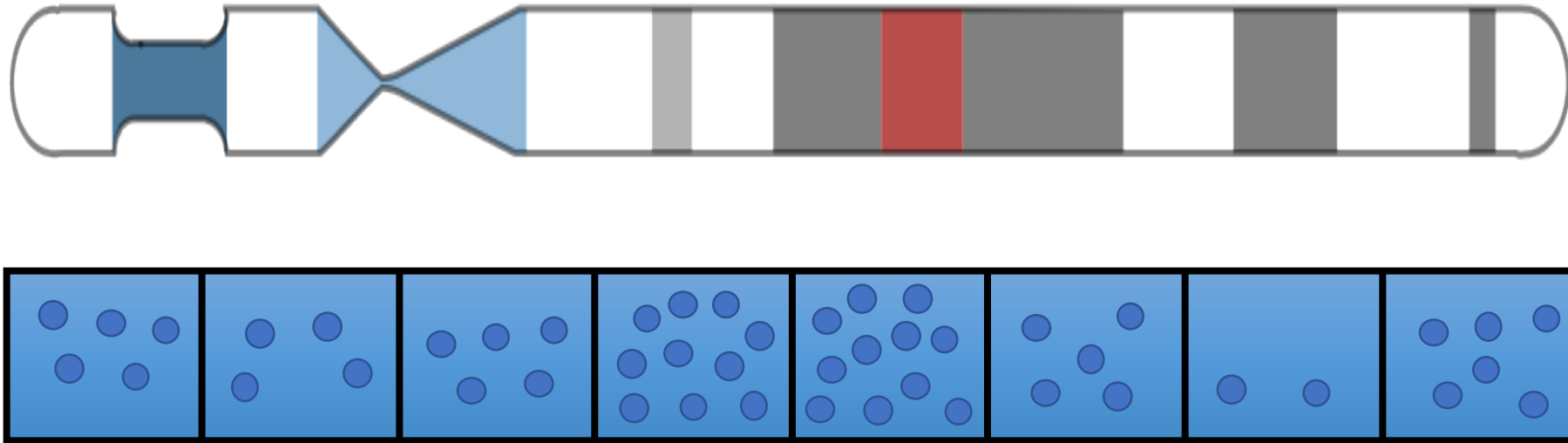


CNV analysis

- Divide the genome into “bins” with ~50 – 100 reads / bin
- Map the reads and count reads per bin

Use uniquely mappable bases to establish bins

1. Binning

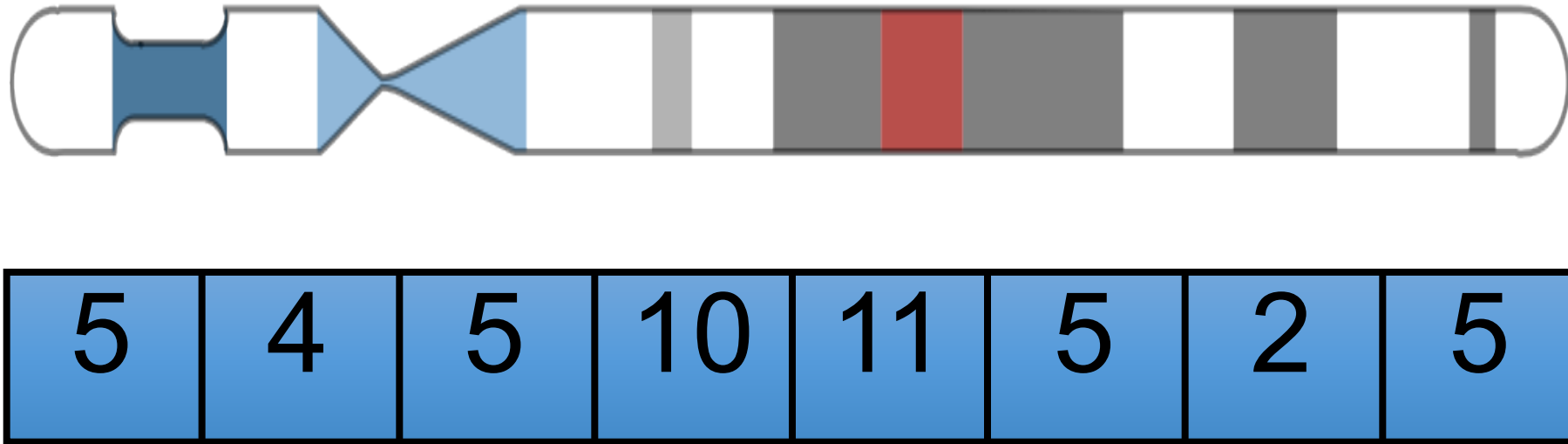


CNV analysis

- Divide the genome into “bins” with ~50 – 100 reads / bin
- Map the reads and count reads per bin

Use uniquely mappable bases to establish bins

1. Binning

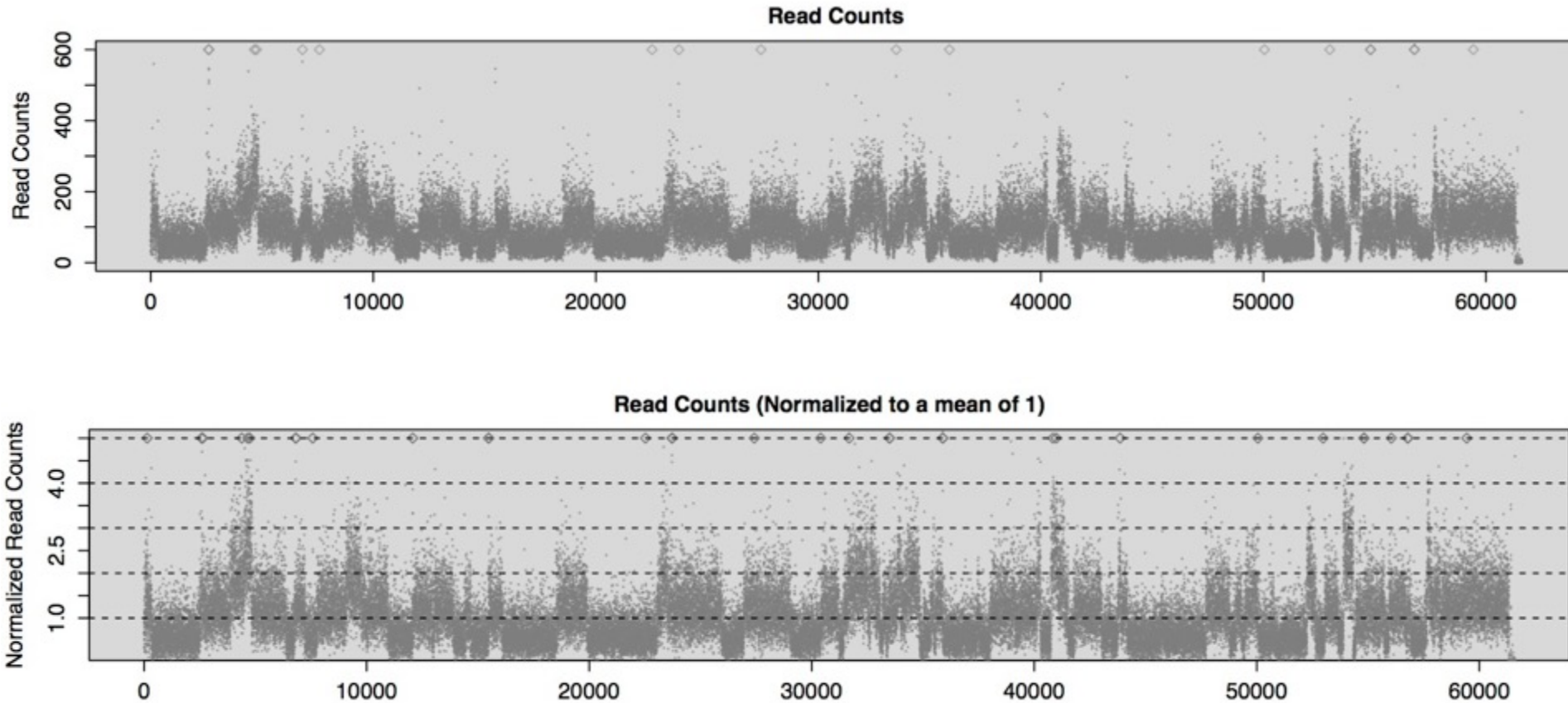


CNV analysis

- Divide the genome into “bins” with ~50 – 100 reads / bin
- Map the reads and count reads per bin

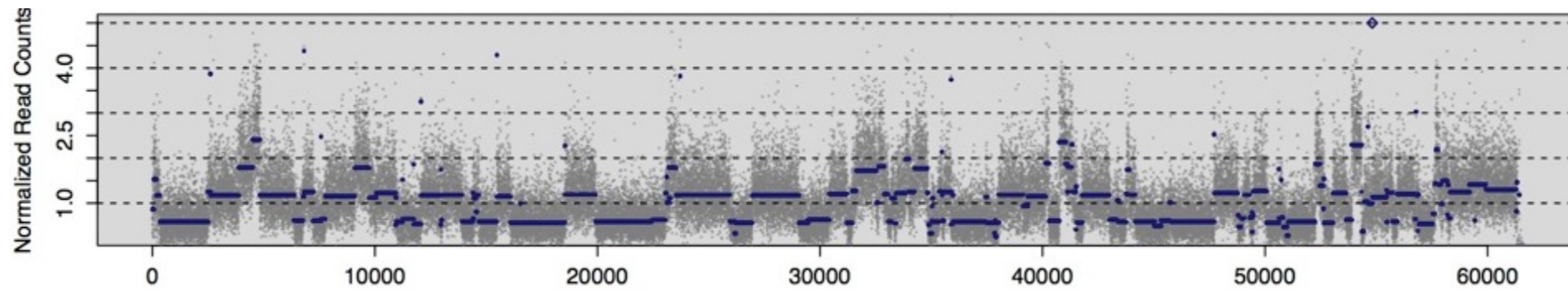
Use uniquely mappable bases to establish bins

2. Normalization

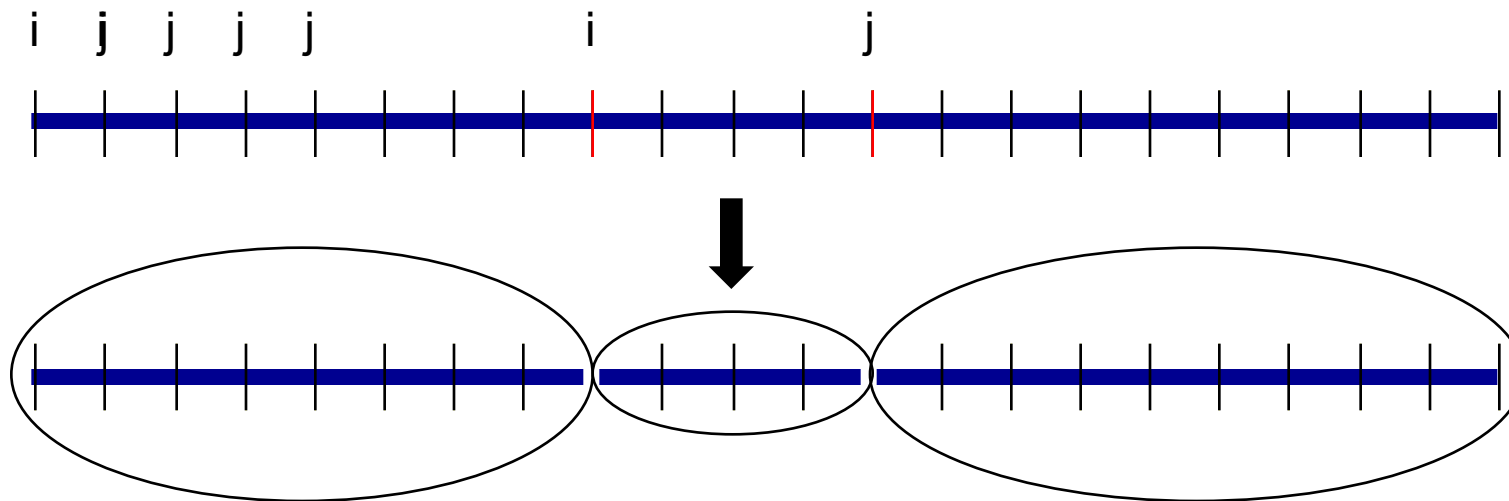


Also correct for mappability, GC content, amplification biases

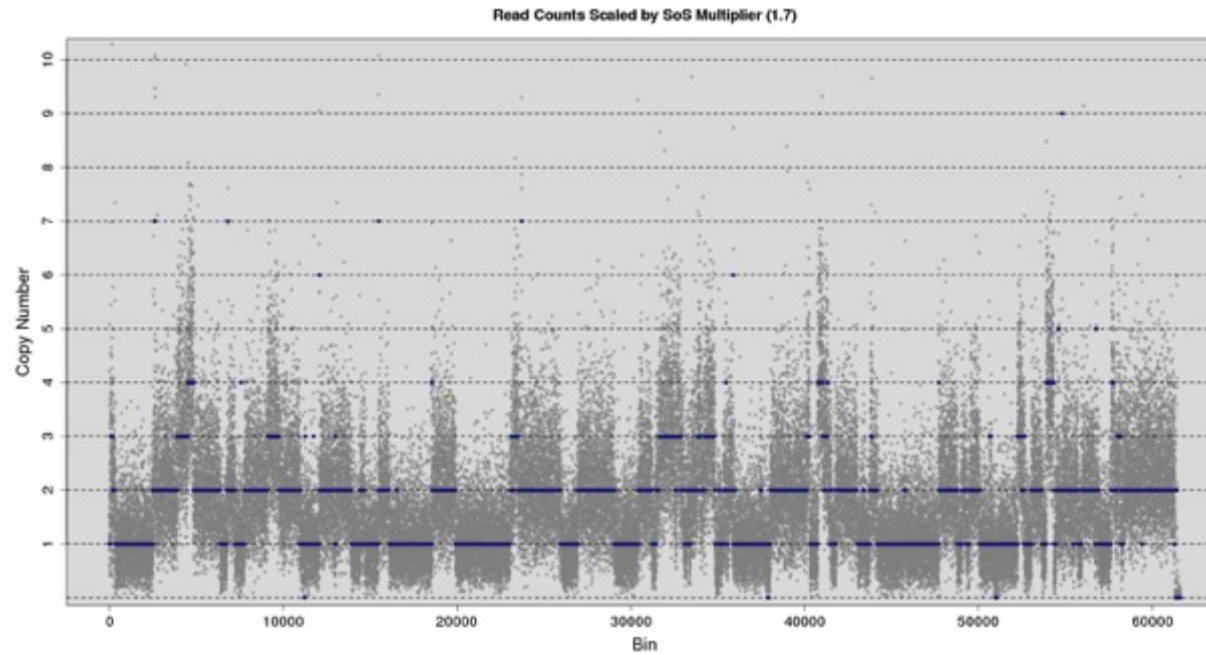
3. Segmentation



Circular Binary Segmentation (CBS)



4. Estimating Copy Number

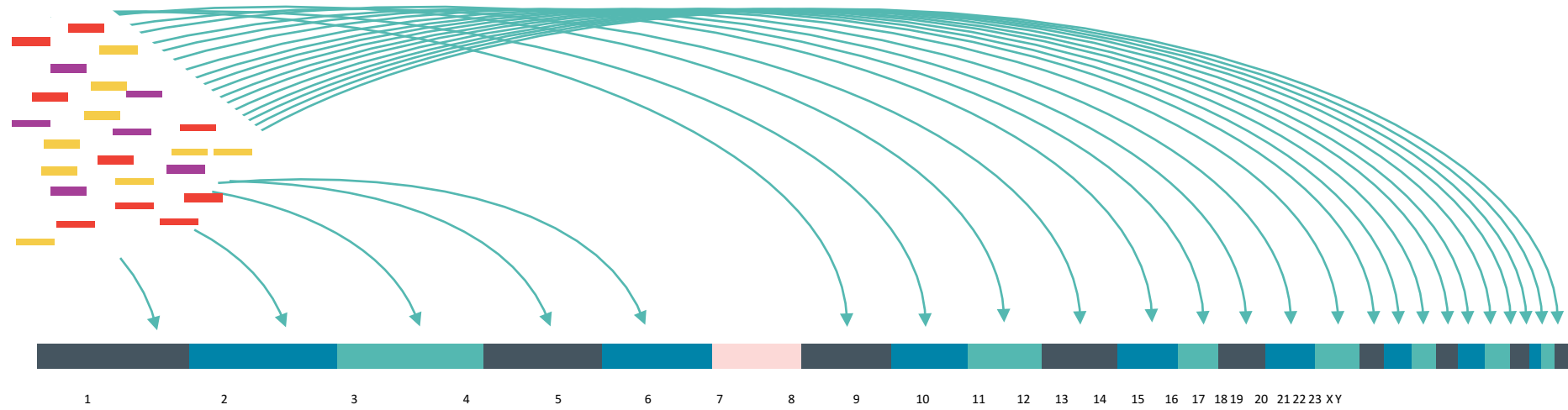


$$CN = \underset{i,j}{\operatorname{argmin}} \left\{ \sum (\hat{Y}_{i,j} - Y_{i,j})^2 \right\}$$

