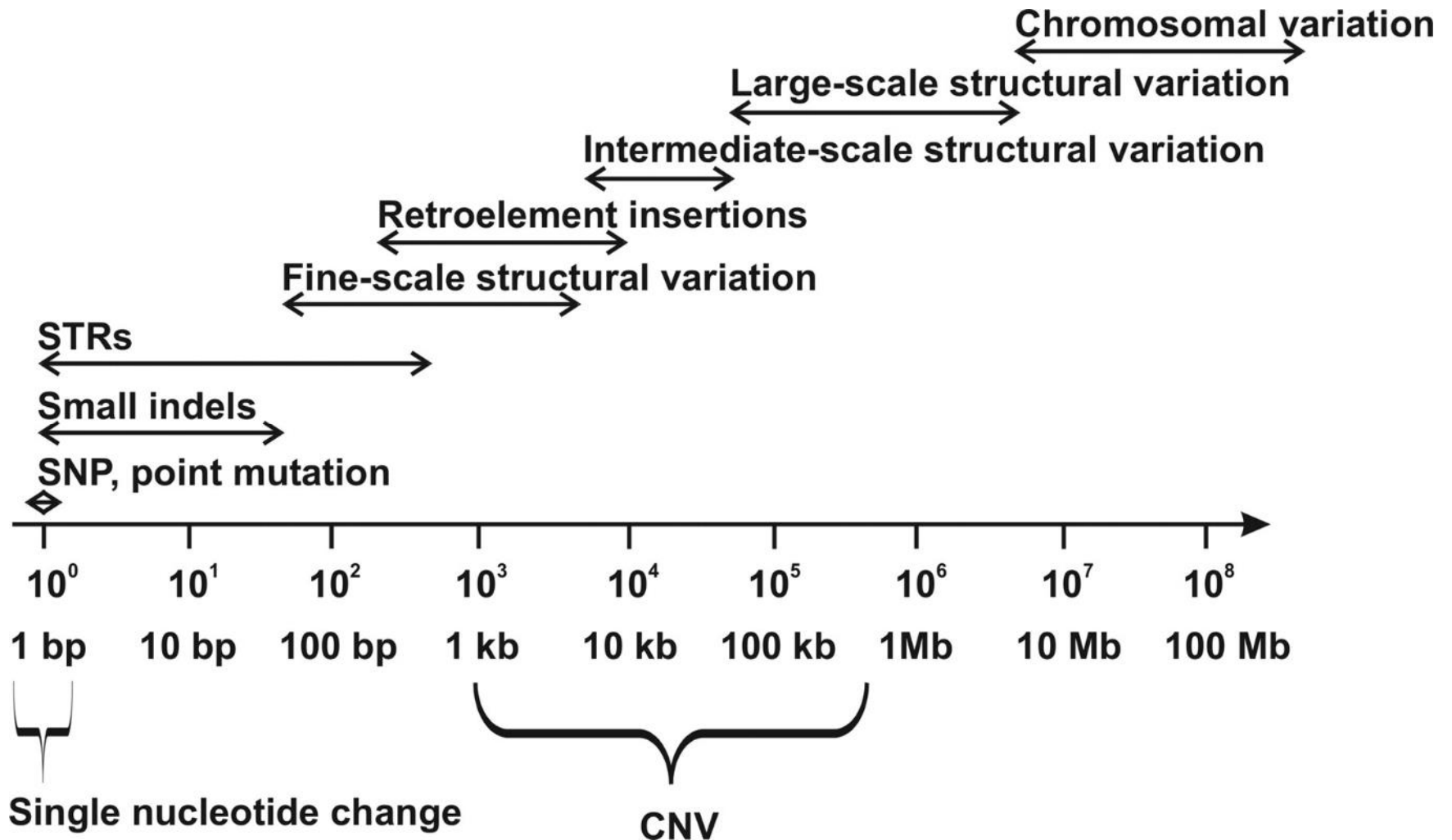


# Detection of structural variants in human diseases

2019 Dragon Star Bioinformatics Course (Day 3)

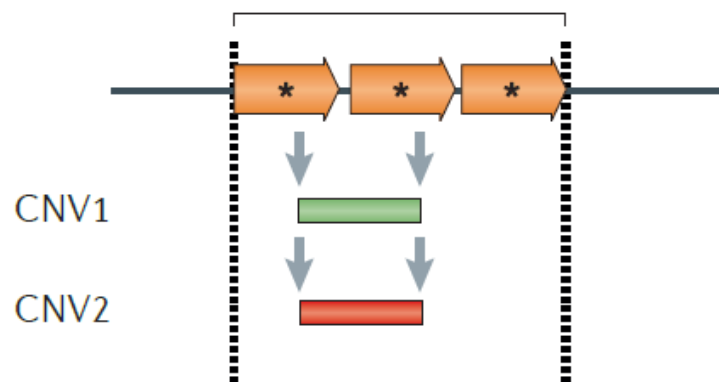
# Human genetic variation



# Mechanisms underlying structural variant formation

- **Recurrent structural variants:**

- Share the same size and genomic content in unrelated individuals
- Often caused by **NAHR** (Nonallelic homologous recombination--Nonallelic pairing of paralogous sequences and crossover leading to deletions, duplications and inversions )
- The breakpoints map within long, highly identical, flanking interspersed paralogous repeats, which mostly consist of segmental duplications(SDs)



# SVs and repeat sequences

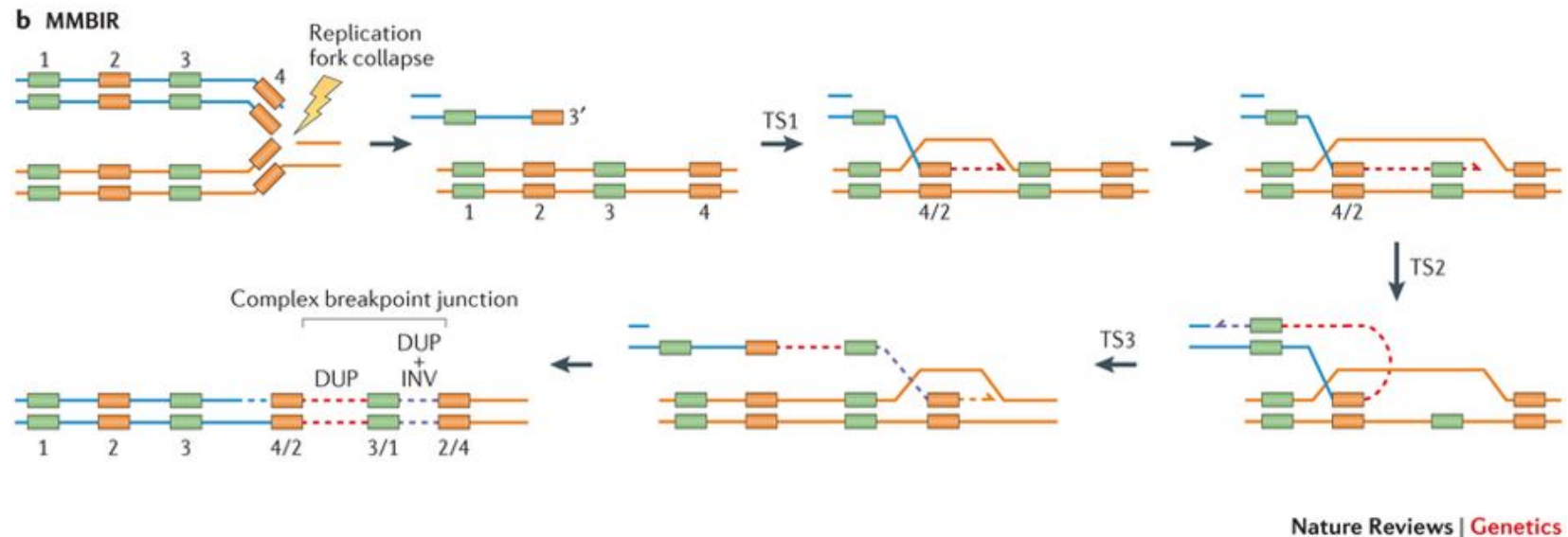
- Approximately 50% of the human genome consists of repeat sequences.
- Different types of repeat sequences:
  - Mobile elements such as *Alu-processed pseudogenes*
  - Simple sequence repeats
  - Tandemly repeated sequences
  - Low-copy repeats (LCRs) such as SDs.
- SDs
  - Computationally defined as segments of DNA that contain  $\geq 90\%$  of sequence identity and  $\geq 1$  kb in length in the reference haploid genome
  - Constitute approximately 4–5% of the human genome.

# Mechanisms underlying structural variant formation

- **Nonrecurrent rearrangements:**
  - Have a unique size and genomic content at a given locus in unrelated individuals.
- Typical mechanisms:
  - NHEJ: Non-homologous end joining
  - MMEJ: Microhomology-mediated end joining
  - FoSTeS/MMBIR: microhomology-mediated break-induced replication
  - SRS: Smaller complex rearrangements caused by serial replication slippage

# Mechanisms underlying structural variant formation

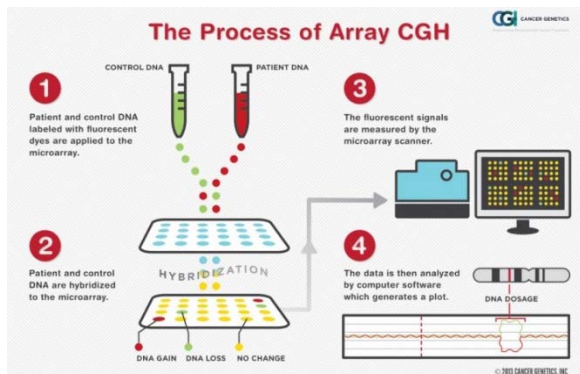
- Microhomology-mediated break-induced replication (MMBIR)



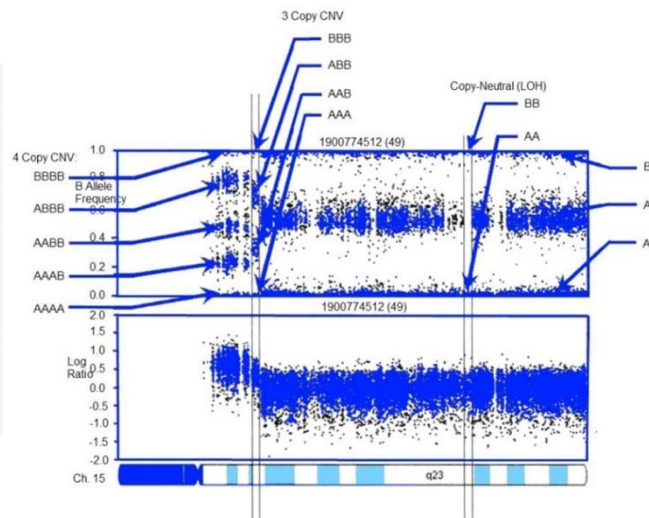
# Technologies for CNV Detection

- Karyotyping and cytogenetic analysis
- Array comparative genomic hybridization (array CGH)
- SNP microarrays (the same arrays used in GWAS)
- Next-generation sequencing (NGS) and long-read sequencing