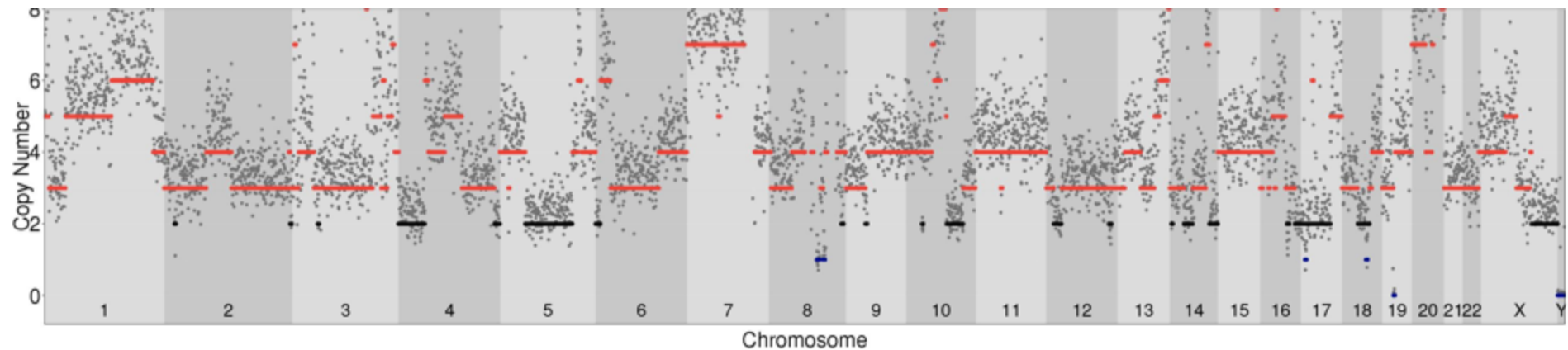
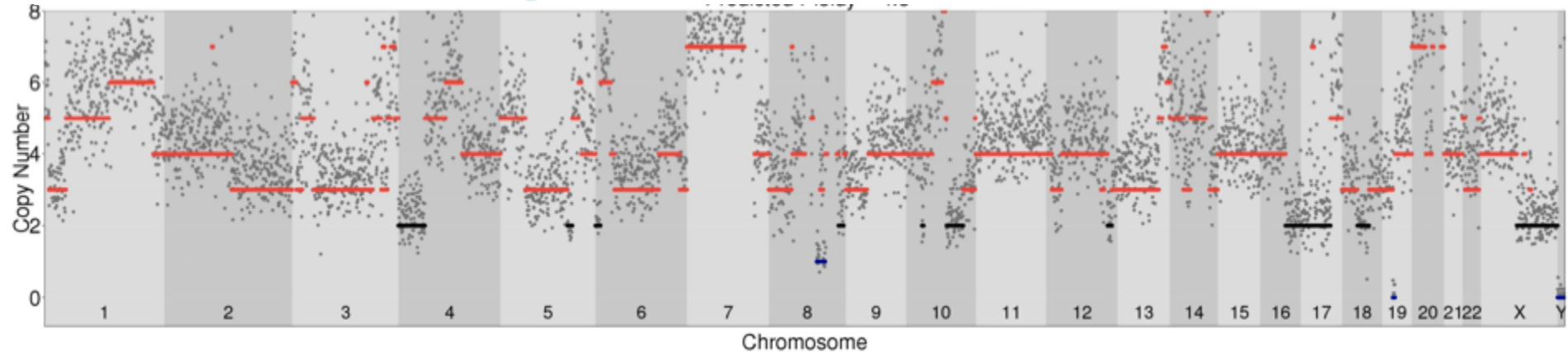
Using Nanopore MinION: CNV karyotyping.



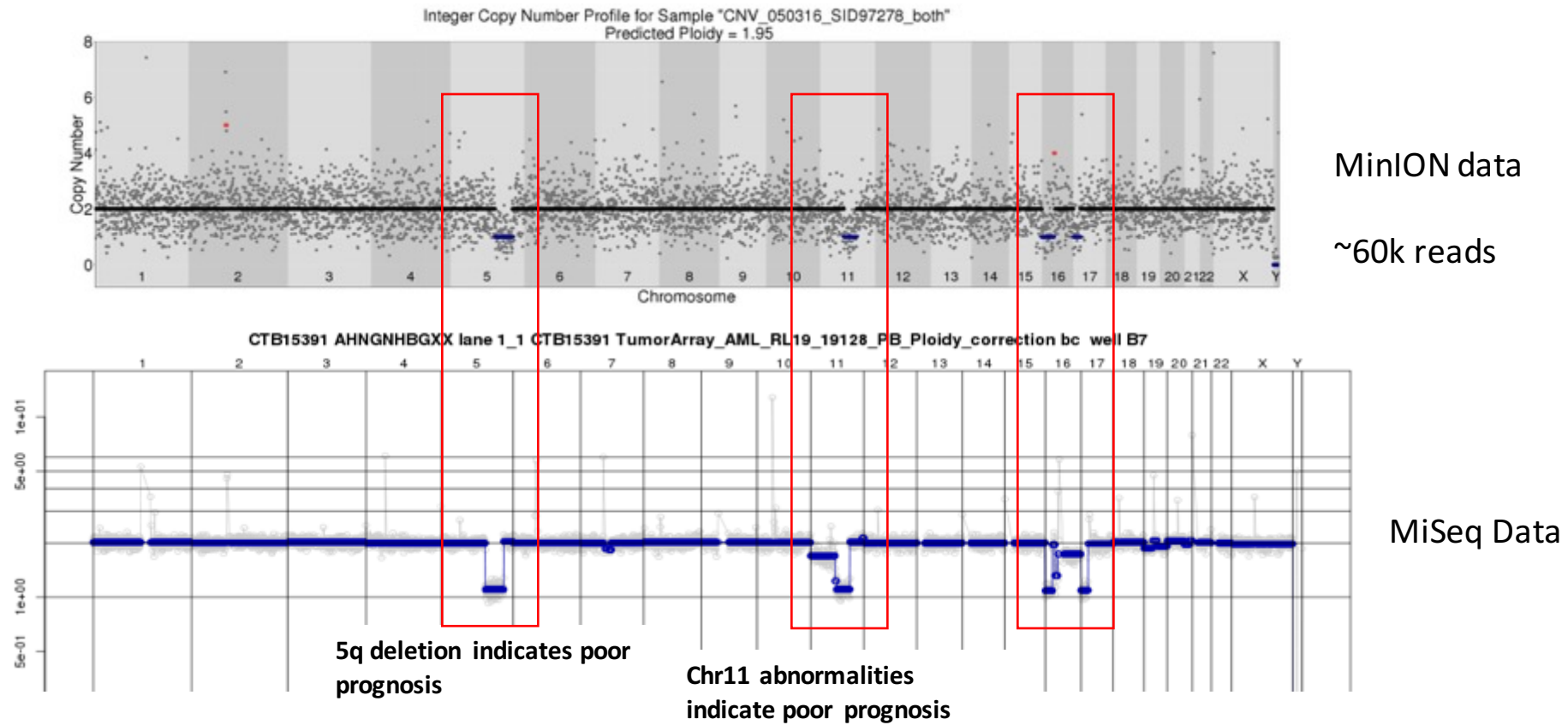
Nanopore sequencing for CNV detection



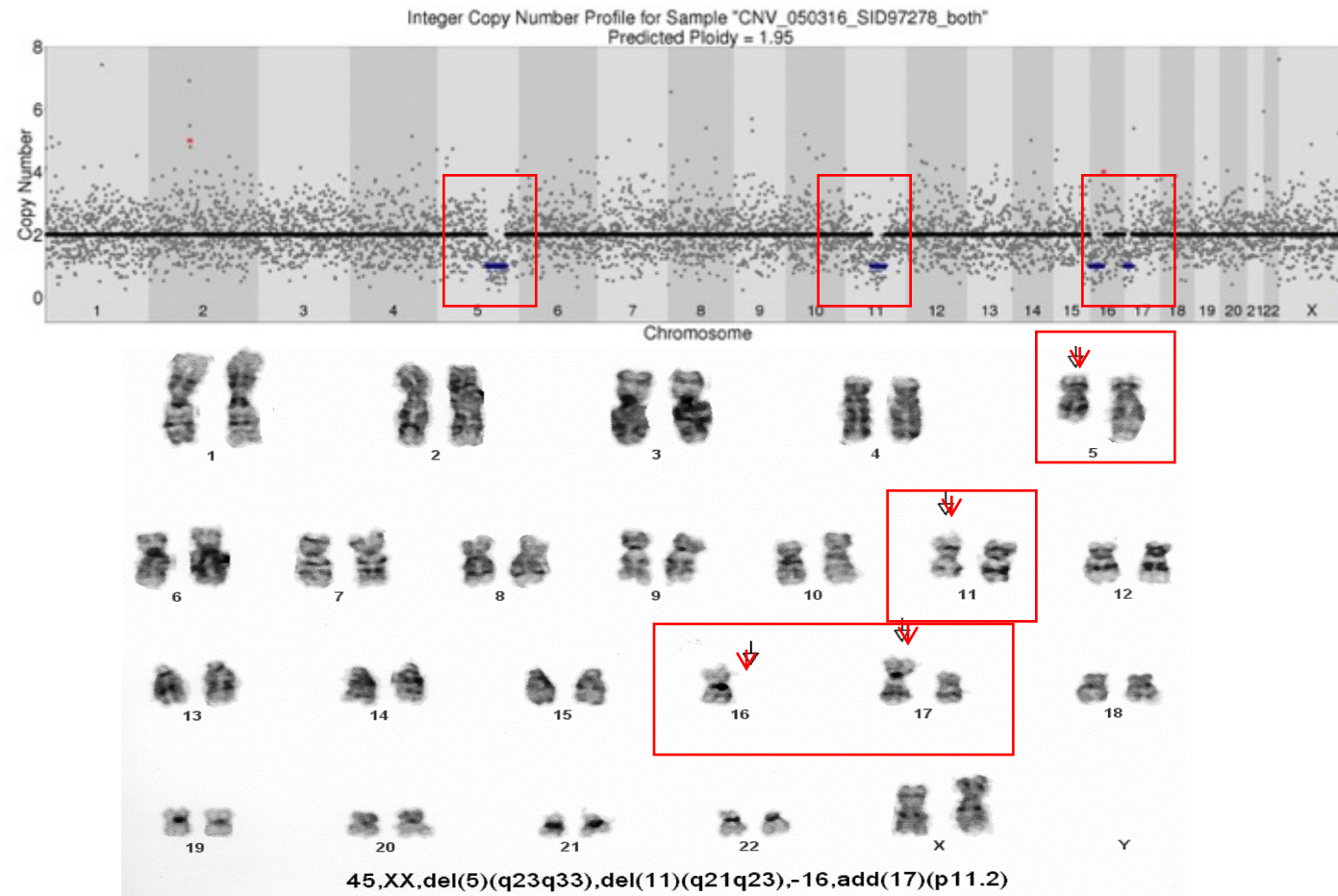
SKBR3 cell line CNV Analysis



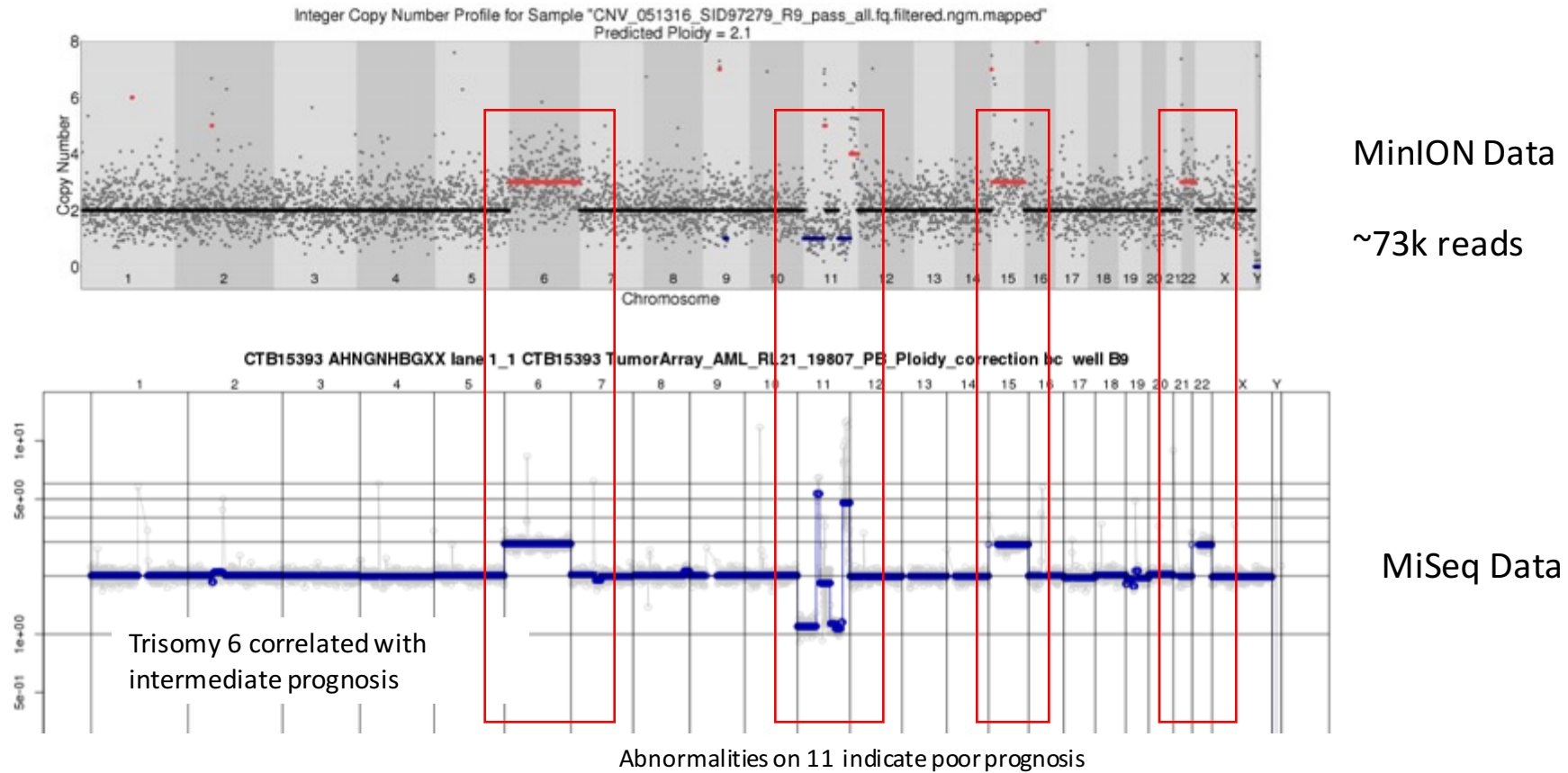
SID97277 - partial chromosomal deletions