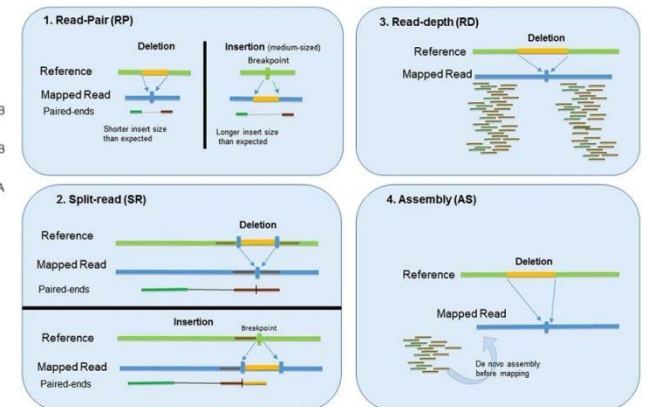
## Array CGH



## SNP array



## Next-generation sequencing



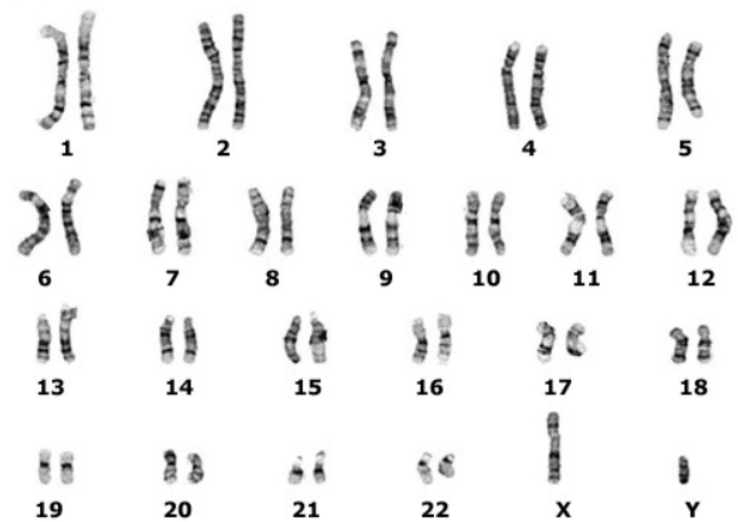
# Commonly used cytogenetic techniques

- Giemsa staining
- Fluorescent in situ hybridization (FISH)
- Comparative genomic hybridization (CGH)
- Spectral karyotyping (SKY)



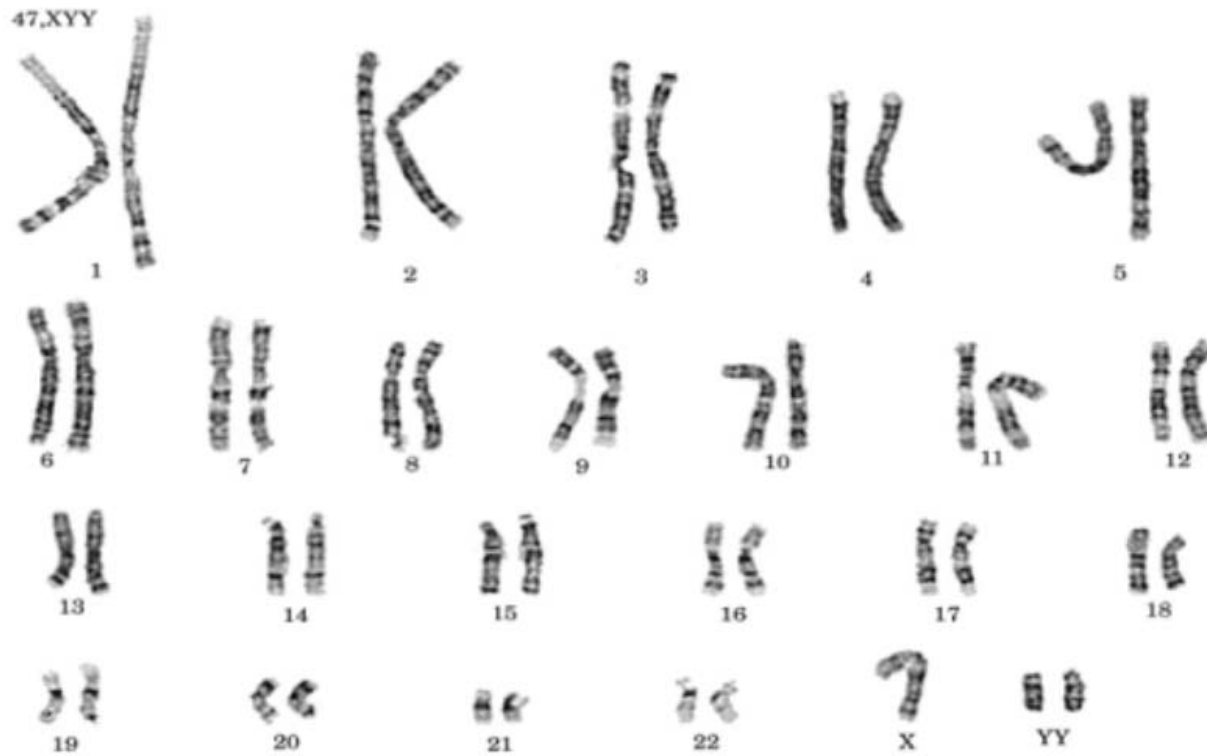
# Cytogenetic techniques

- Giemsa banding (G-banding).
- The metaphase chromosomes are treated with trypsin (to digest proteins in the chromosomes) and stained with Giemsa stain.
- Dark bands are AT-rich and have less genes.
- Light bands are GC-rich DNA and are more transcriptionally active.



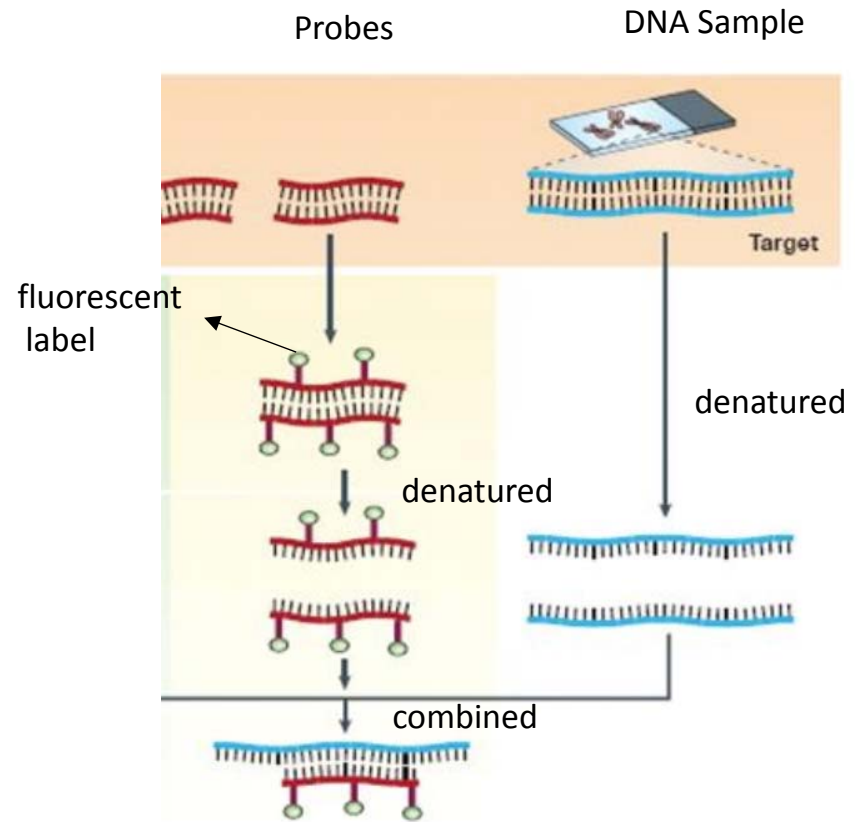
Karyogram of human male using Giemsa staining

# Detection of chromosomal abnormalities by cytogenetic techniques



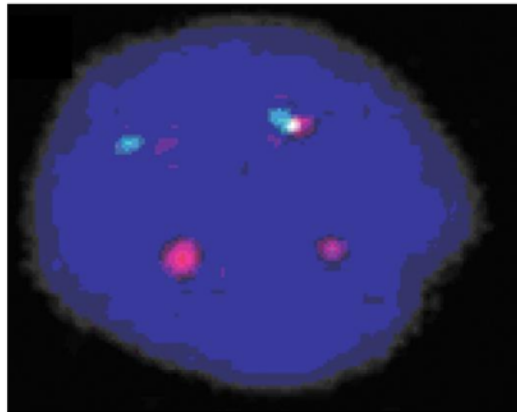
# Cytogenetic techniques

- Fluorescent in situ hybridization (FISH).
  - FISH uses fluorescent probes that bind to specific chromosomal regions where there is a high degree of sequence complementarity.
- Fluorescence microscopy can be used to visualize and evaluate the signals.



Bioscience Horizons: The International Journal of Student Research, Volume 3, Issue 1, 1 March 2010, Pages 85–95,

# Detection of SVs using cytogenetic techniques (FISH)



Using interphase FISH to detect the *BCR/ABL* translocation.

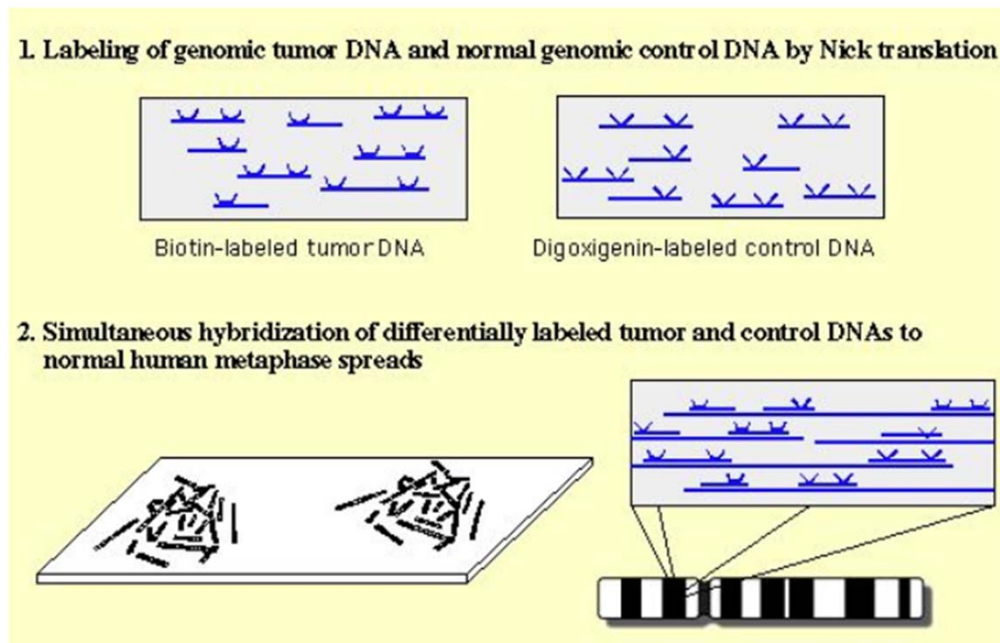
Green signal indicates the presence of the *BCR* gene

Red signals indicate the presence of the *ABL* gene

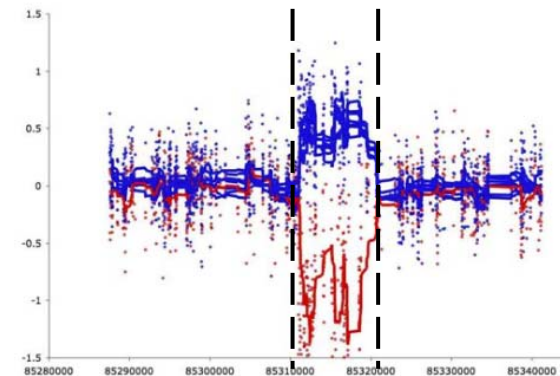
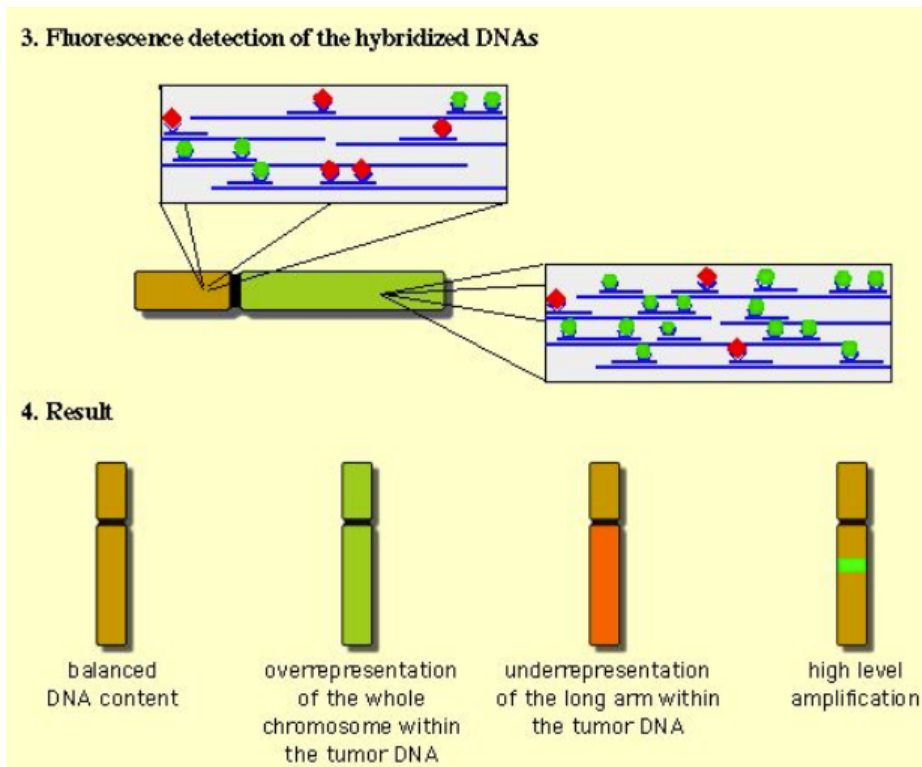
Red-green fusion (yellow) signal confirms *BCR/ABL* translocation.

# Comparative genomic hybridization (CGH)

- A molecular cytogenetic method for detection of copy number variations (CNVs)
  - A reference sample is used as a control.



# Comparative genomic hybridization (CGH)

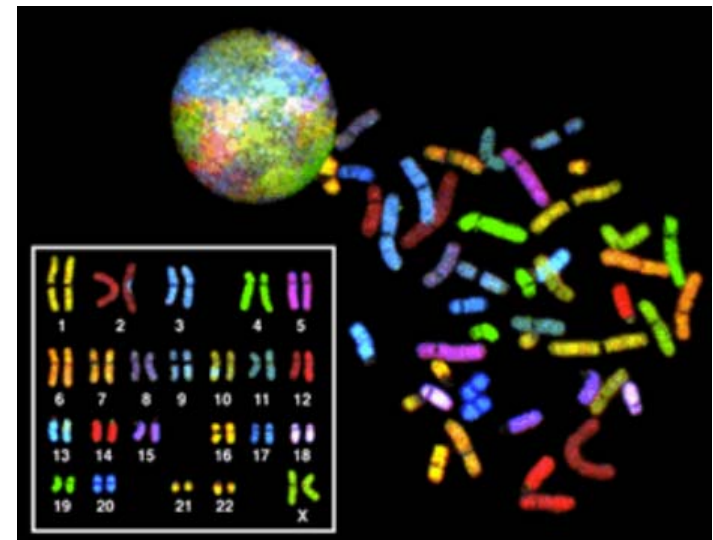


Blue line: individuals with two copies  
Red line: individual with zero copy

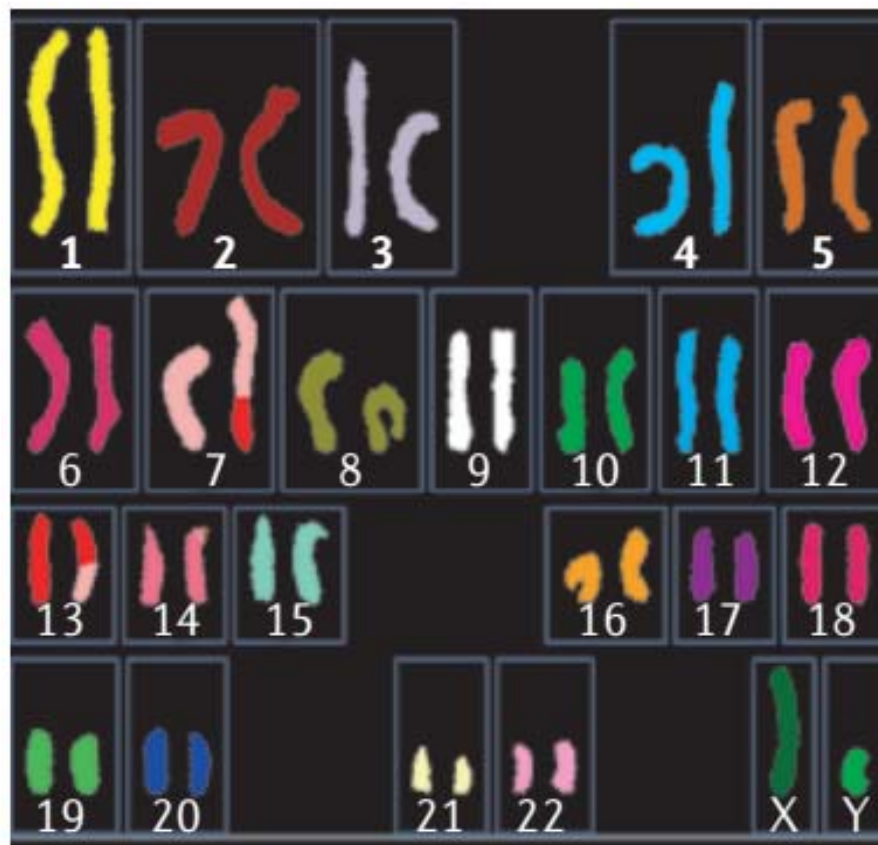
# Spectral karyotyping (SKY)

- Spectral karyotyping (SKY) is a laboratory technique
  - Allows the visualization of all the human chromosomes at one time by "painting" each pair of chromosomes in a different fluorescent color.

SKY also uses fluorescent probes. Each probe is complementary to a unique region of one chromosome. The probes that bind to different chromosomes are designed to have different fluorescent color.



# Detection of interchromosomal translocations using cytogenetic techniques (SKY)



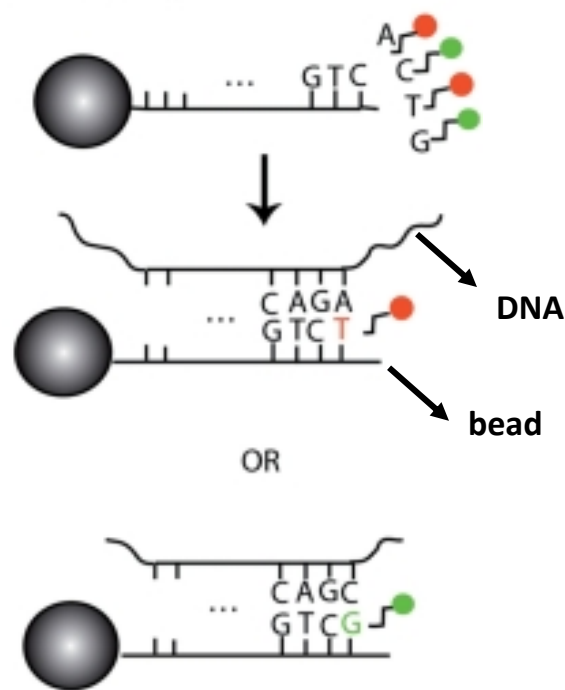
The example shows the detection of a t(7;13) translocation.



# SNP genotyping arrays

- SNP genotyping array is a type of DNA microarray which is used to detect SNPs.
- Two major SNP array companies:
  - Affymetrix arrays
  - Illumina arrays

# Illumina SNP array technology

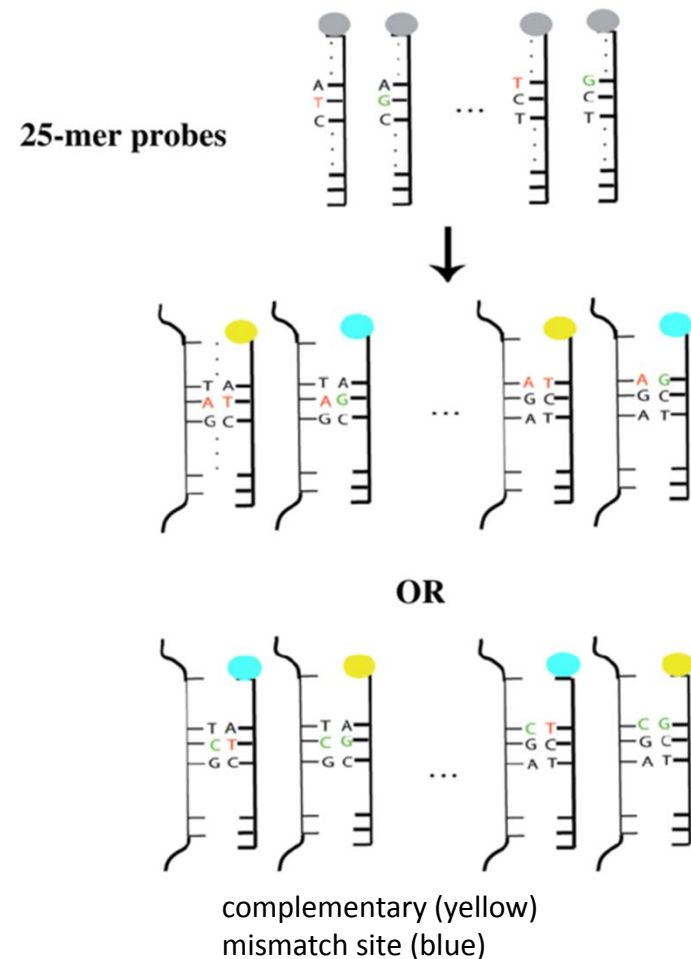


Nucleic Acids Res. 2009 Jul; 37(13): 4181–4193.

- In the Illumina array, attached to each Illumina bead is a 50-mer sequence complementary to the sequence adjacent to the SNP site.
- The single-base extension (T or G) that is complementary to the allele carried by the DNA (A or C, respectively) then binds and results in the appropriately-colored signal (red or green, respectively).

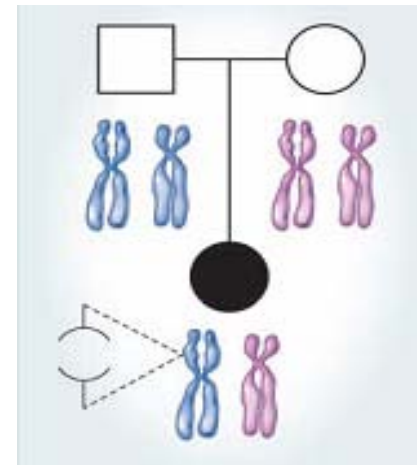
# Affymetrix SNP array technology

- In the Affymetrix assay, there are 25-mer probes for both alleles.
  - Assuming there are two alleles (e.g. A-Allele and B-allele) at a particular site.
  - The DNA can bind to both probes
  - But will have much higher affinity for the perfectly matched probe.
  - For example,
    - if the DNA is B-allele, it will bind to both probes
    - But have much higher binding affinity to the probe of B-allele.
    - Therefore, the signal of B-allele probe is much higher than A-allele probe.



# CNV Detection

- There is a need to develop a high-resolution CNV detection algorithm using high-density SNP genotyping data:
  - Identify location of the CNVs.
  - Estimate the copy numbers.
  - Model family relationships.
  - Incorporate *de novo* events.



# Log R Ratio (LRR) and B Allele Frequency (BAF)

- For both platforms, the computational algorithms convert the raw signals into Log R Ratio (LRR) and B Allele Frequency (BAF).
- LRR is a measure of normalized total signal intensity.
- BAF is a measure of normalized allelic intensity ratio.
- The combination of LRR and BAF can be used together to determine different copy numbers and to differentiate copy-neutral LOH regions from normal copy regions.