SID97277 karyotype

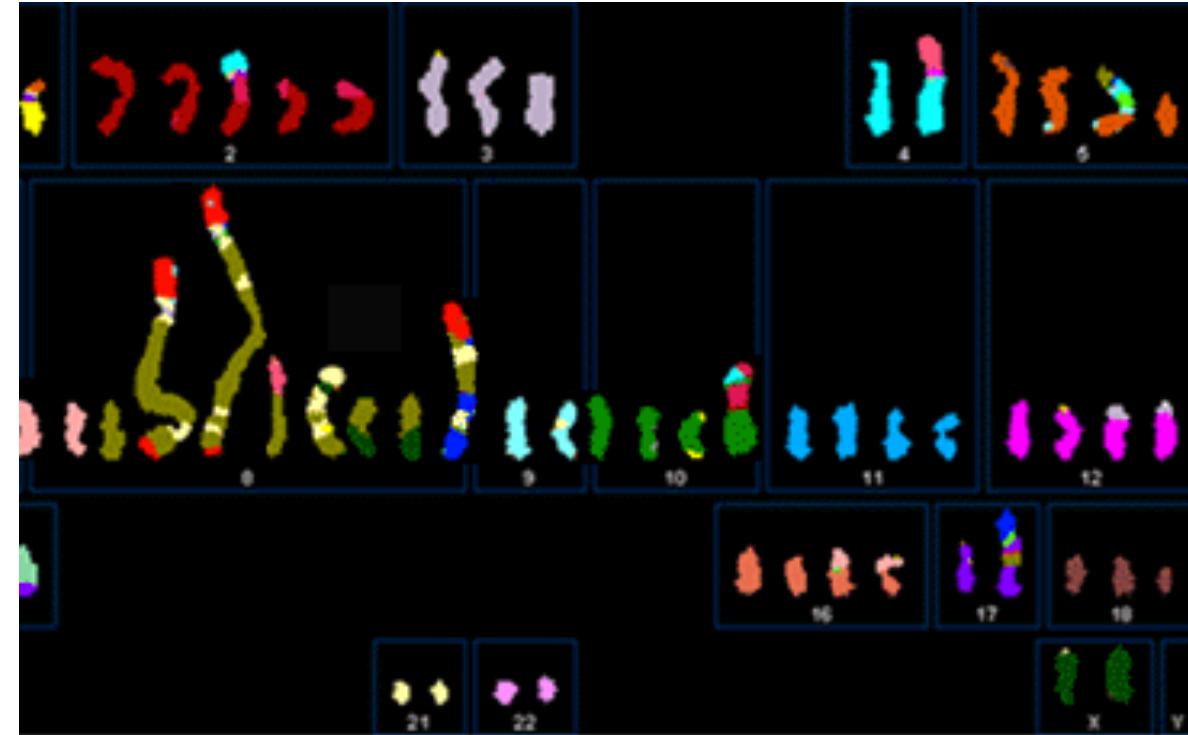


SID97279 – trisomy 6, 15, 22 and deletions in chr11



CNV detection summary

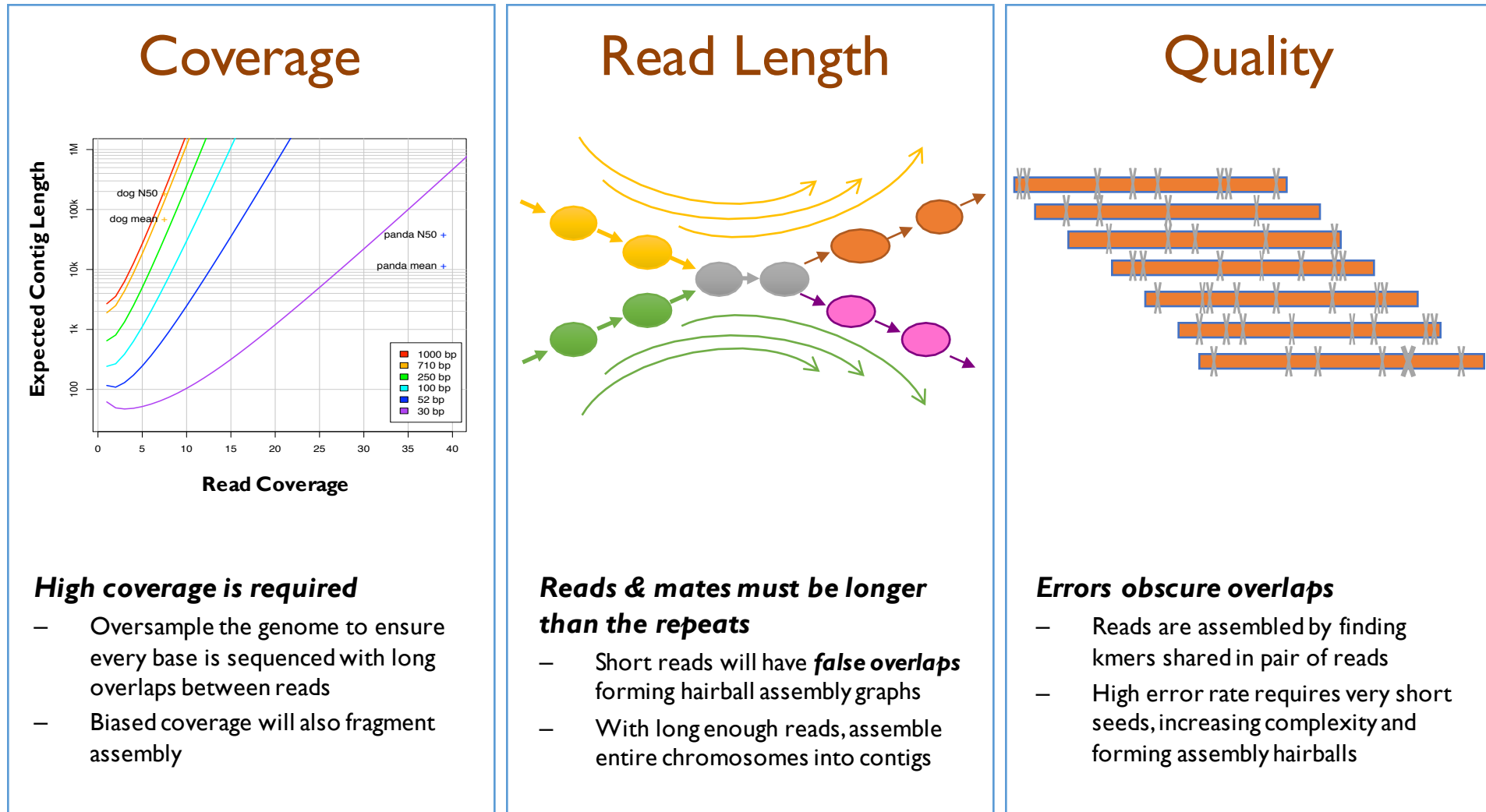
- Advantages
 - Less coverage is required
 - -> Applications such as single cell sequencing
- Disadvantages
 - Resolution of events
 - usually in the multi kbp
 - Only deletions and duplications
 - Coverage biases in short reads



Assembly based

1. De novo assembly
2. Genomic alignment (WGA)
3. Detangle the genomic alignment to identify variants.

Ingredients for a good assembly

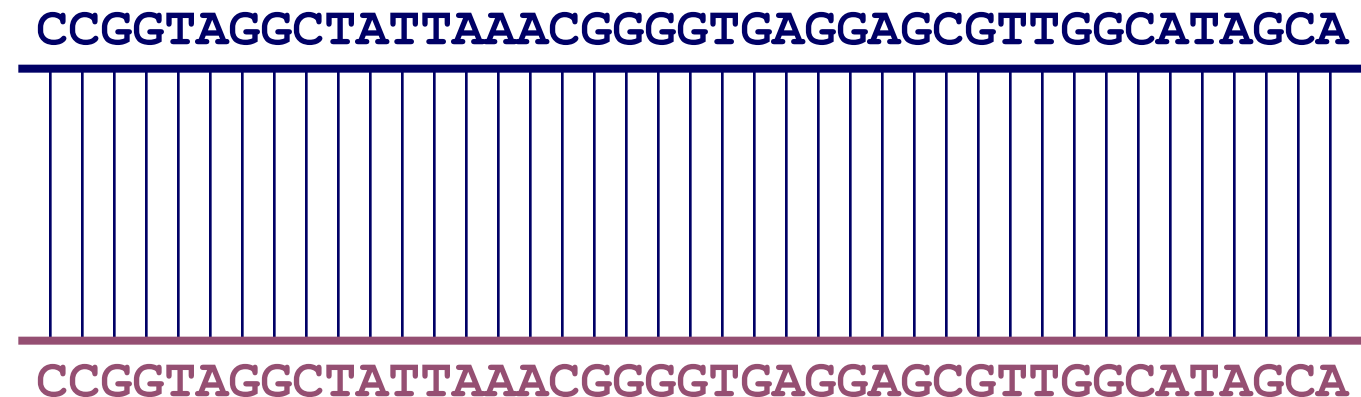


Current challenges in *de novo* plant genome sequencing and assembly

Schatz MC, Witkowski, McCombie, WVR (2012) *Genome Biology*. 12:243

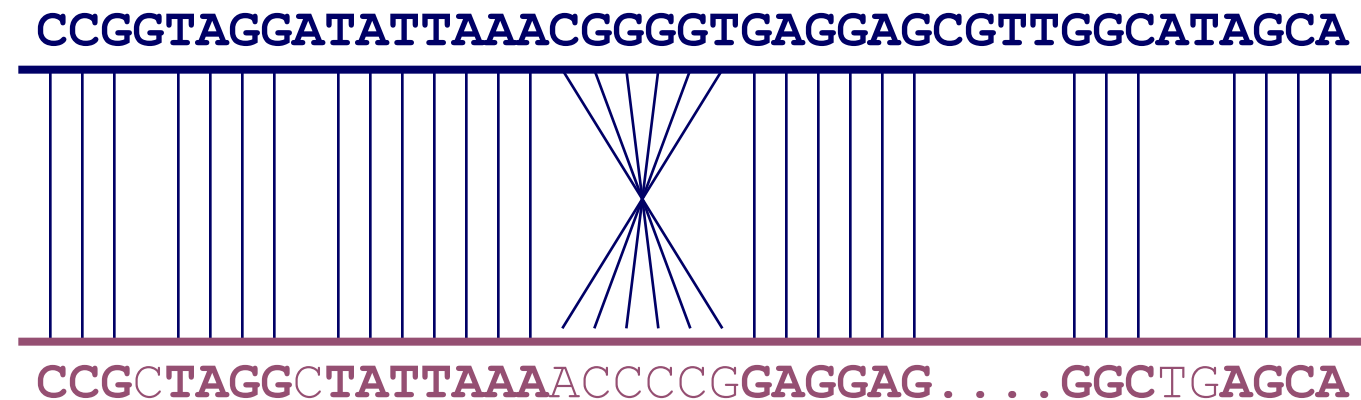
Goal of WGA

- For two genomes, A and B , find a mapping from each position in A to its corresponding position in B



Not so fast...

- Genome *A* may have insertions, deletions, translocations, inversions, duplications or SNPs with respect to *B* (sometimes all of the above)



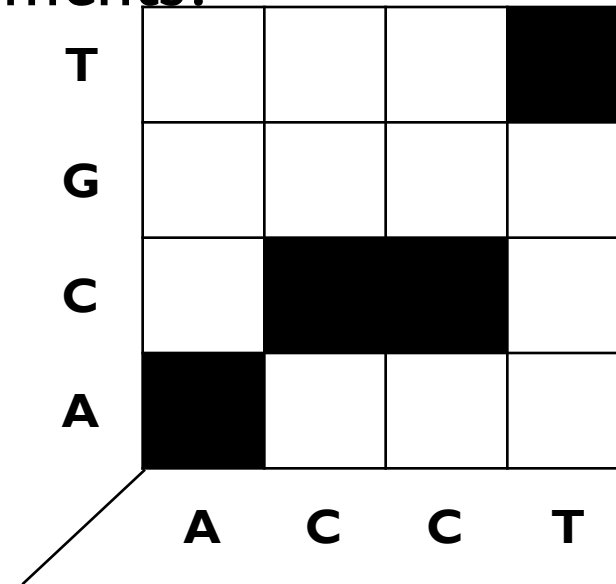
WGA visualization

- How can we visualize *whole* genome alignments?

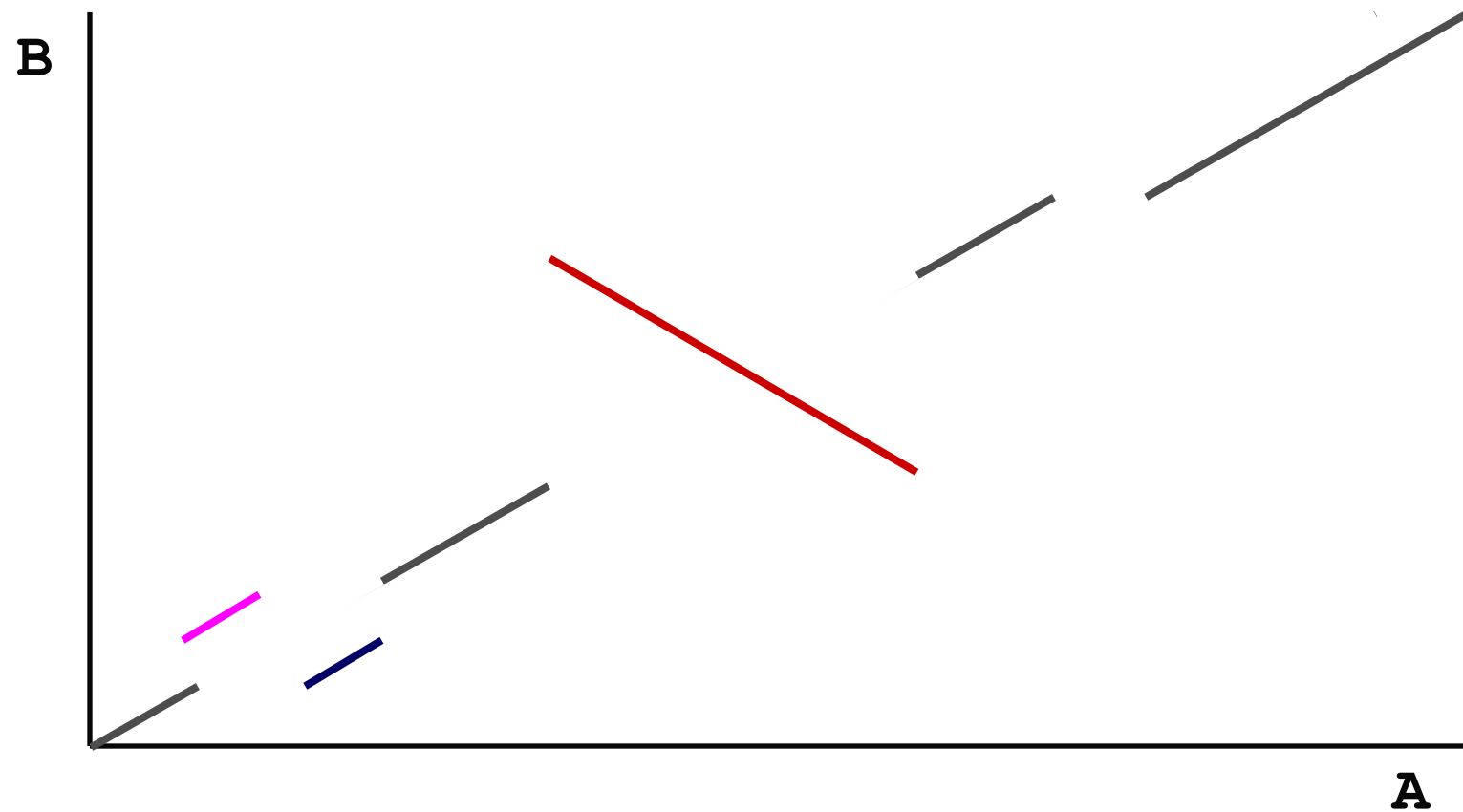
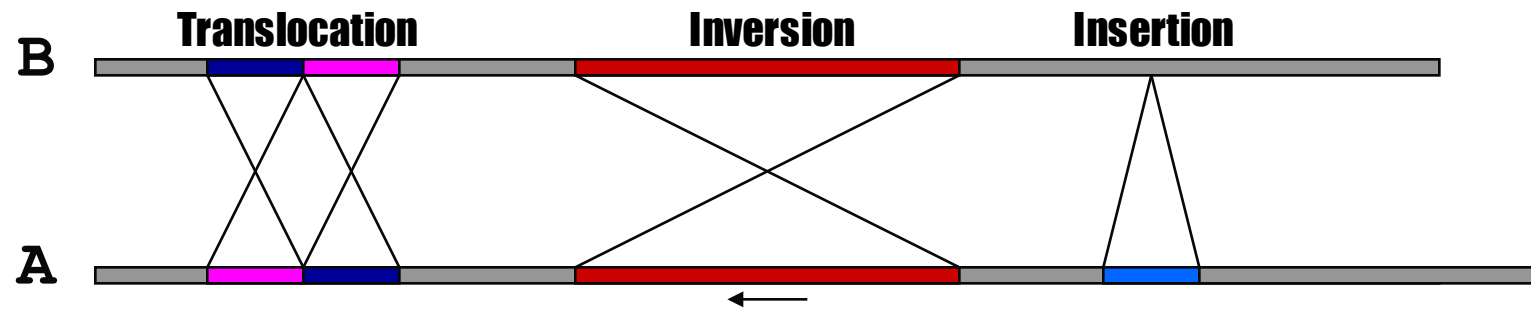
- With an alignment dot plot

- $N \times M$ matrix

- Let i = position in genome A
 - Let j = position in genome B
 - Fill cell (i,j) if A_i shows similarity to B_j

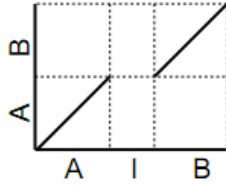


- A perfect alignment between A and B would completely fill the positive diagonal



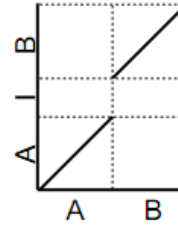
Insertion into Reference

R: AIB
Q: AB



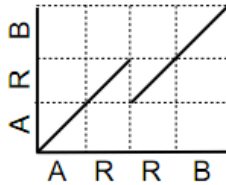
Insertion into Query

R: AB
Q: AIB



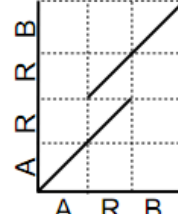
Collapse Query

R: ARRB
Q: ARB



Collapse Reference

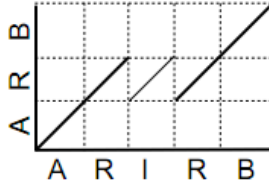
R: ARB
Q: ARRB



Collapse Query
w/ Insertion

R: ARIRB
Q: ARB

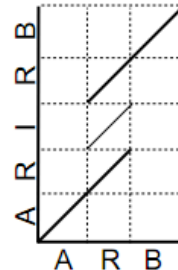
Exact tandem
alignment if I=R



Collapse Reference
w/Insertion

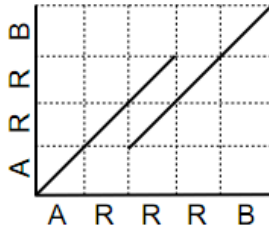
R: ARB
Q: ARIRB

Exact tandem
alignment if I=R



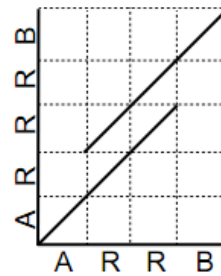
Collapse Query

R: ARRRB
Q: ARRB



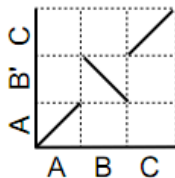
Collapse Reference

R: ARRB
Q: ARRRB



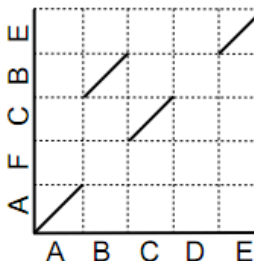
Inversion

R: ABC
Q: AB'C



Rearrangement
w/ Disagreement

R: ABCDE
Q: AFCBE



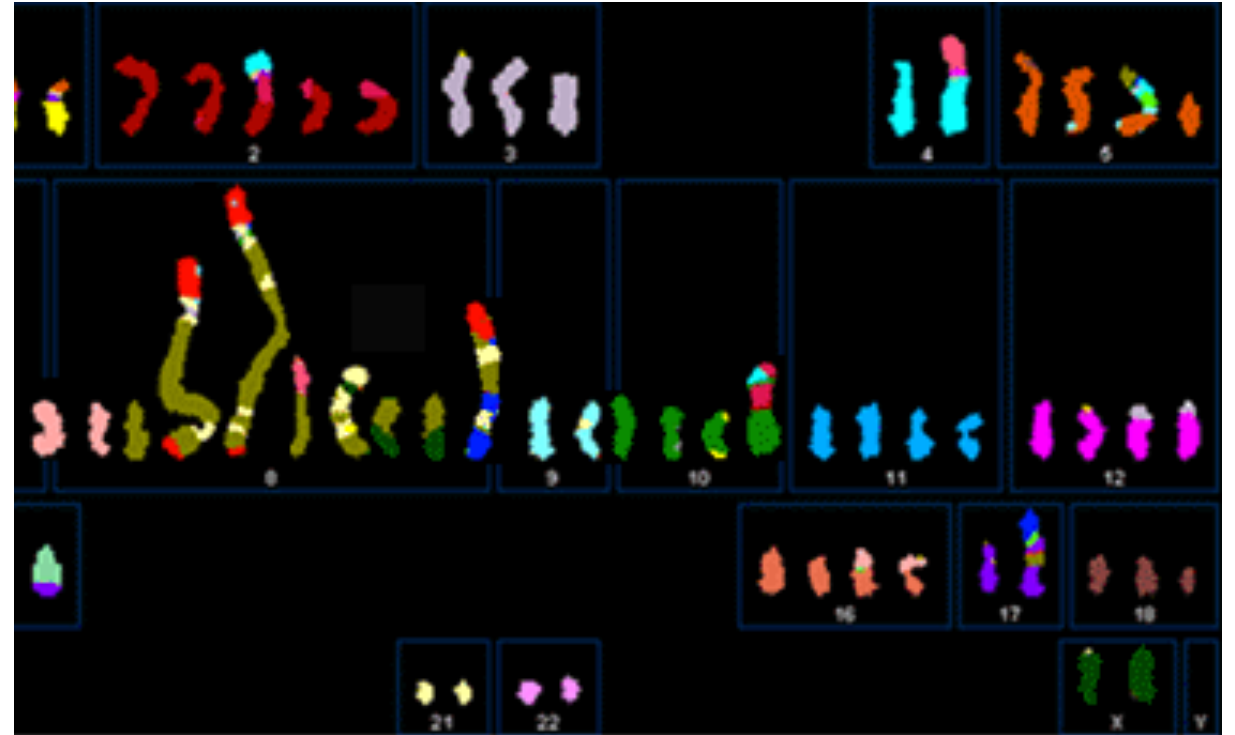
- Different structural variation types / misassemblies will be apparent by their pattern of breakpoints
- Most breakpoints will be at or near repeats
- Things quickly get complicated in real genomes

Hands on: Identify SV from Assembly

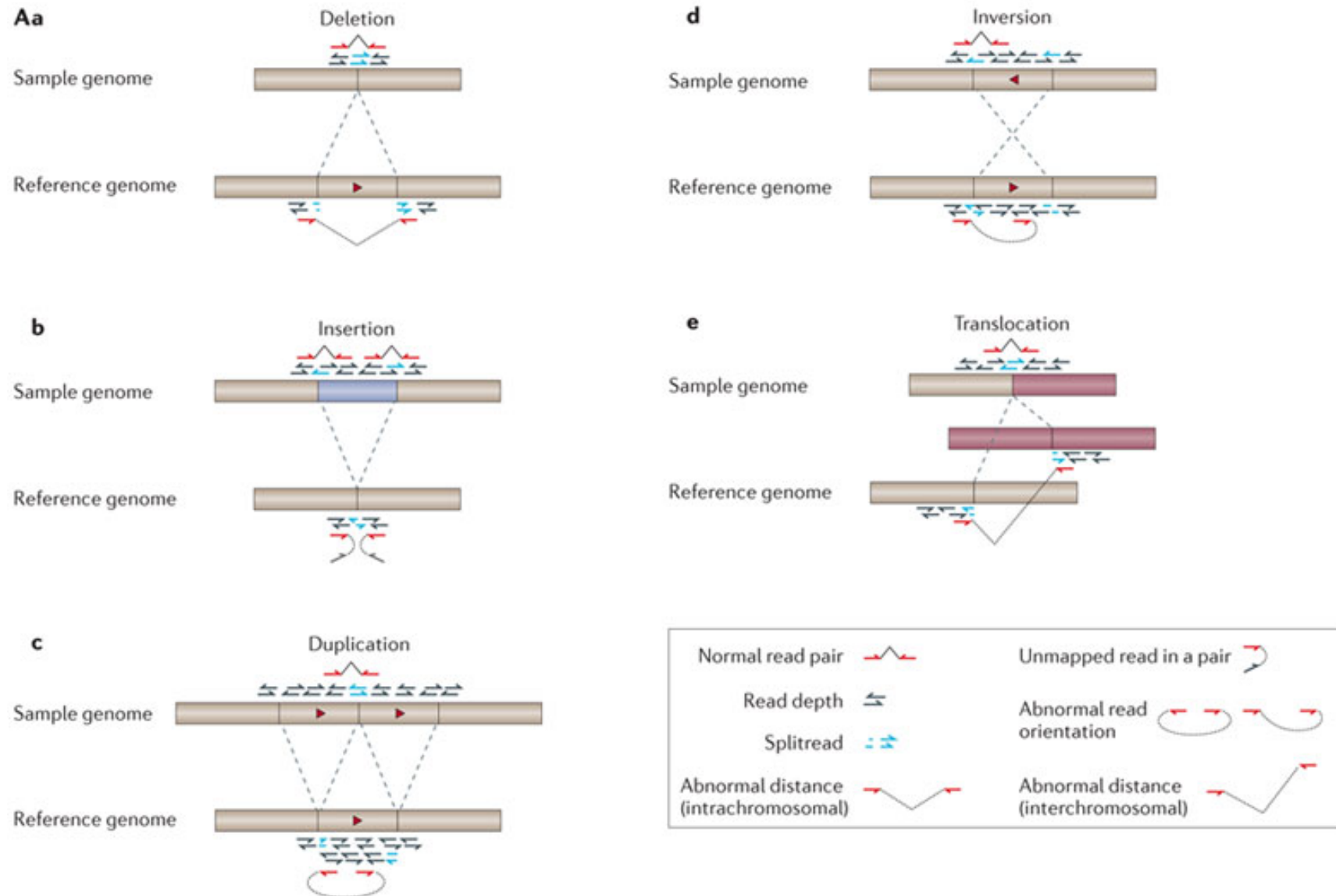
1. Identify SVs using a de novo assembly.
 1. Get a previously made ONT based de novo assembly
 2. Align it using: `nucmer -maxmatch -l 100 -c 500 ref.fa assembly.fa`
 3. Run `show-coords` to extract coordinates
 4. Upload the nucmer output to <http://assemblytics.com/>
 1. What do you see?
 5. Download the results

Assembly based detection summary

- Advantages
 - Enables the detection of every event
 - Good quality for insertions
- Disadvantages
 - Genomic alignment is challenging.
 - Heterozygous events are likely missed.



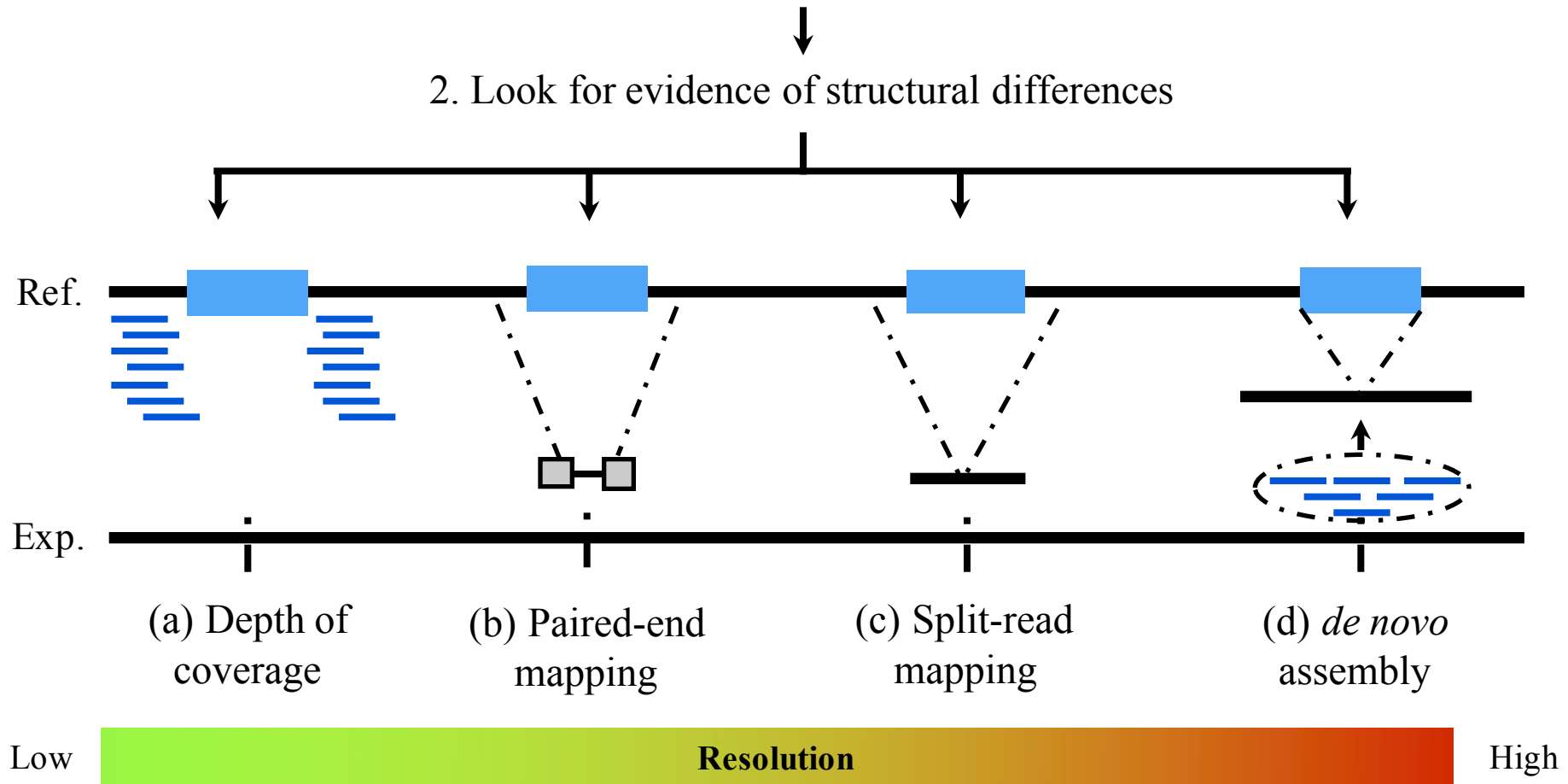
How to detect Structural Variations



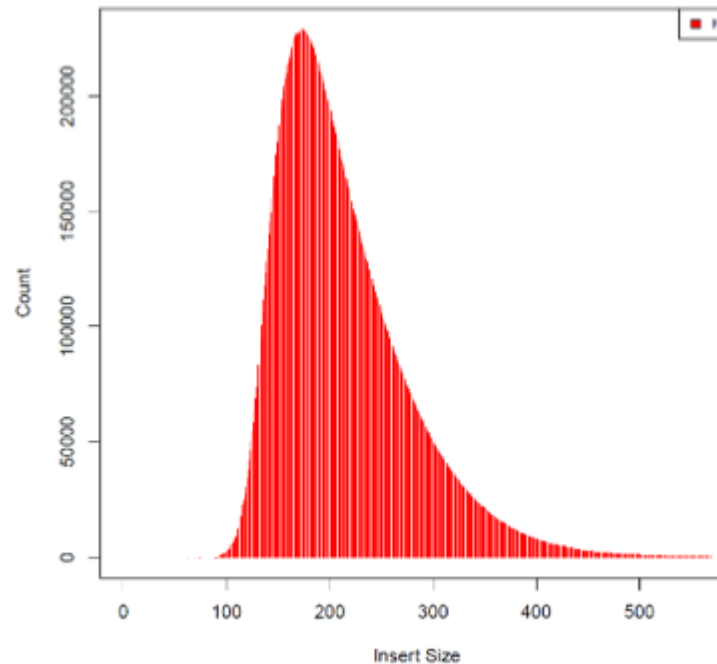
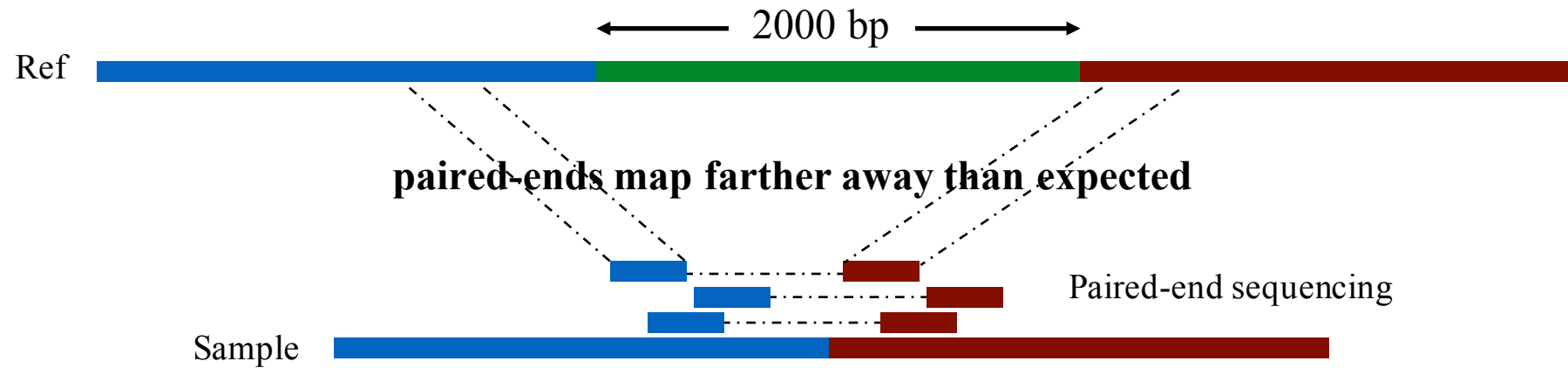
Sequence alignment “signals” for structural variation