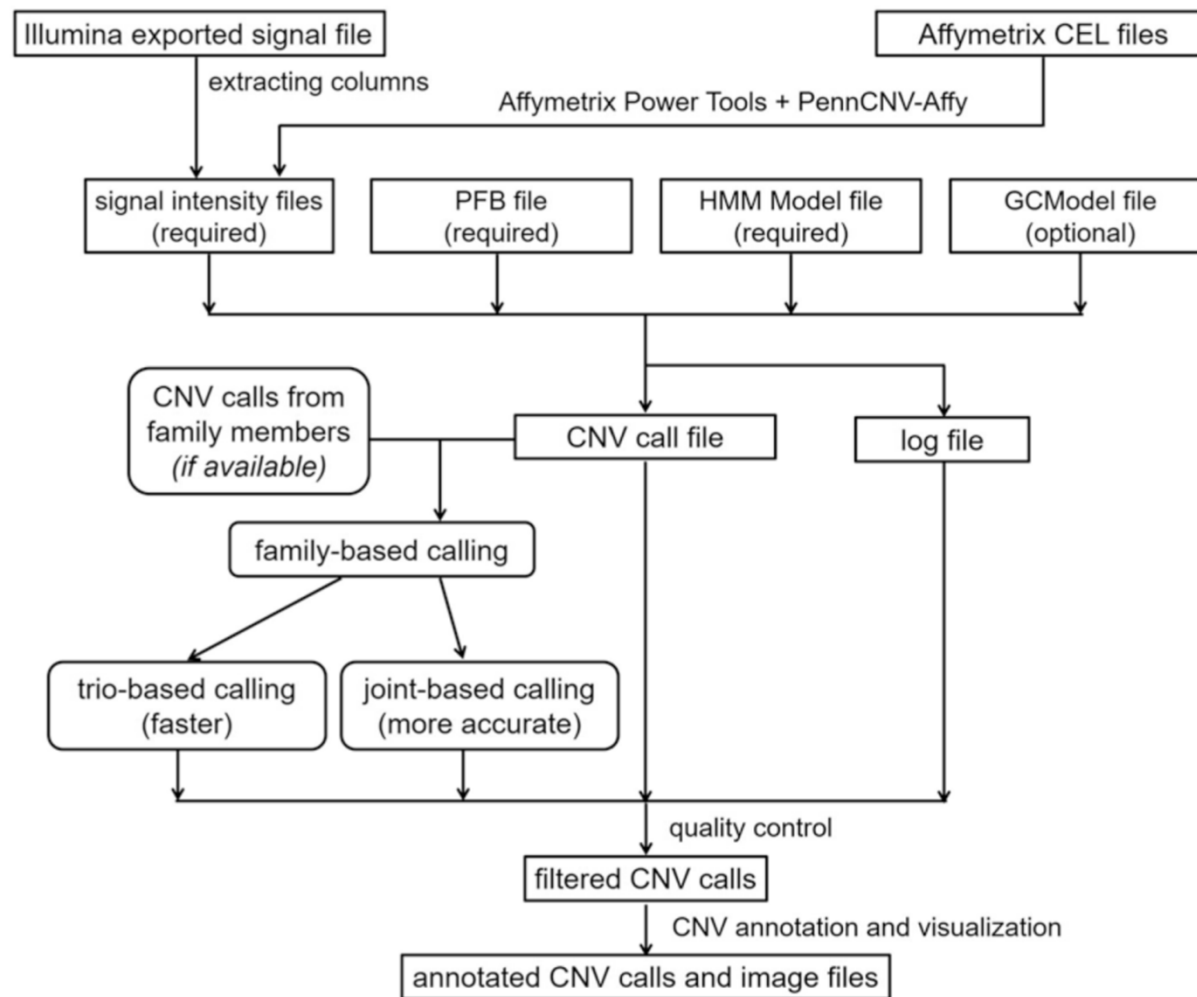
# Detection of CNVs from SNP arrays using PennCNV

PennCNV: An integrated hidden Markov model designed for high-resolution copy number variation detection in whole-genome SNP genotyping data

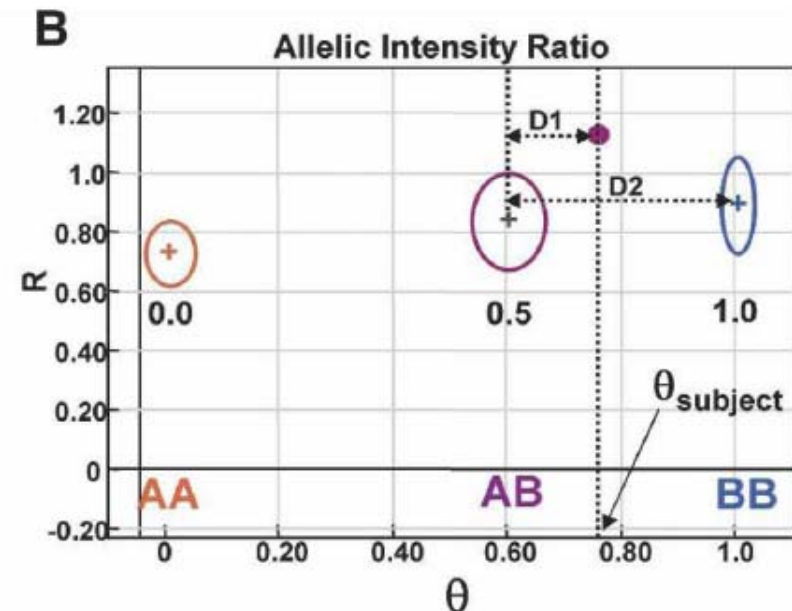
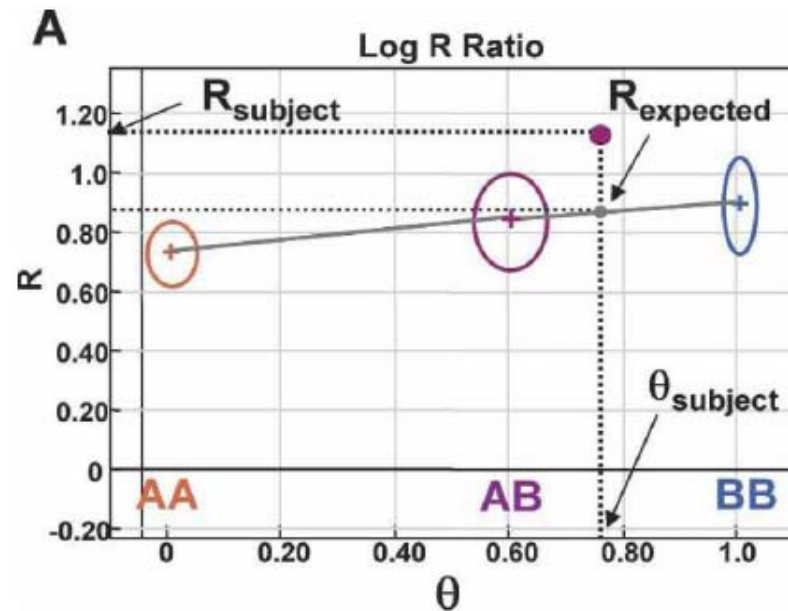
Kai Wang,<sup>1</sup> Mingyao Li,<sup>2</sup> Dexter Hadley,<sup>1,3</sup> Rui Liu,<sup>1</sup> Joseph Glessner,<sup>4</sup>  
Struan F.A. Grant,<sup>4</sup> Hakon Hakonarson,<sup>4</sup> and Maja Bucan<sup>1,5</sup>

- Hidden Markov Model (HMM) is a statistical Markov model in which the system being modeled is assumed to be a Markov process with hidden states.
- What we know are: LRR and BAF
- What we want to know is: copy number

# PennCNV Flowchart



# SNP Signal Intensities



$$R = X_A + X_B, \quad \theta = (2/\pi) \times \arctan(X_B/X_A)$$

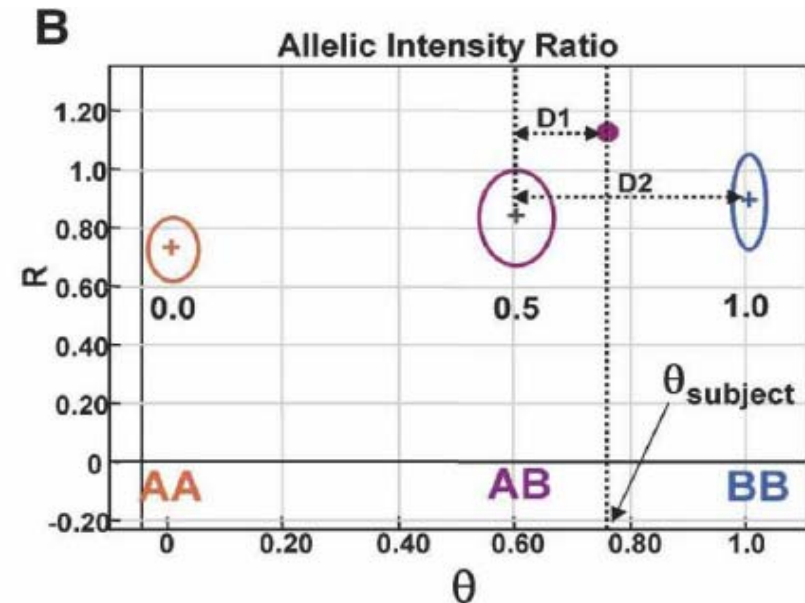
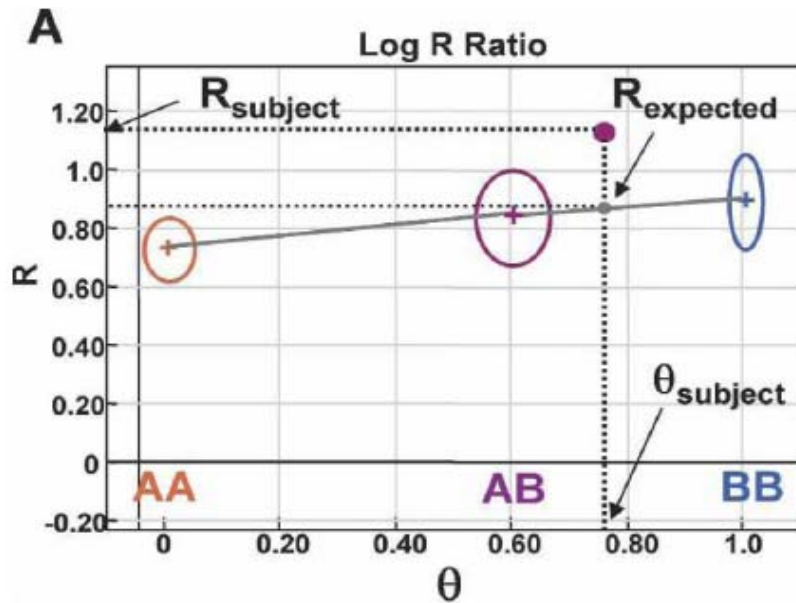
$$\text{LRR} = \log_2 R_{\text{subject}} / R_{\text{expected}}$$

$X_A$  and  $X_B$ : normalized signal intensities for alleles A and B

$R_{\text{expected}}$ : calculated based on a reference dataset assuming copy number = 2