1. Align DNA sequences from sample to human reference genome

2. Look for evidence of structural differences

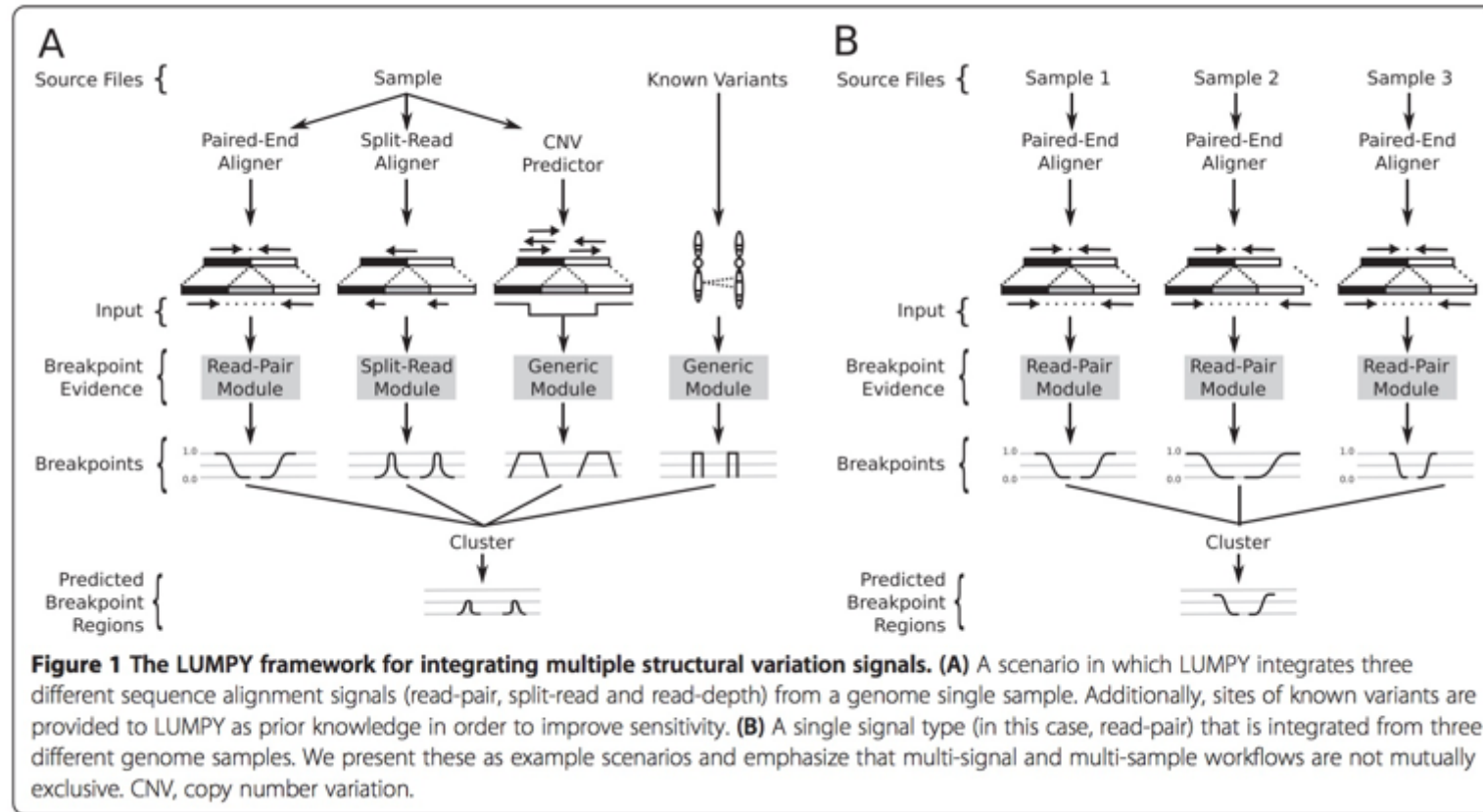


Looking for "discordant" paired-end fragments





A probabilistic framework for SV discovery



Lumpy integrates paired-end mapping, split-read mapping, and depth of coverage for better SV discovery accuracy

Ryan Layer

Problem #1: Often many false positives

- Short reads + heuristic alignment + rep. genome = **systematic alignment artifacts (false calls)**
- Chimeras and duplicate molecules
- Ref. genome errors (e.g., gaps, mis-assemblies)
- **ALL SV mapping studies use strict filters for above**

Problem #2: The false negative rate is also typically high

- Most current datasets have low to moderate *physical* coverage due to small insert size ($\sim 10\text{-}20\text{X}$)
- Breakpoints are enriched in repetitive genomic regions that pose problems for sensitive read alignment
- FILTERING!
- The false negative rate is usually hard to measure, but is thought to be extremely high for most paired-end mapping studies ($>30\%$)
- When searching for spontaneous mutations in a family or a tumor/normal comparison, a false negative call in one sample can be a false positive somatic or de novo call in another.

How to filter / choose the SV caller?

- Each method applies its own heuristics.

Method	# Sim. SV	avg FDR	avg Sensitivity
DELLY	33-198	0.13	0.75
LUMPY	33-198	0.06	0.62
Pindel	33-198	0.04	0.55
SURVIVOR	33-198	0.01	0.70

Hands on: File Formats:

- VCF file: (main format)
 - Tab separated text file
 - Header holds information on what means what.
 - Body: 1 entry per variant/position
- Bedpe file:
 - Tab separated text file, 12 defined columns.
 - 1 entry per variant/position

Hands on: VCF-Header

```
##fileformat=VCFv4.2
##source=LUMPY
##INFO=<ID=SVTYPE,Number=1,Type=String,Description="Type of structural variant">
##INFO=<ID=SVLEN,Number=.,Type=Integer,Description="Difference in length between REF and ALT alleles">
##INFO=<ID=END,Number=1,Type=Integer,Description="End position of the variant described in this record">
##INFO=<ID=STRANDS,Number=.,Type=String,Description="Strand orientation of the adjacency in BEDPE format (DEL:+-, DUP:-+, INV:++/--)">
##INFO=<ID=IMPRECISE,Number=0,Type=Flag,Description="Imprecise structural variation">
##INFO=<ID=CIPPOS,Number=2,Type=Integer,Description="Confidence interval around POS for imprecise variants">
##INFO=<ID=CIEND,Number=2,Type=Integer,Description="Confidence interval around END for imprecise variants">
##INFO=<ID=CIPPOS95,Number=2,Type=Integer,Description="Confidence interval (95%) around POS for imprecise variants">
##INFO=<ID=CIEND95,Number=2,Type=Integer,Description="Confidence interval (95%) around END for imprecise variants">
##INFO=<ID=MATEID,Number=.,Type=String,Description="ID of mate breakends">
##INFO=<ID=EVENT,Number=1,Type=String,Description="ID of event associated to breakend">
##INFO=<ID=SECONDARY,Number=0,Type=Flag,Description="Secondary breakend in a multi-line variants">
##INFO=<ID=SU,Number=.,Type=Integer,Description="Number of pieces of evidence supporting the variant across all samples">
##INFO=<ID=PE,Number=.,Type=Integer,Description="Number of paired-end reads supporting the variant across all samples">
##INFO=<ID=SR,Number=.,Type=Integer,Description="Number of split reads supporting the variant across all samples">
##INFO=<ID=BD,Number=.,Type=Integer,Description="Amount of BED evidence supporting the variant across all samples">
##INFO=<ID=EV,Number=.,Type=String,Description="Type of LUMPY evidence contributing to the variant call">
##INFO=<ID=PRPOS,Number=.,Type=String,Description="LUMPY probability curve of the POS breakend">
##INFO=<ID=PREND,Number=.,Type=String,Description="LUMPY probability curve of the END breakend">
##ALT=<ID=DEL,Description="Deletion">
##ALT=<ID=DUP,Description="Duplication">
##ALT=<ID=INV,Description="Inversion">
##ALT=<ID=DUP:TANDEM,Description="Tandem duplication">
##ALT=<ID=INS,Description="Insertion of novel sequence">
##ALT=<ID=CNV,Description="Copy number variable region">
##FORMAT=<ID=GT,Number=1,Type=String,Description="Genotype">
##FORMAT=<ID=SU,Number=1,Type=Integer,Description="Number of pieces of evidence supporting the variant">
##FORMAT=<ID=PE,Number=1,Type=Integer,Description="Number of paired-end reads supporting the variant">
##FORMAT=<ID=SR,Number=1,Type=Integer,Description="Number of split reads supporting the variant">
##FORMAT=<ID=BD,Number=1,Type=Integer,Description="Amount of BED evidence supporting the variant">
```

Holds important information about the data listed below, file format

Hands on: VCF entries

1	10196130	11153_2	N	[2:11128811[N	.	.	SVTYPE=BND;STRANDS=--:4;SECONDARY;EVENT=1115
1	10196158	11154_2	N	N]2:11129218]	.	.	SVTYPE=BND;STRANDS=++:7;SECONDARY;EVENT=1115
1	10199540	7653_1	N	[1:16717319[N	.	.	SVTYPE=BND;STRANDS=--:6;EVENT=7653;MATEID=76
1	10199552	7654_1	N	N]1:16717620]	.	.	SVTYPE=BND;STRANDS=++:6;EVENT=7654;MATEID=76
1	10271879	7020	N		.	.	SVTYPE=DEL;STRANDS=+-:11;SVLEN=-256;END=10272135;CIP
1	10272132	7021	N	<DUP>	.	.	SVTYPE=DUP;STRANDS=-+:6;SVLEN=9059;END=10281191;CIP
1	10274057	7022	N	<DUP>	.	.	SVTYPE=DUP;STRANDS=-+:9;SVLEN=9644;END=10283701;CIP
1	10274072	7023	N		.	.	SVTYPE=DEL;STRANDS=+-:6;SVLEN=-9299;END=10283371;CIP
Start chromosome	Start position	Variant ID	Reference allele	Alternative allele	Quality	Filter	Additional information defined in the header

Hands on: short read based calling

1. Obtain the provided bam file + reference file for yeast.
2. Make sure you are building the indexes for the reference and bam file
 1. `samtools faidx my_ref.fa`
 2. `samtools index my.bam`
3. Go on and run Delly (-n speed it up)
 1. `delly call -n -o delly.vcf -g my_ref.fa my.bam`
4. How many SVs did you obtain per caller and what types?
 1. `SURVIVOR stats delly.vcf`

PacBio / ONT sequencer



Advantage:

- Long reads,

Disadvantage:

- Throughput/yield
- Costs
- High error rates

Long Read Technologies

- (+) SVs in repetitive regions
 - (+) Span SVs
 - (+) Uniform coverage
 - (+) Can identify more complex SVs
-
- (-) Higher seq. error rate
 - (-) Hard to align



Mapping challenges

BWA-MEM:

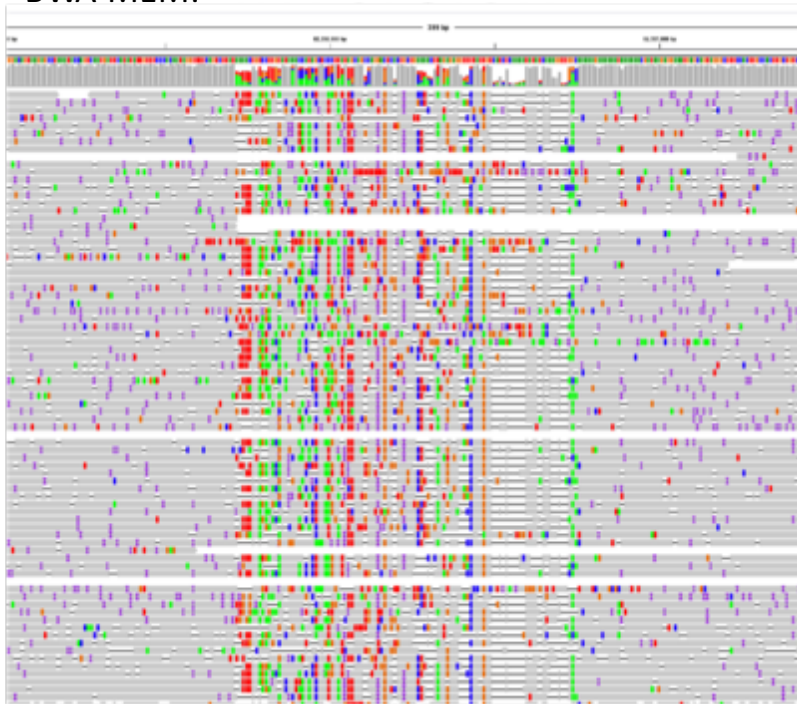


NGMLR:



Mapping challenges

BWA-MEM:



NGMLR:

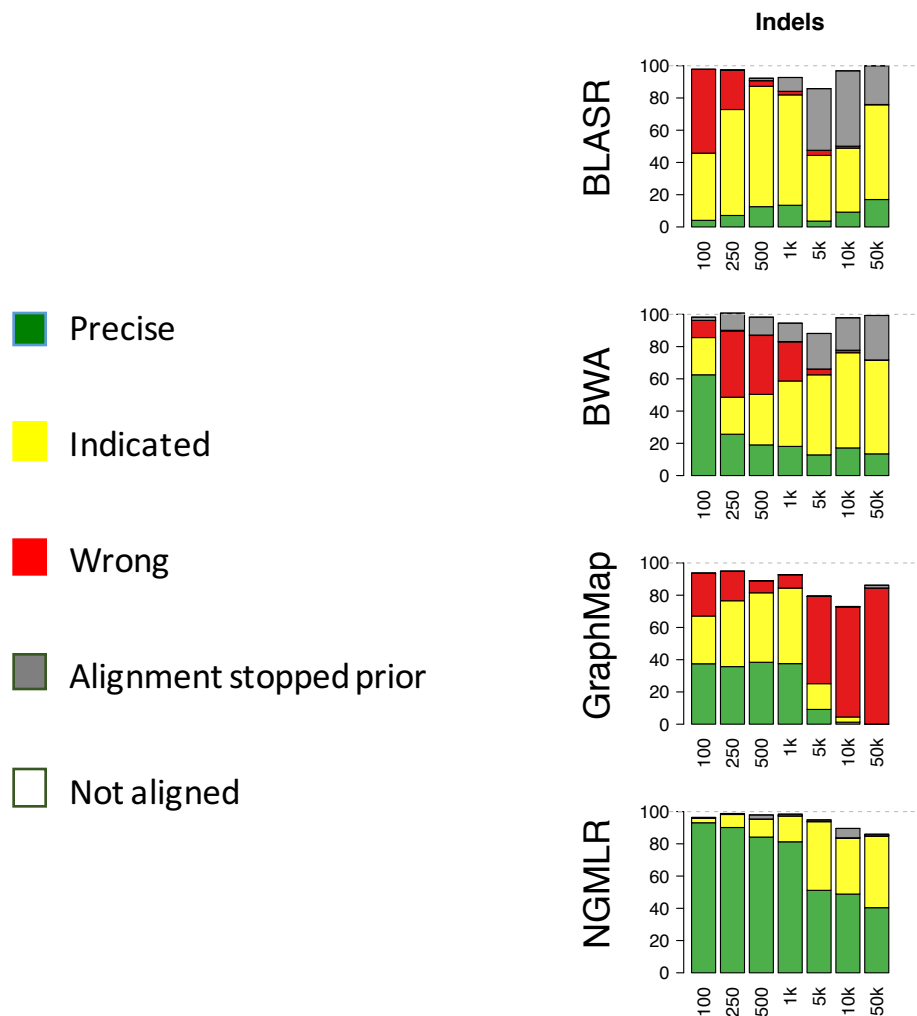


NGMLR + Sniffles

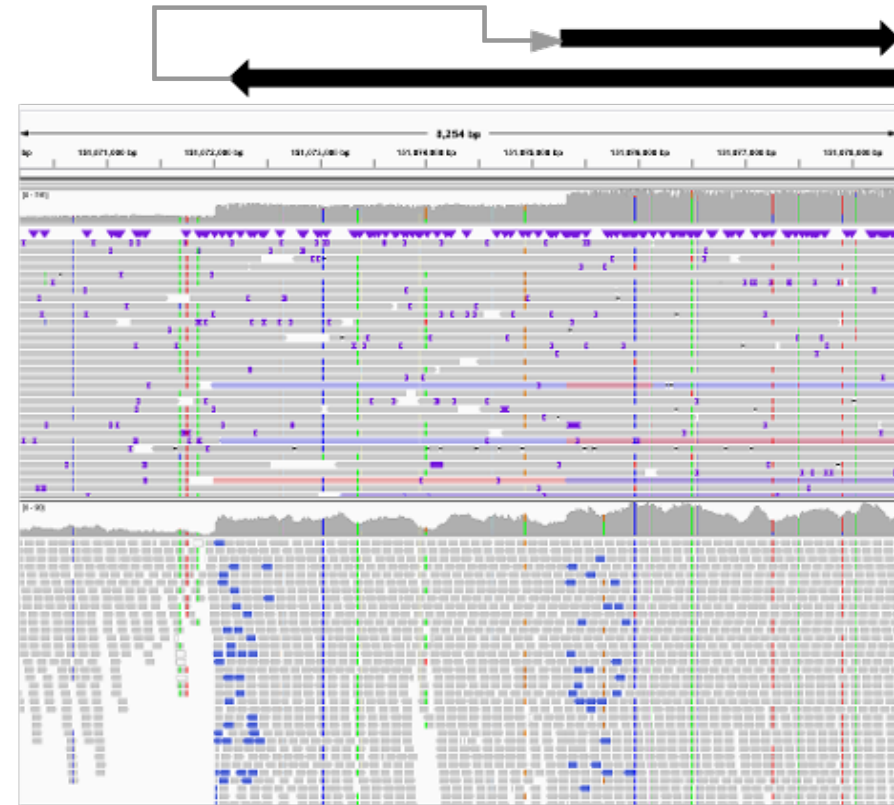
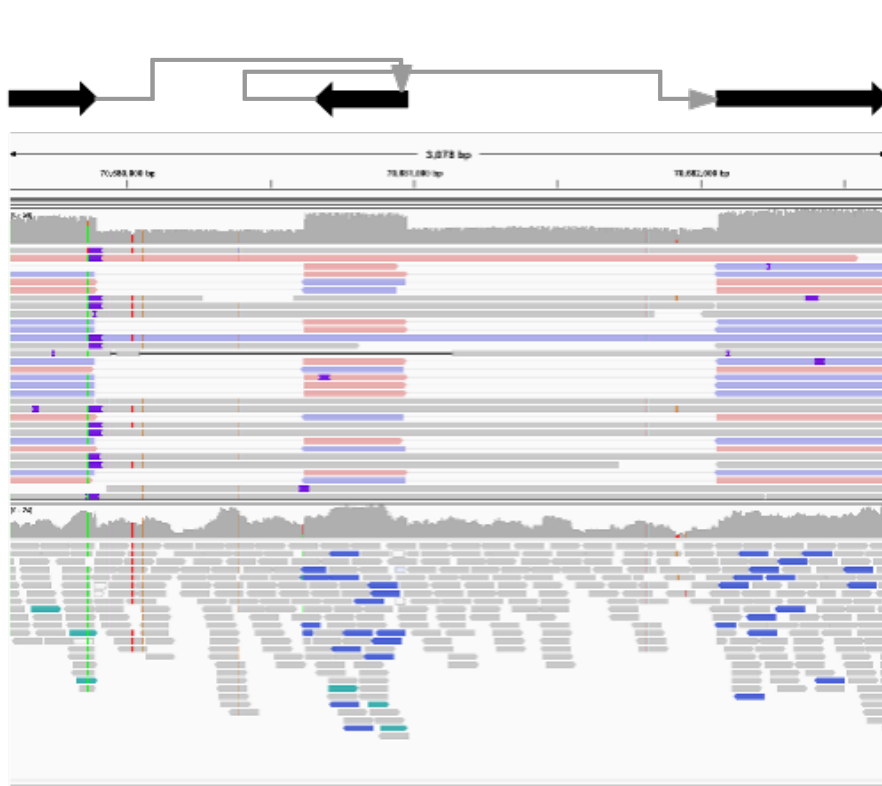
- NGMLR
 - Convex gap cost model to better distinguish seq. error vs. signal
 - Novel method for split read alignment.
- Sniffles
 - Includes multiple statistical models to distinguish noise vs. signal