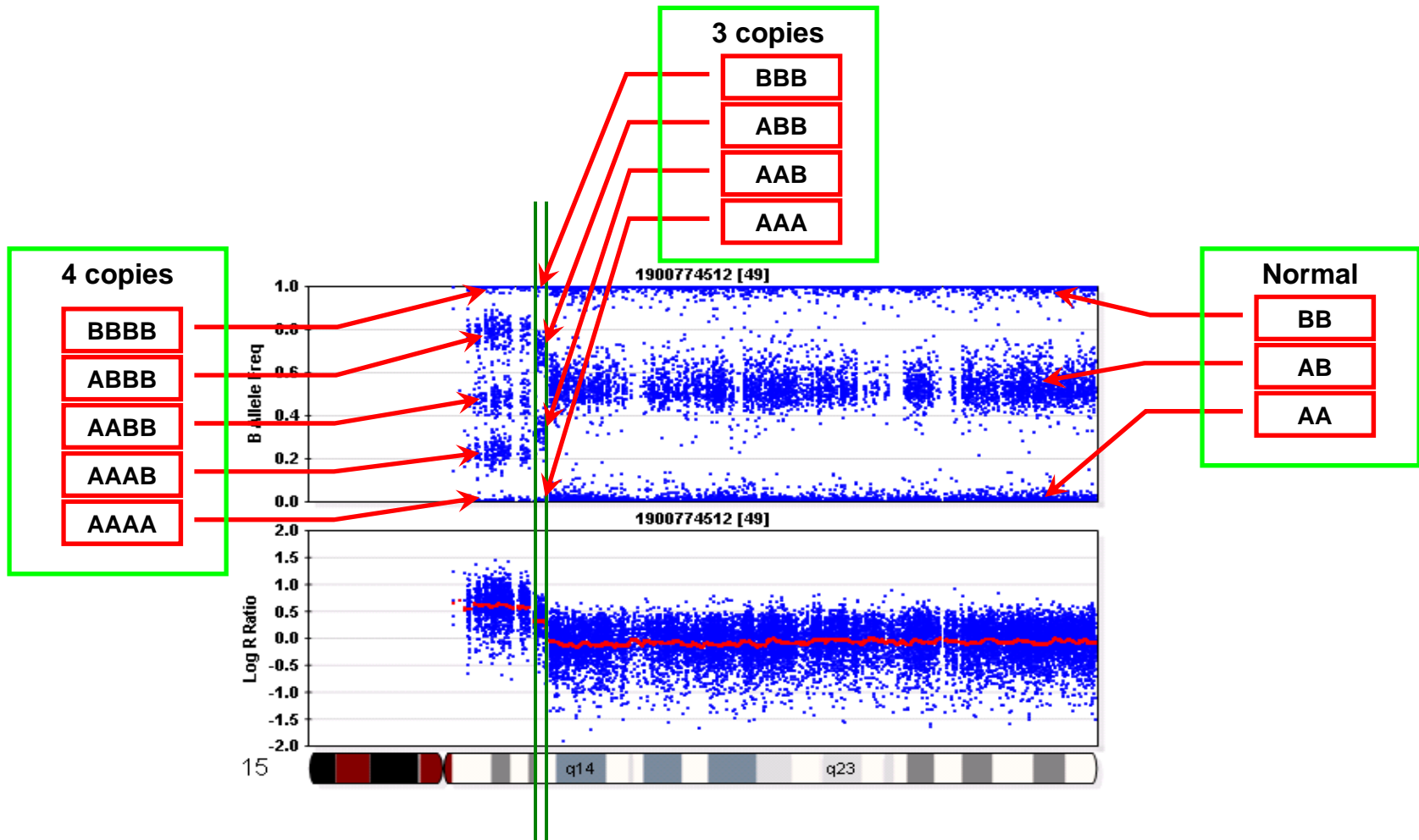


# SNP Signal Intensities

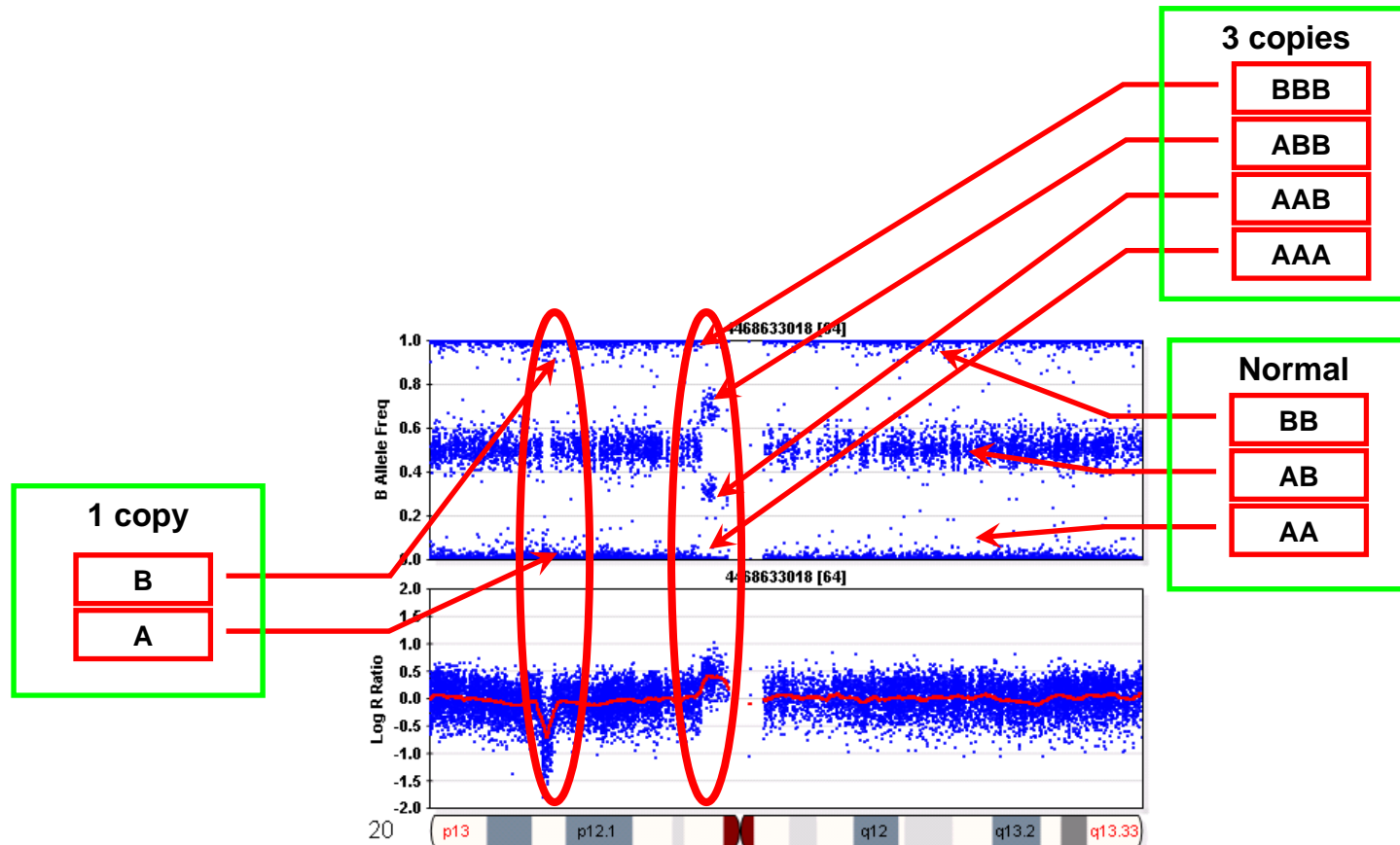


$$BAF = \begin{cases} 0, & \text{if } \theta_{\text{subject}} < \theta_{AA} \\ 0.5(\theta_{\text{subject}} - \theta_{AA}) / (\theta_{AB} - \theta_{AA}), & \text{if } \theta_{AA} \leq \theta_{\text{subject}} \leq \theta_{AB} \\ 0.5 + 0.5(\theta_{\text{subject}} - \theta_{AB}) / (\theta_{BB} - \theta_{AB}), & \text{if } \theta_{AB} \leq \theta_{\text{subject}} \leq \theta_{BB} \\ 1, & \text{if } \theta_{\text{subject}} > \theta_{BB} \end{cases}$$

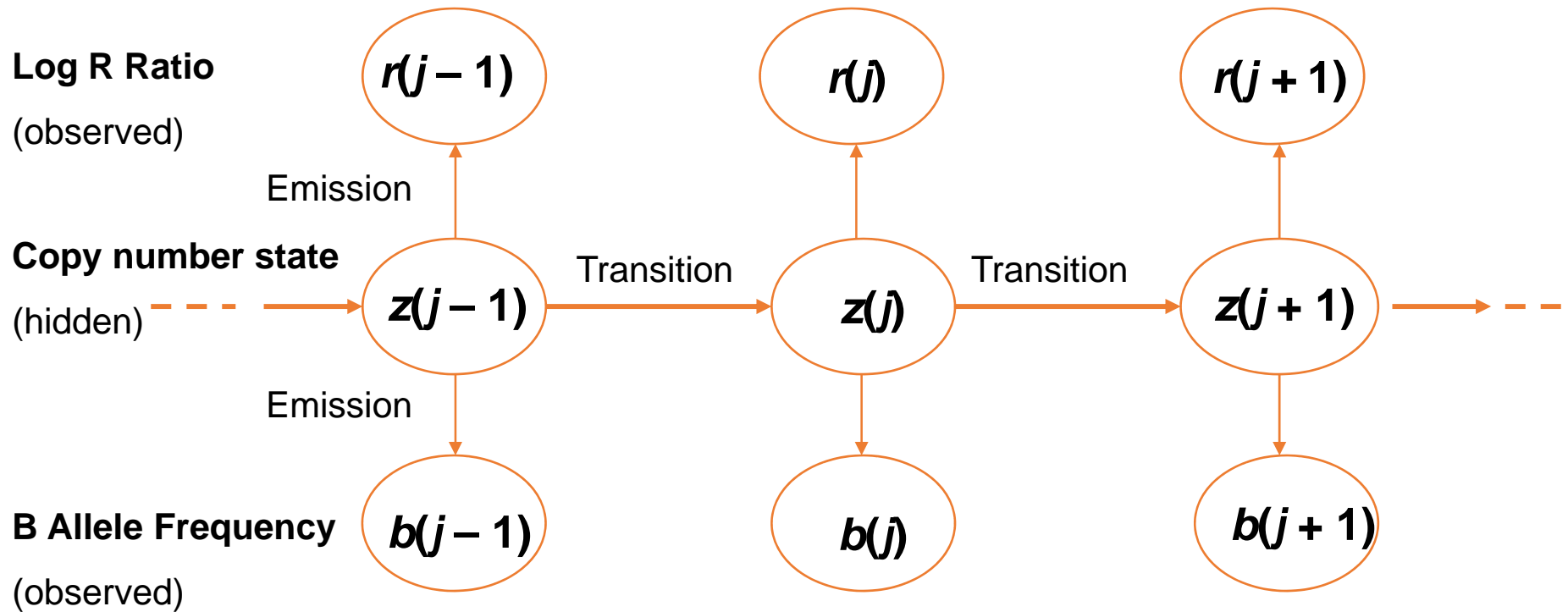
# Visualization of CNVs



# Visualization of CNVs



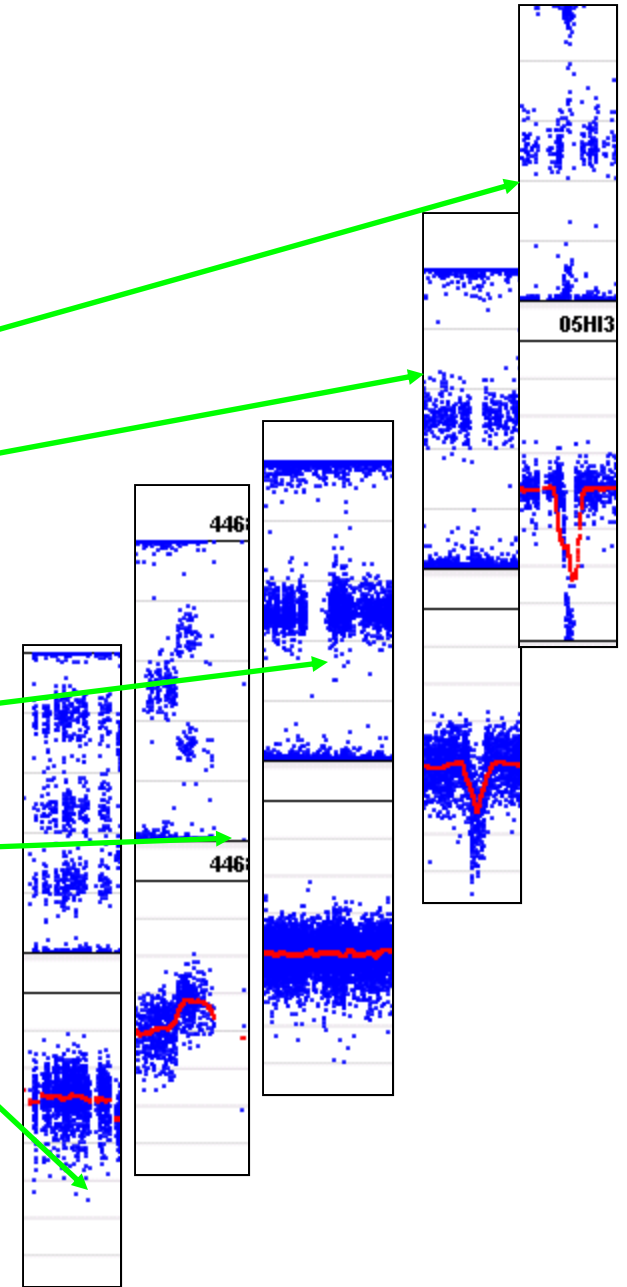
# Hidden Markov Model in PennCNV



# Copy Number States

6 States:

- State1: CNV=0 (double deletions)
- State2: CNV=1 (single deletion)
- State3: CNV=2 (normal)
- State4: CNV=2 (normal with LOH)
- State5: CNV=3 (single duplication)
- State6: CNV=4 (double duplications)



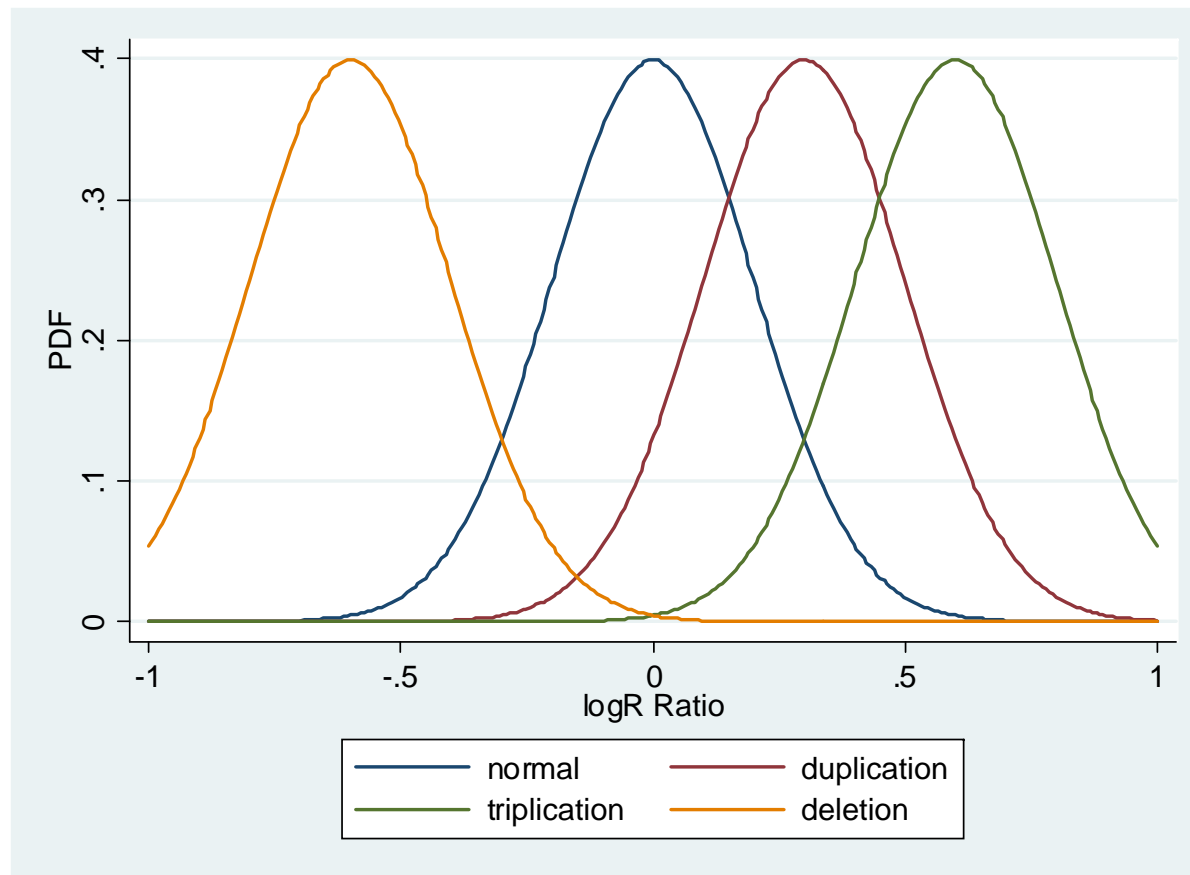
**Table 1.** Hidden states, copy numbers, and their descriptions

| Copy no. state | Total copy no. | Description (for autosome) | CNV genotypes                |
|----------------|----------------|----------------------------|------------------------------|
| 1              | 0              | Deletion of two copies     | Null                         |
| 2              | 1              | Deletion of one copy       | A, B                         |
| 3              | 2              | Normal state               | AA, AB, BB                   |
| 4              | 2              | Copy-neutral with LOH      | AA, BB                       |
| 5              | 3              | Single copy duplication    | AAA, AAB, ABB, BBB           |
| 6              | 4              | Double copy duplication    | AAAA, AAAB, AABB, ABBB, BBBB |

Each state has a different distribution of CNV genotypes.

# Emission Probability of LRR

- Given a copy number state, LRR is normally distributed



# Emission Probability of LRR

## Emission probability of log R ratio

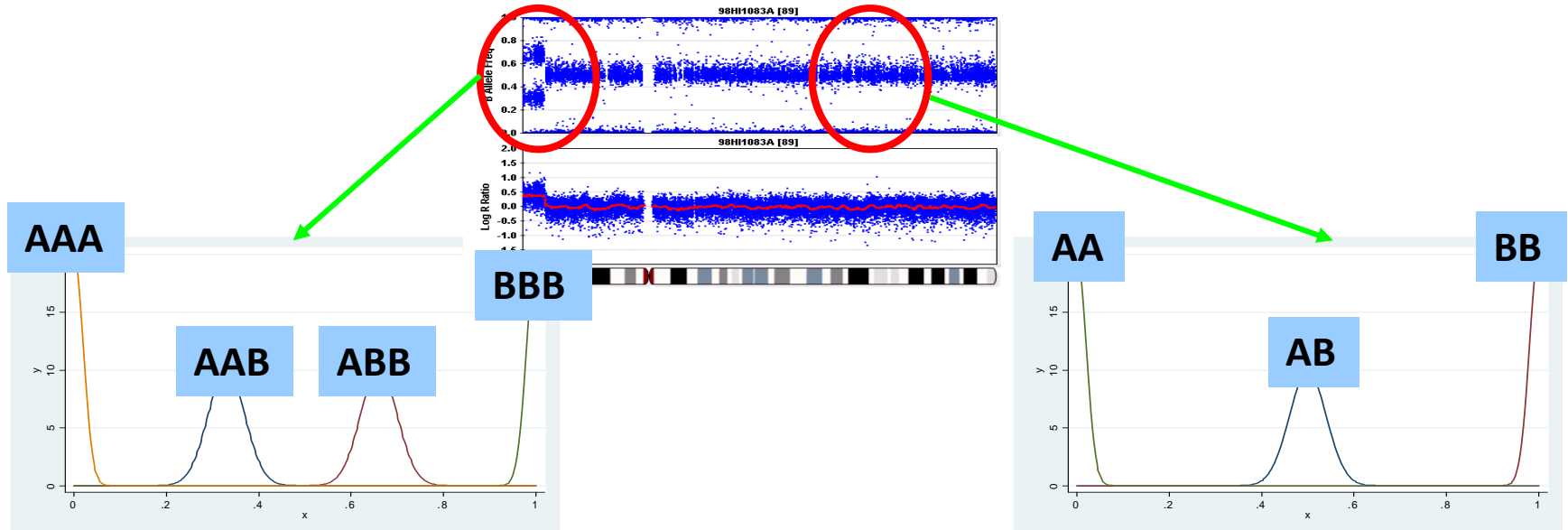
Given each hidden copy number state, the emission probability of the log R ratio is modeled as a mixture of uniform and normal distributions,

$$P(r|Z) = \pi_r + (1 - \pi_r)\phi(r; \mu_{r,z}, s_{r,z})$$

where  $(\phi\cdot;\cdot)$  is the density function of a normal distribution with mean  $\mu_{r,z}$  and standard deviation  $s_{r,z}$ . Here the uniform distribution is used to model both random fluctuation of signal measures in chemical assays and the possible genome misannotation and misassembly.



# Emission Probability of BAF



$$P(b_j | z_j, \lambda) = \sum_g P(b_j | g, z_j, \lambda) P(g | z_j, \lambda)$$

$$P(b_j | g, z_j, \lambda) = \begin{cases} \phi(b_j; \mu_{BAF, z_j, g}, \sigma_{BAF, z_j, g}), & \text{if } 0 < g < C(z_j) \\ I_{\{b_j=0\}} M_0 + I_{\{0 < b_j < 1\}} \phi(b_j; \mu_{BAF, z_j, g}, \sigma_{BAF, z_j, g}), & \text{if } g = 0 \\ I_{\{b_j=1\}} M_1 + I_{\{0 < b_j < 1\}} \phi(b_j; \mu_{BAF, z_j, g}, \sigma_{BAF, z_j, g}), & \text{if } g = C(z_j) \end{cases}$$

# Emission Probability of BAF

| Copy number state | Total copy number | Mode of B Allele Frequency distribution                                   |
|-------------------|-------------------|---|
| 1                 | 0                 | $\mu_{1,1}=0.5$   |
| 2                 | 1                 | $\mu_{2,1}=0, \mu_{2,2}=1$  |
| 3                 | 2                 | $\mu_{3,1}=0, \mu_{3,2}=0.5, \mu_{3,3}=1$                                 |
| 4                 | 2                 | $\mu_{4,1}=0, \mu_{4,2}=1$  |
| 5                 | 3                 | $\mu_{5,1}=0, \mu_{5,2}=0.33, \mu_{5,3}=0.66, \mu_{5,4}=1$                |
| 6                 | 4                 | $\mu_{6,1}=0, \mu_{6,2}=0.25, \mu_{6,3}=0.5, \mu_{6,4}=0.75, \mu_{6,5}=1$ |

# Hidden states, copy numbers, CNV genotypes, and their descriptions

| Copy number state | Total copy number | Description             | CNV genotypes                | BAF values            |
|-------------------|-------------------|-------------------------|------------------------------|-----------------------|
| 1                 | 0                 | Deletion of two copies  | Null                         | –                     |
| 2                 | 1                 | Deletion of one copy    | A, B                         | 0, 1                  |
| 3                 | 2                 | Normal state            | AA, AB, BB                   | 0, 0.5, 1             |
| 4                 | 2                 | Copy-neutral with LOH   | AA, BB                       | 0, 1                  |
| 5                 | 3                 | Single copy duplication | AAA, AAB, ABB, BBB           | 0, 0.33, 0.67, 1      |
| 6                 | 4                 | Double copy duplication | AAAA, AAAB, AABB, ABBB, BBBB | 0, 0.25, 0.5, 0.75, 1 |

# Transition Probability

Transition of copy number states from SNP  $j$  to SNP  $j + 1$

$$P(z_{j+1} = l \mid z_j = h, \lambda) = \begin{cases} 1 - \sum_{s \neq h} p_{h,s} (1 - e^{-d_j/D}) & \text{if } l = h \\ p_{h,l} (1 - e^{-d_j/D}) & \text{if } l \neq h \end{cases}$$

$d_j$ : physical distance between SNP  $j$  and SNP  $j + 1$

$D$ : standardizing constant

# Likelihood

Assume  $M$  SNPs are genotyped, then the likelihood of LRR and BAF is

$$P(r_1, \dots, r_M, b_1, \dots, b_M) = \sum_{z_1} \cdots \sum_{z_M} P(r_1, \dots, r_M, b_1, \dots, b_M \mid z_1, \dots, z_M) P(z_1, \dots, z_M)$$

Assume conditional independence between LRR and BAF given copy number state, then

$$P(r_1, \dots, r_M, b_1, \dots, b_M) = \sum_{z_1} \cdots \sum_{z_M} \left\{ \left( \prod_{i=1}^M P(r_i \mid z_i) P(b_i \mid z_i) \right) \left( P(z_1) \prod_{i=2}^M P(z_i \mid z_{i-1}) \right) \right\}$$

# CNV Calling

- Use Viterbi algorithm to infer the most likely state path  $z = (z_1, \dots, z_M)$ , by maximizing  $P(z | r, b, \lambda)$ .
- Calculation is speed up using Baum's forward-backward algorithm.
- A CNV is called whenever a stretch of states different from the normal state is observed.
- Algorithm is implemented in software PennCNV.