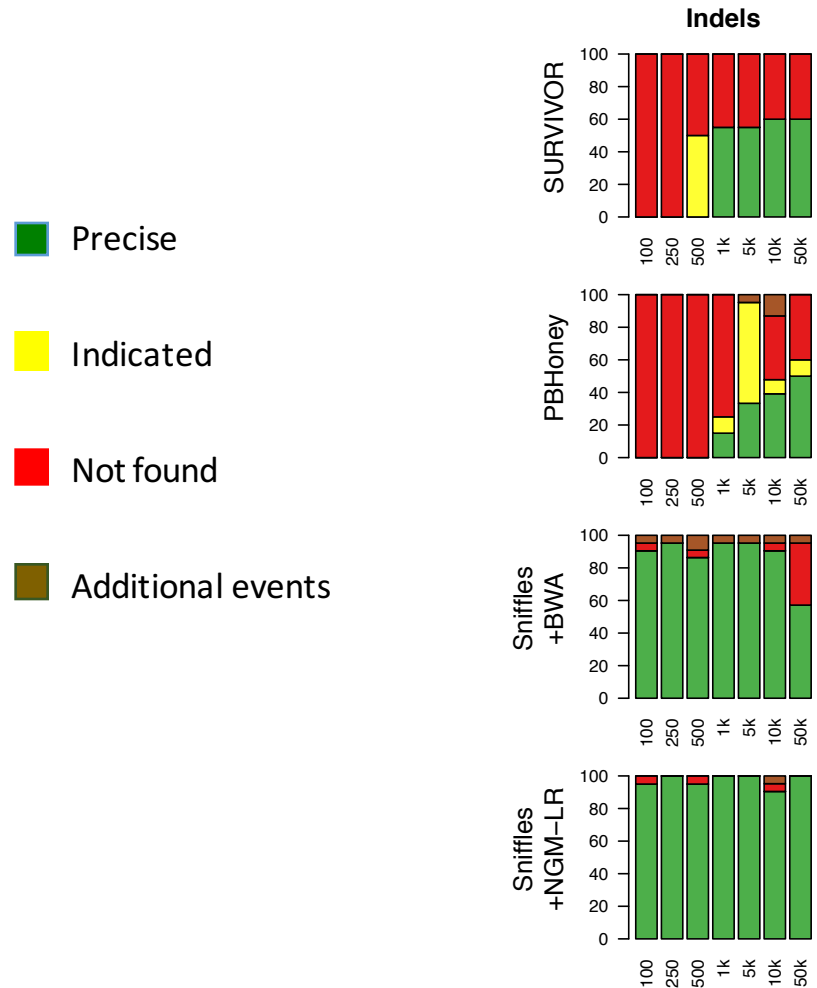
1.3 Long read mapping



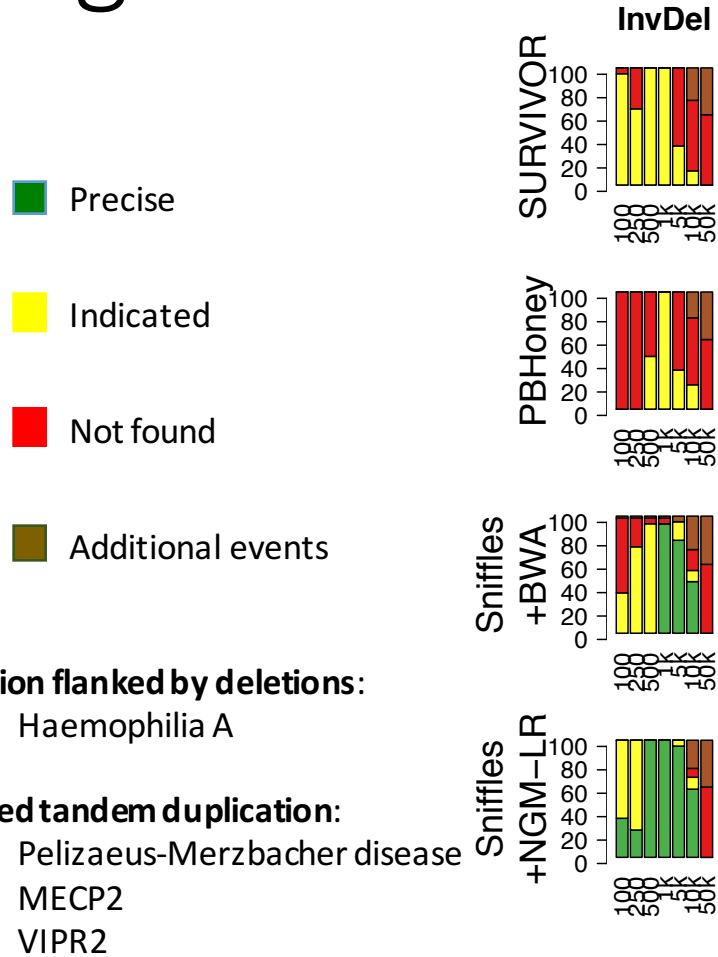
More complex types



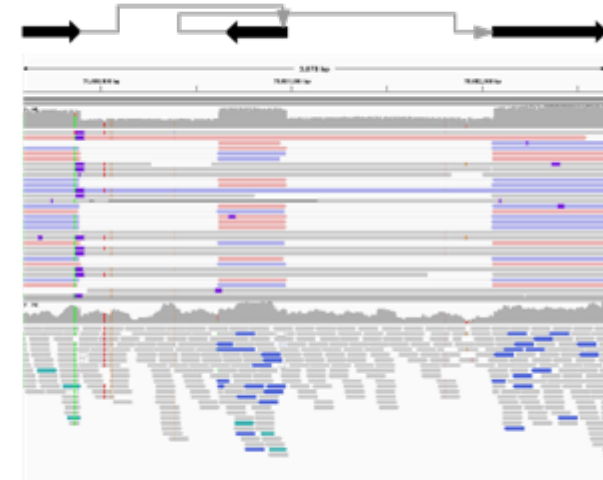
2.4 Long read SV calling



2.4 Long read SV calling



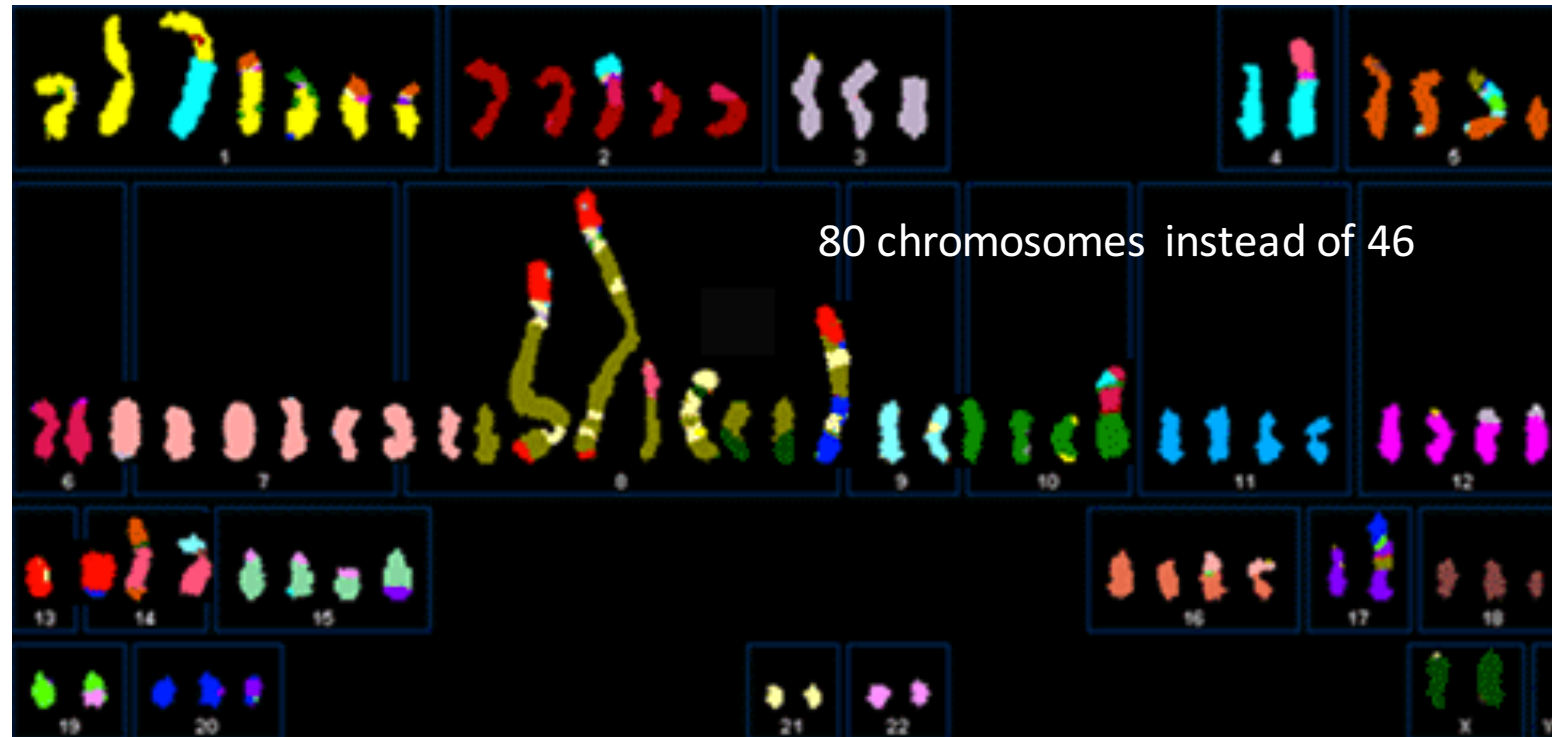
INVDEL



SKBR-3 using Pacbio

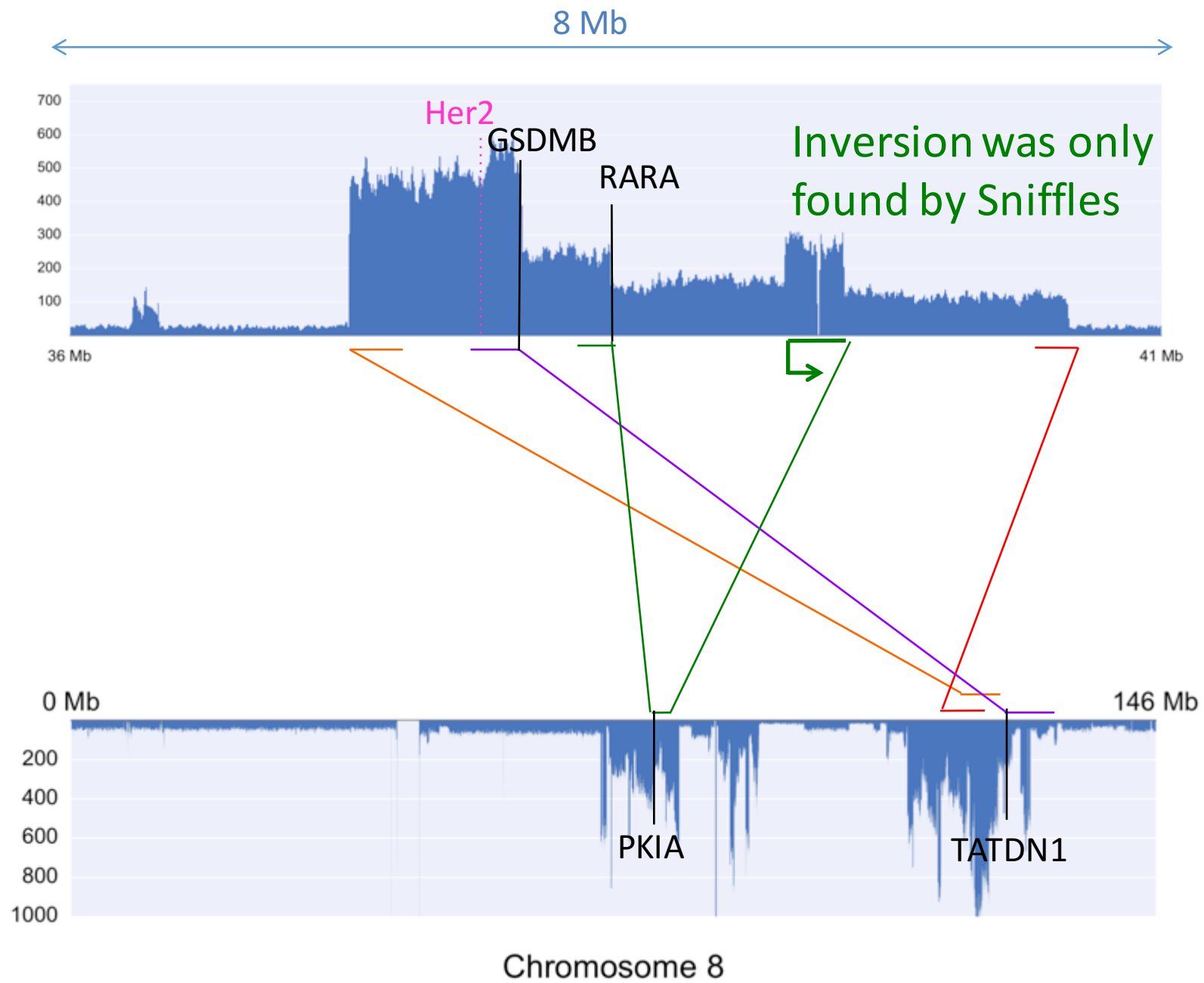


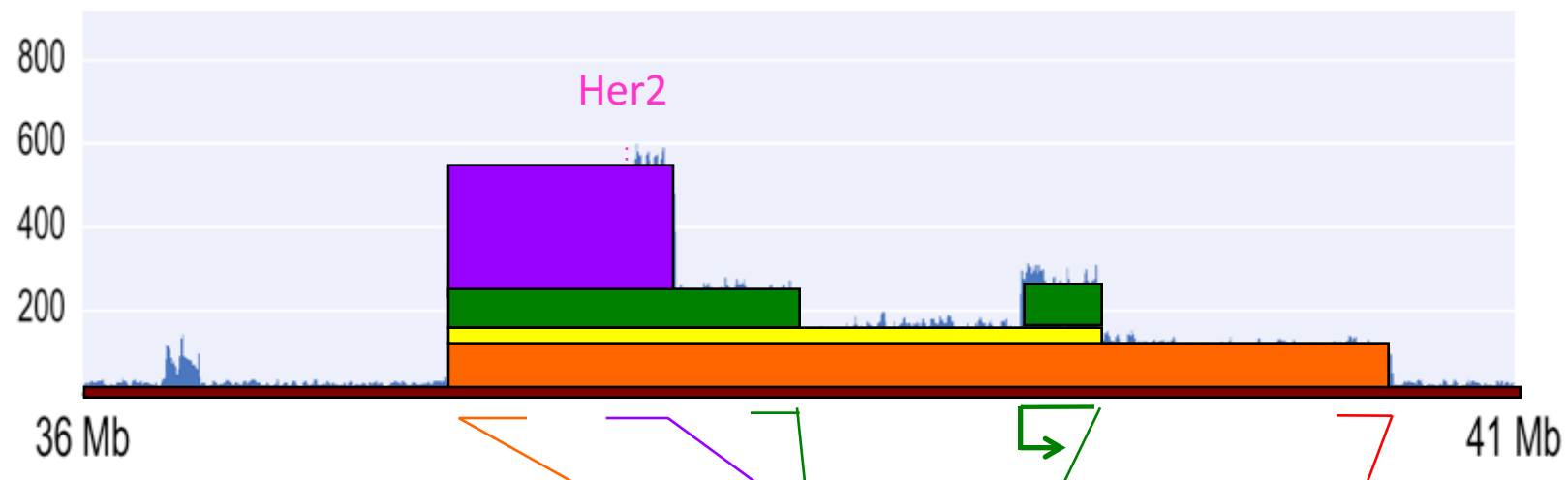
Most commonly used Her2-amplified breast cancer cell line



Often used for pre-clinical research on Her2-targeting therapeutics such as Herceptin (Trastuzumab) and resistance to these therapies.

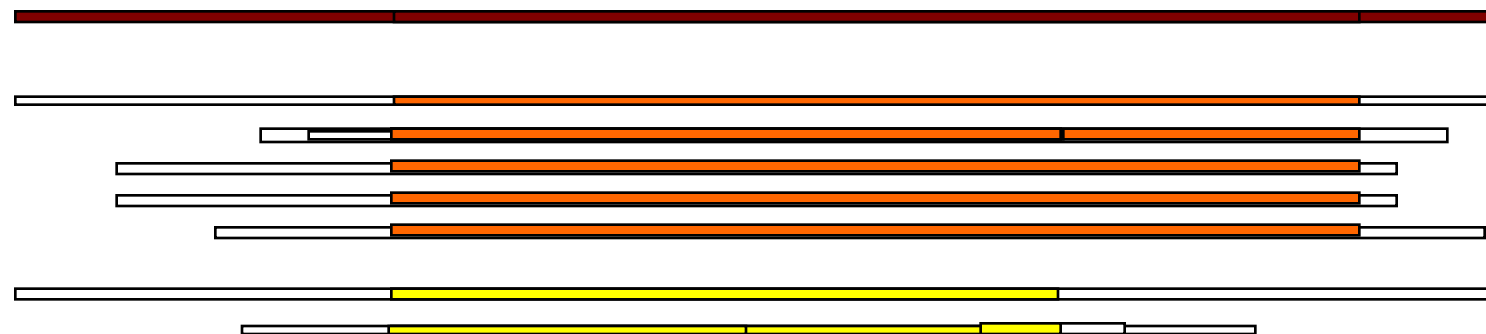
(Davidson et al, 2000)



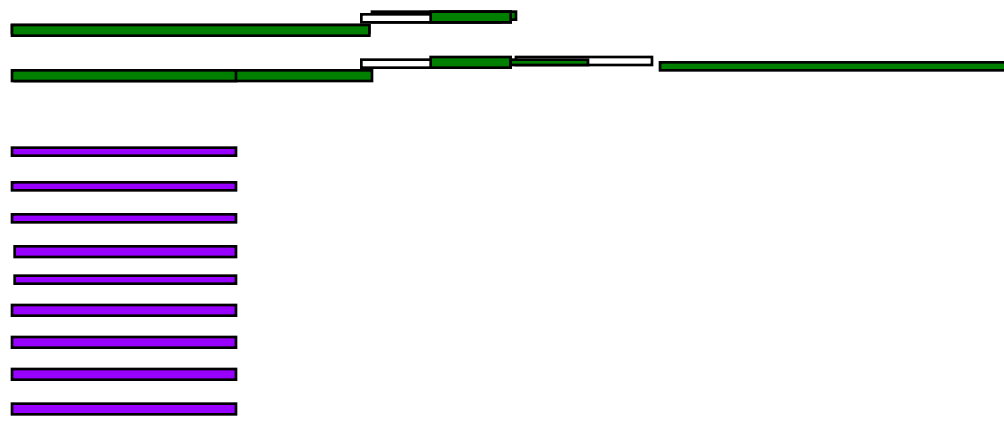


Chr 17

Chr 8



1. Healthy chromosome 17 & 8
2. Translocation into chromosome 8
3. Translocation within chromosome 8
4. Complex variant and inverted duplication within chromosome 8
5. Translocation within chromosome 8



3.2 NA12878

- Healthy female
- Gold standard in genomics
- Sequenced with many technologies independently:
 - Illumina, PacBio, Oxford Nanopore

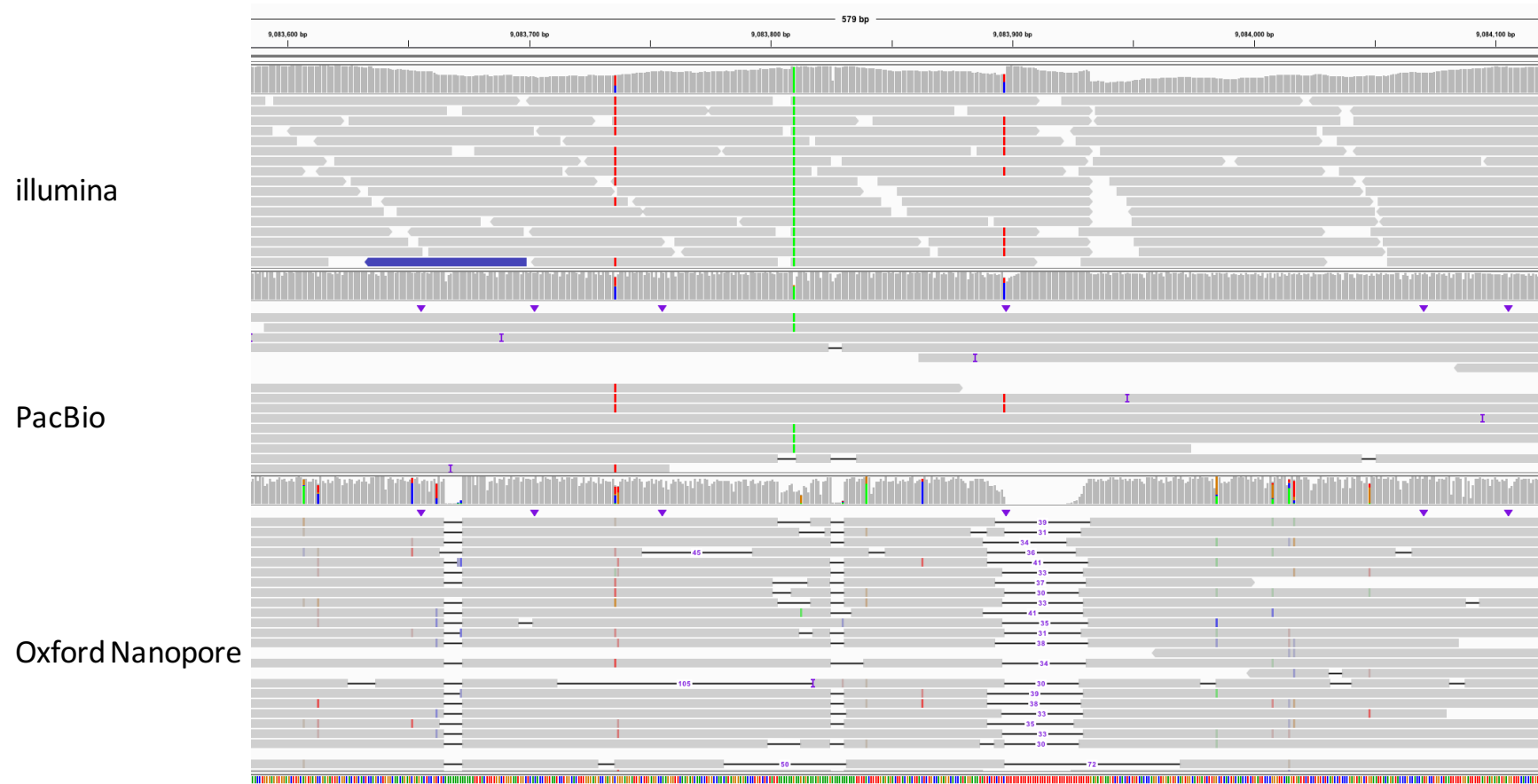
3.2 NA12878: Deletion calling

Tech.	Cov.	Avg len	SVs	DEL	DUP	INV	INS	TRA
PacBio	55x	4,334	22,877	9,933	162	611	12,052	119
Oxford Nanopore	28x	6,432	32,409	27,147	87	323	4,809	43
Illumina	50x	2 x 101	7,275	3,744	731	553	0	2,247

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3.2 Oxford Nanopore deletions



3.2 NA12878: Deletion calling

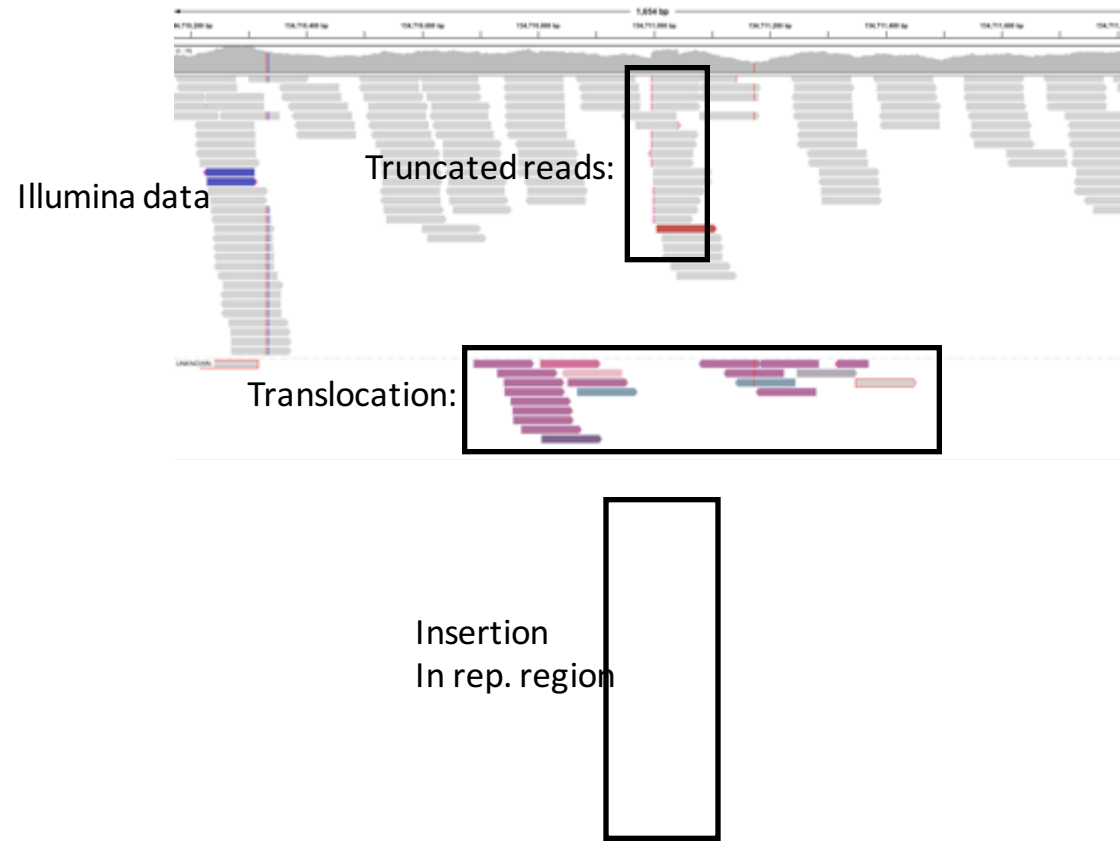
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Oxford Nanopore @Baylor	34x	4,982	12,596	7,102	169	113	5,166	46
Illumina	50x	2 x 101	7,275	3,744	731	553	0	2,247