<http://penncnv.openbioinformatics.org/en/latest/>

# CNV Calling

- Viterbi algorithm for calling
  - Calculate the most likely path in HMM (a path of state 1-6 for each SNP marker)
  - Collect any non-normal state path as the CNV calls
  - Example:

Most likely CN sequence is:

222222221111111222222222222222222222224444422222222222

CNV !

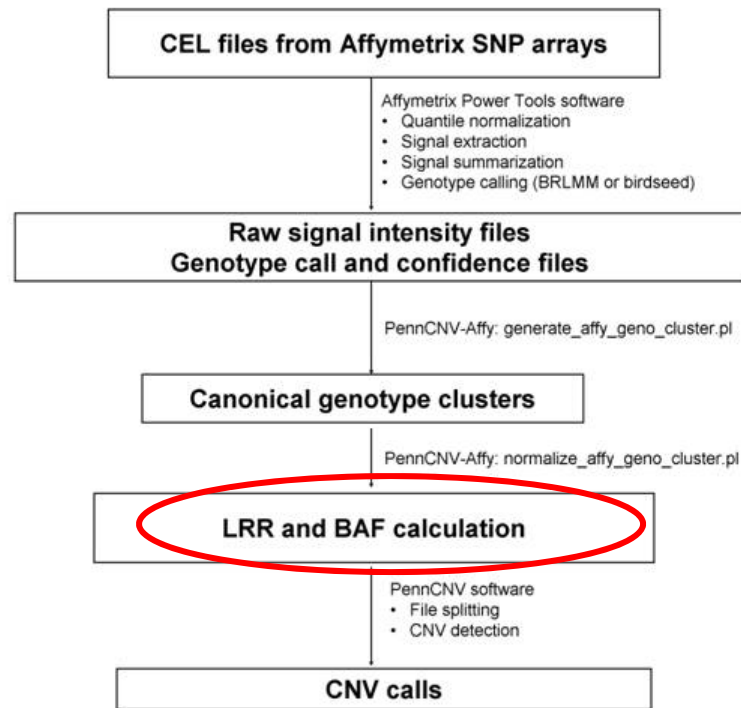
CNV !

# Other Types of Signal Data

- PennCNV can be applied to data from other technical platforms:
  - Transformation of signal data to LRR/BAF:
    - Affymetrix whole-genome SNP genotyping array
    - Perlegen whole-genome SNP genotyping array
  - Use information from LRR only:
    - BAC clone based array-CGH
    - Oligonucleotide arrays
    - Non-polymorphic markers in recent SNP genotyping arrays

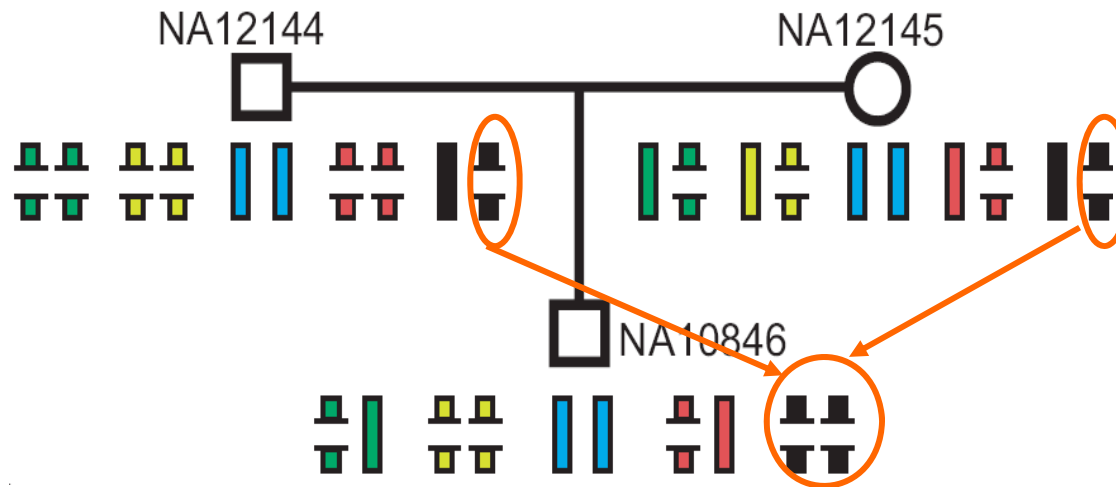


# PennCNV-Affy Pipeline



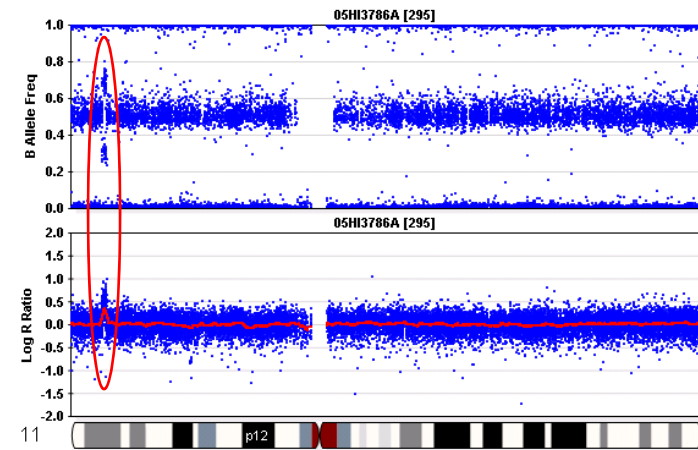
# Joint Modeling on Family Data

- Most CNVs demonstrate Mendelian inheritance

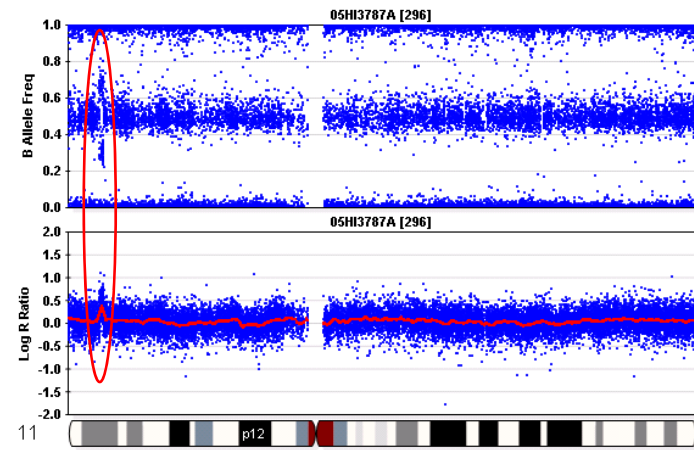


- Incorporate family relationship can potentially improve sensitivity of CNV calling

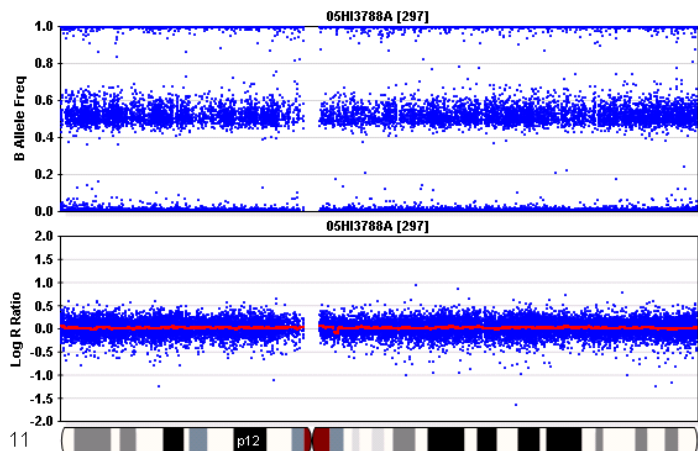
# Example of Inherited CNV



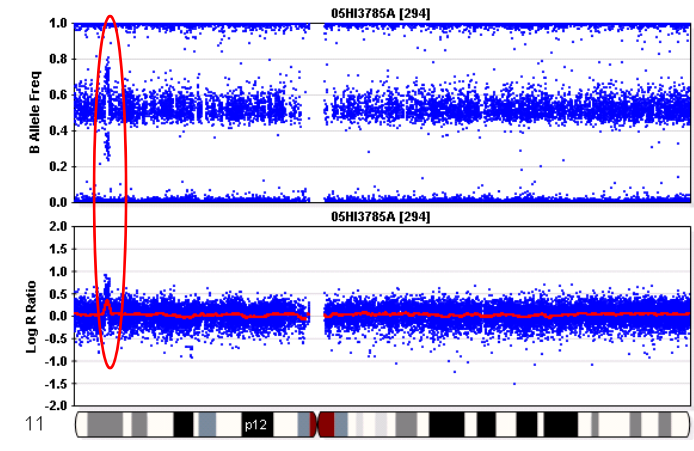
**Father**



**Child 1**



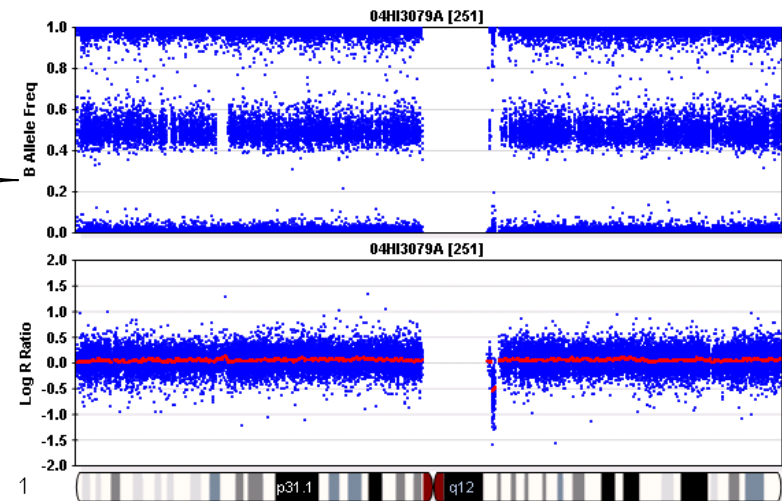
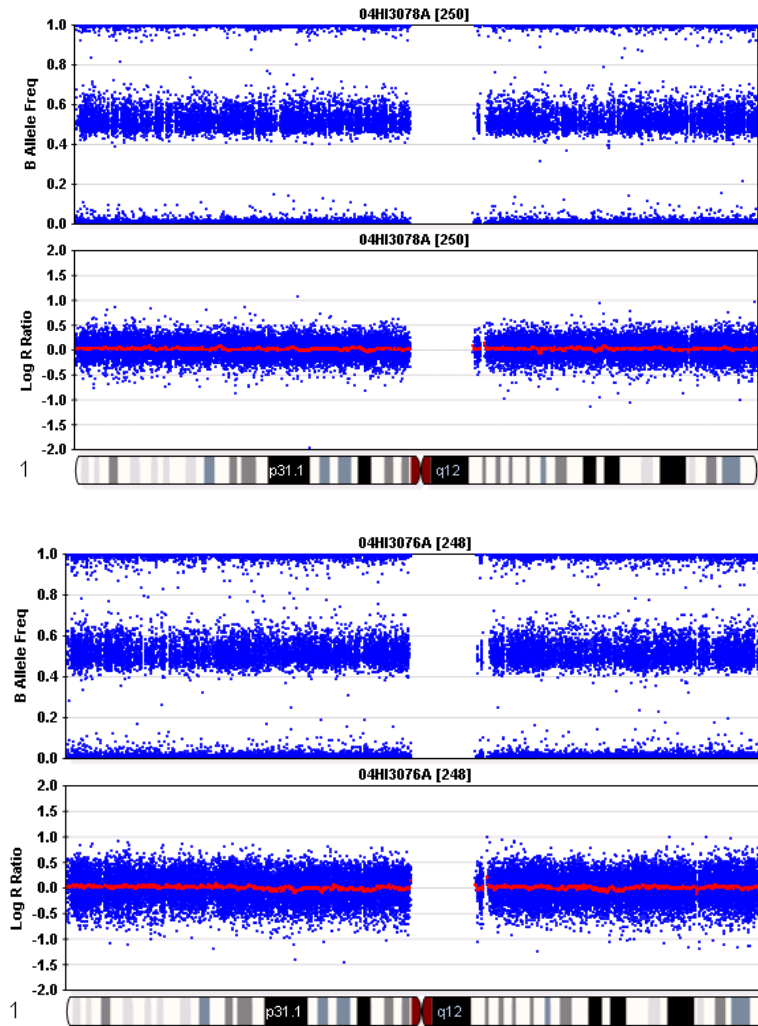
**Mother**