3.2 NA12878: Deletion calling

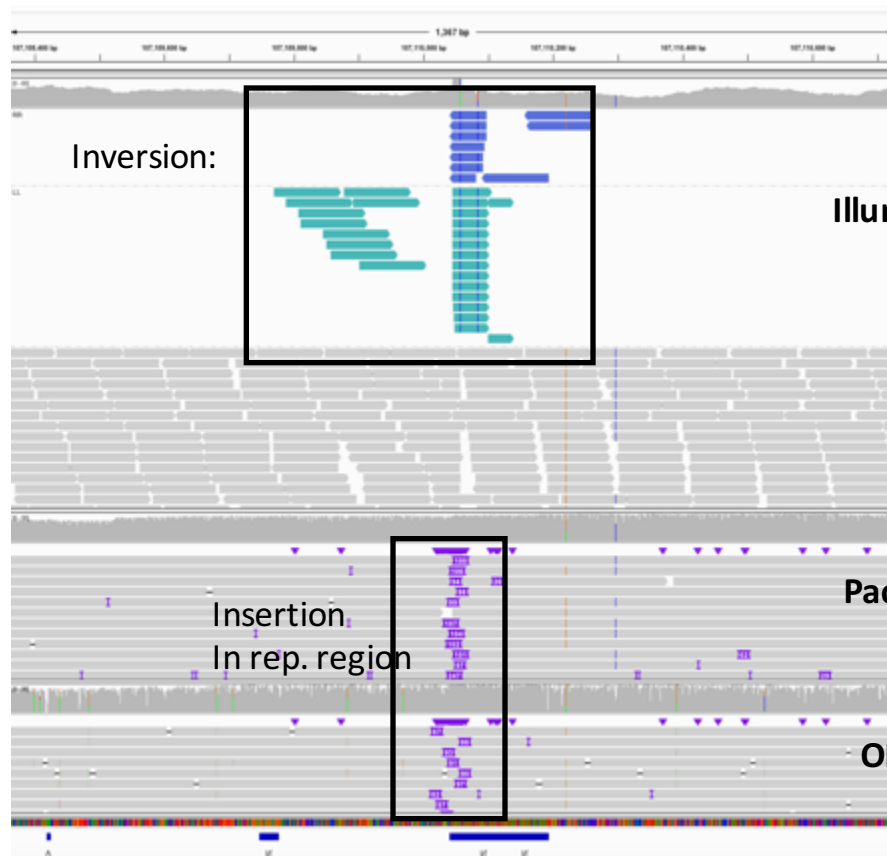
Tech.	Cov.	Avg len	SVs	DEL	DUP	INV	INS	TRA
PacBio	55x	4,334	22,877	9,933	162	611	12,052	119
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Illumina	50x	2 x 101	7,275	3,744	731	553	0	2,247

3.2 NA12878: check 2,247 vs 119 TRA

Overlap	Illumina TRA(%)
Translocations	7.74
Insertions	53.05
Deletions	12.06
Duplications	0.57
Nested	0.31
High coverage	1.87
Low complexity	9.79
Explained	85.40



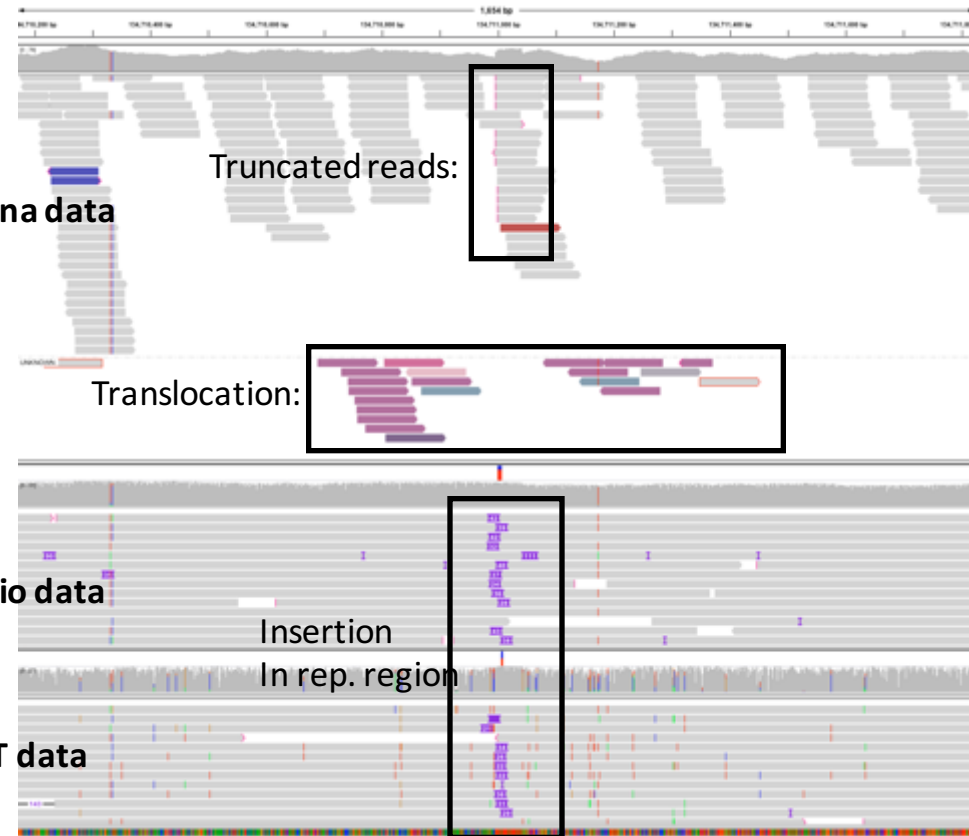
NA12878: check 2,247 TRA



Illumina data

PacBio data

ONT data



Truncated reads:

Translocation:

Insertion
In rep. region

Hands on: Long reads and comparison.

1. Identify SVs over long reads: Sniffles

1. `Sniffles -m my_ont.bam -v test.vcf`

2. Comparison of SVs: SURVIVOR

1. Characterize the overlap between Assembly, short and long reads
 1. `ls *vcf > myfiles`
 2. `SURVIVOR merge myfiles 1 1 0 0 0 merged_output.vcf`
2. Identify deletions that are unique to ONT

3. Optional: Annotate the SVs using VCFanno.

1. Configure the config file for vcf anno
 2. `bgzip merged_output.vcf`
 3. `Tabix -p vcf merged_output.vcf`
 4. `vcfanno configfile merged_output.vcf > merged_output.anno.vcf`
1. How many genes are impacted? (use `grep`)
 2. How many SVs are called on XIII: 184169- 808535 using e.g. `bedtools intersect`

Applications: Using Nanopore MinION

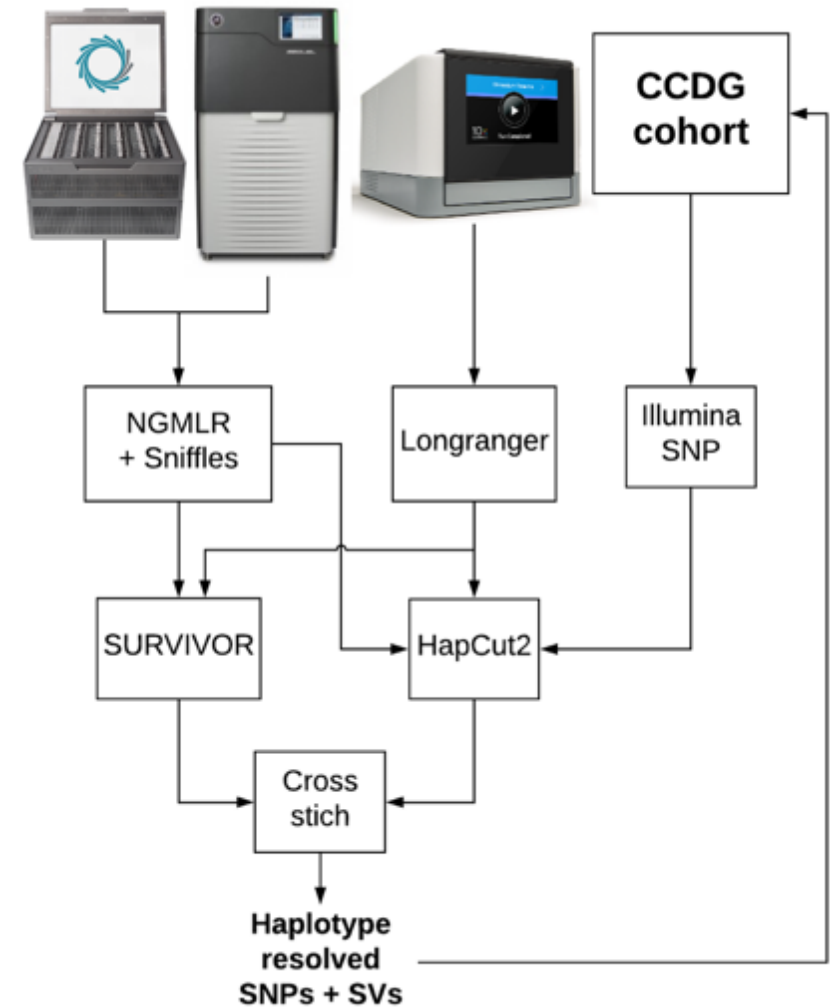


GBA Mutations in Parkinson and Gaucher



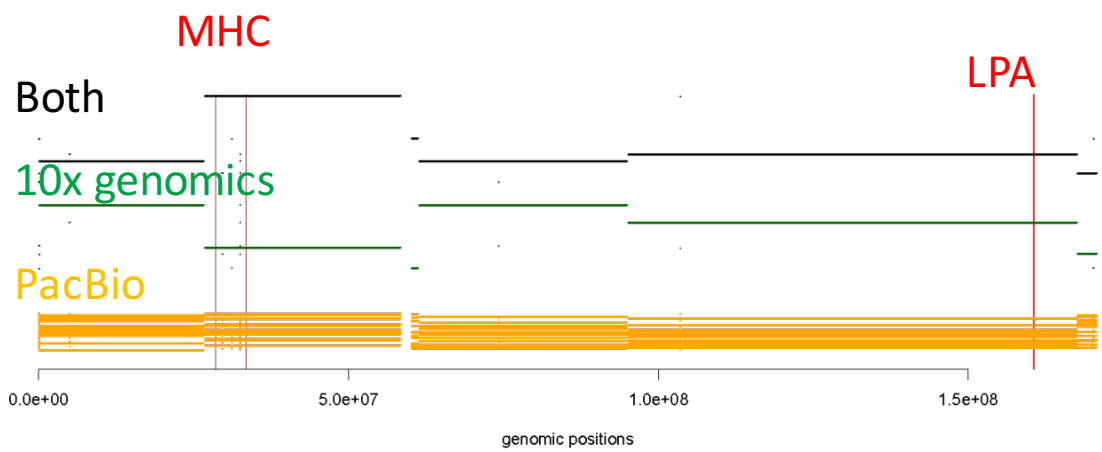
Future directions: Comprehensive Genomes

- Phased SVs + SNP genomes with RNA-Seq data
 - Prepilot 3 samples (4 techs)
 - ~100 Pacbio genomes
 - 2019: 500 Pacbio/ONT genomes



4. Phasing of SNV + SV: chr6

NA24385: DNA Mol. Length 99.9 kb



Technology	N50 Phasing (Mbp)
PacBio	0.276
10x-Longranger	8.523
10x-Hapcut2	67.576
PacBio+10x	67.576

4. HLA-F deletion: Long + RNA-Seq

PacBio:
HS-1011

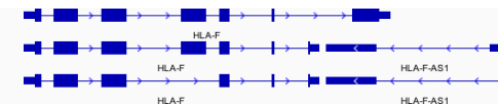
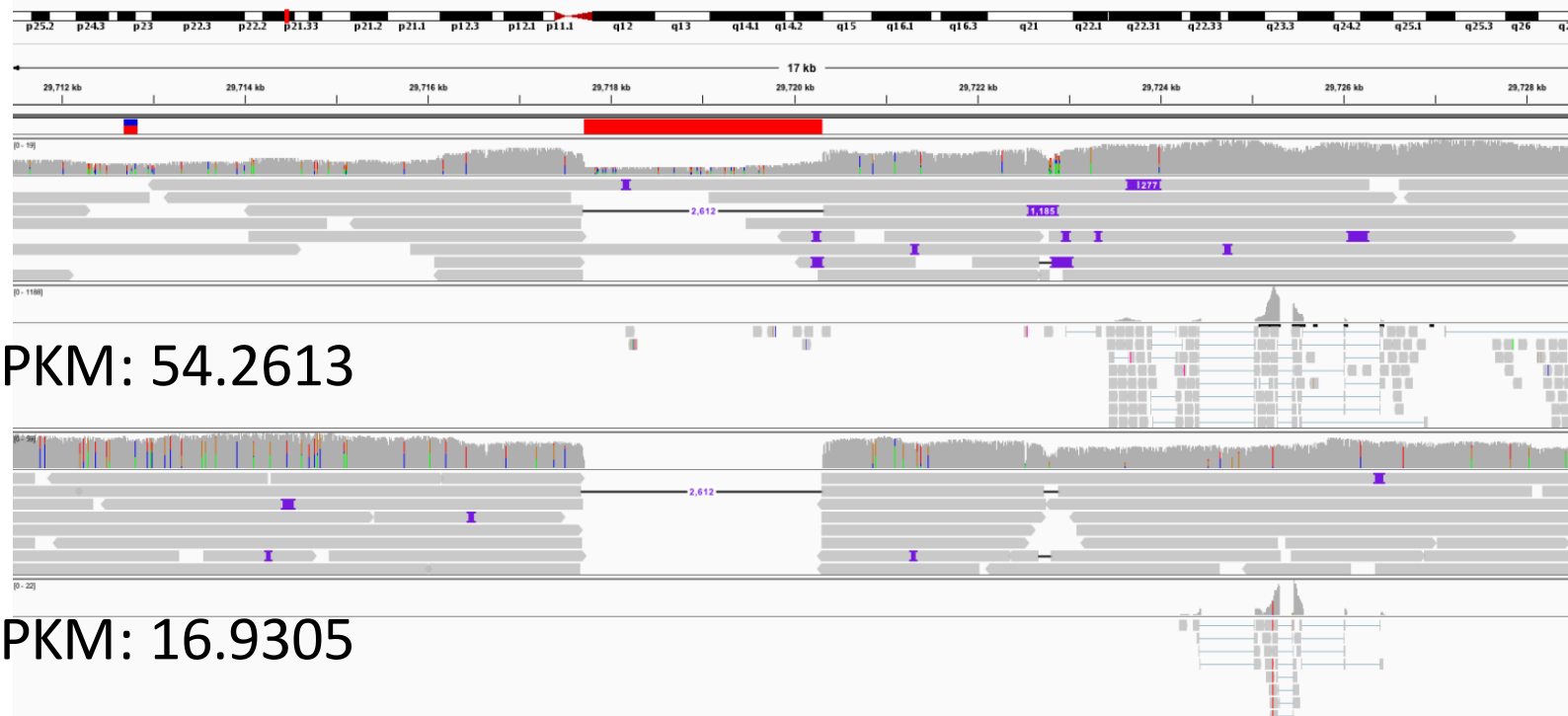
RNA-Seq
HS-1011

FPKM: 54.2613

PacBio:
NA12878

RNA-Seq
NA12878

FPKM: 16.9305



Thank you

- SV calling is SNP calling of 2008
 - Reads are typically shorter than the allele.
 - Lot of noise in the data
-
- **I am here until Friday morning and happy to discuss things with you!**