**Child 2**

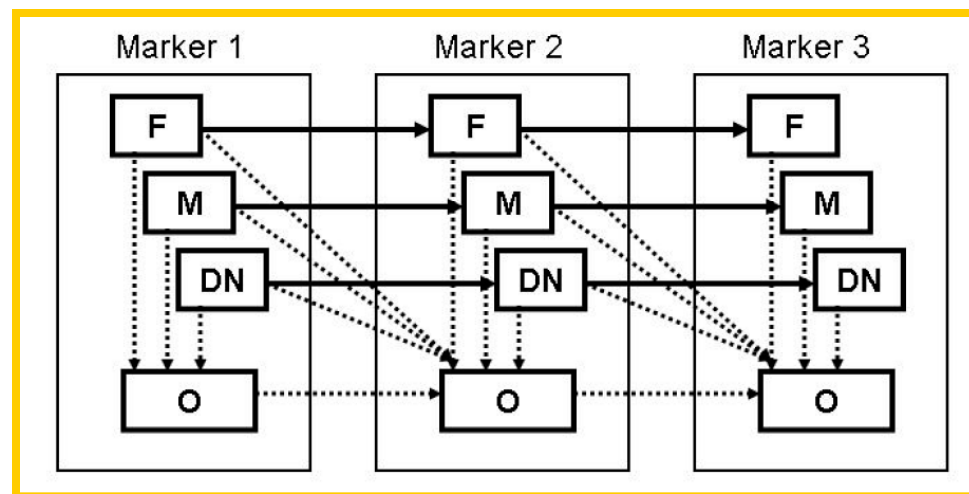
# Example of *de novo* CNV

Some CNVs are due to *de novo* events, which occur as germline, somatic or cell line-induced chromosome aberrations in offspring that are not inherited from either parent.



# Joint modeling of the CNVs in a trio

- A HMM that jointly models a trio simultaneously
- Do not assume that CNV region is already known



**F**: father; **M**: mother; **O**: offspring; **DN**: *de novo* event status.

# Likelihood of Signal Intensities

$$\begin{aligned}
 & P(r_1, \dots, r_T, b_1, \dots, b_T \mid \lambda) \\
 &= \sum_{z_1} \cdots \sum_{z_T} \sum_{DN_1} \cdots \sum_{DN_T} \{ P(r_1, \dots, r_T \mid z_1, \dots, z_T, \lambda) \times \\
 &\quad P(b_1, \dots, b_T \mid z_1, \dots, z_T, \lambda) \times \\
 &\quad P(z_1, \dots, z_T \mid DN_1, \dots, DN_T, \lambda) \times \\
 &\quad P(DN_1, \dots, DN_T \mid \lambda) \} \\
 &= \sum_{z_1} \cdots \sum_{z_T} \sum_{DN_1} \cdots \sum_{DN_T} \{ \underbrace{P(r_1 \mid z_1, \lambda)}_{\text{Emission prob of LRR}} \underbrace{P(b_1 \mid z_1, \lambda)}_{\text{Emission prob of BAF}} \underbrace{P(z_1 \mid DN_1, \lambda)}_{\text{Initial prob of CN states}} \underbrace{P(DN_1 \mid \lambda)}_{\text{Initial prob of de novo event status}} \times \\
 &\quad \prod_{j=2}^T \underbrace{P(r_j \mid z_j, \lambda)}_{\text{Emission prob of LRR}} \underbrace{P(b_j \mid z_j, \lambda)}_{\text{Emission prob of BAF}} \underbrace{P(z_j \mid z_{j-1}, DN_j, DN_{j-1}, \lambda)}_{\text{Transition prob of CN states}} \underbrace{P(DN_j \mid DN_{j-1}, \lambda)}_{\text{Transition prob of de novo event status}} \}
 \end{aligned}$$

By treating the trio as a unit, this calling algorithm can avoid generating calls that are Mendelian inconsistent but preserve the ability to allow *de novo* events.

# Inferring chromosome-specific copy numbers

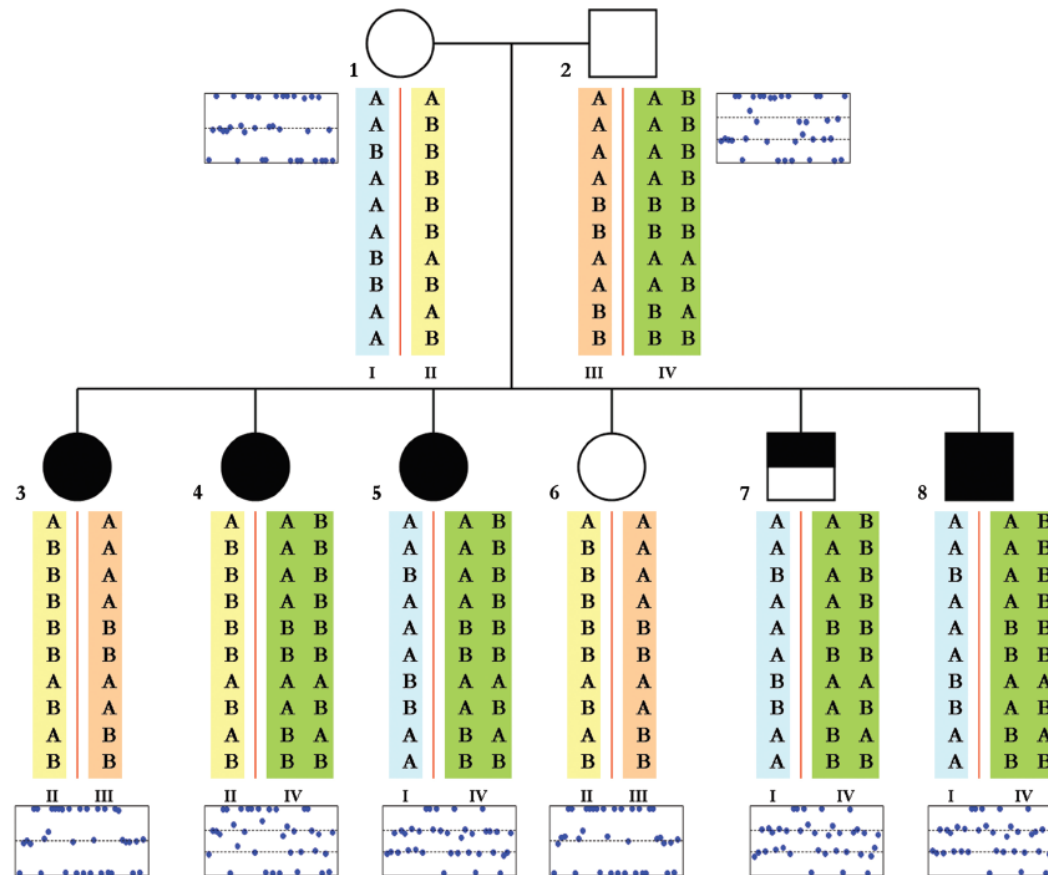
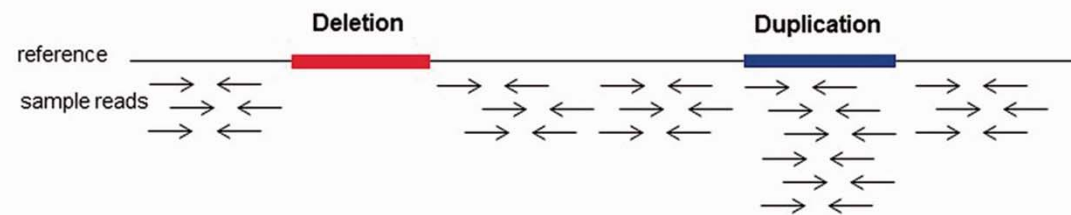


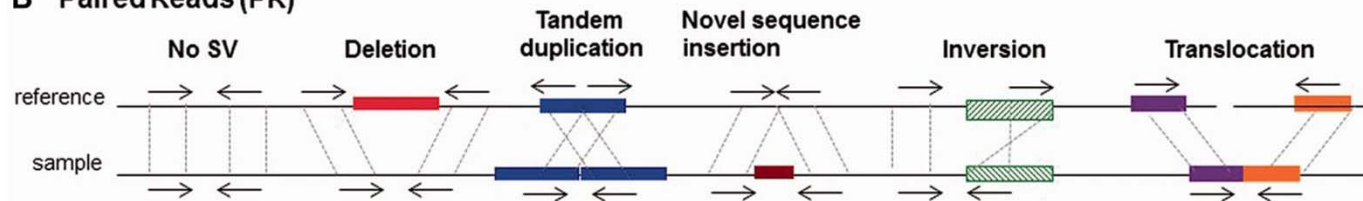
Figure 4. Illustration of a duplication CNV on 10q11.22 that exists in the father and is transmitted to four offspring. The CNV calls are made on six trios separately by the joint-calling algorithm. For each individual, the BAF values for all SNPs within the CNV and the chromosome-specific SNP genotypes (for the first 10 SNPs) are displayed, and the SNP genotypes for the entire region are listed at Supplementary Table 4. The four different parental CNV haplotypes are marked by different colors and denoted by I through IV beneath the genotypes. Combining information from total copy number and the SNP genotypes, we can infer the SNP allele compositions within each homologous chromosome confidently for each offspring.

# NGS-based SV detection

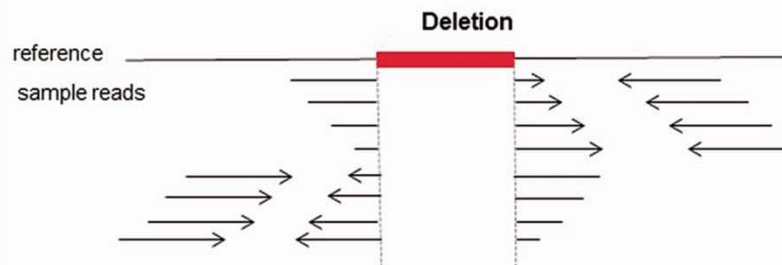
## A Read Depth (RD)



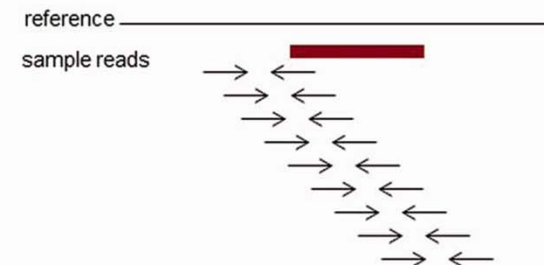
## B Paired Reads (PR)



## C Split Reads (SR)



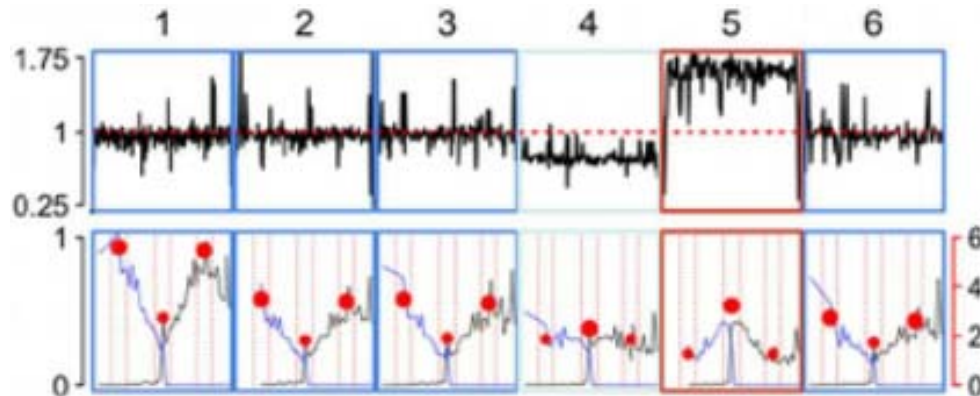
## D. De Novo Assembly (AS)





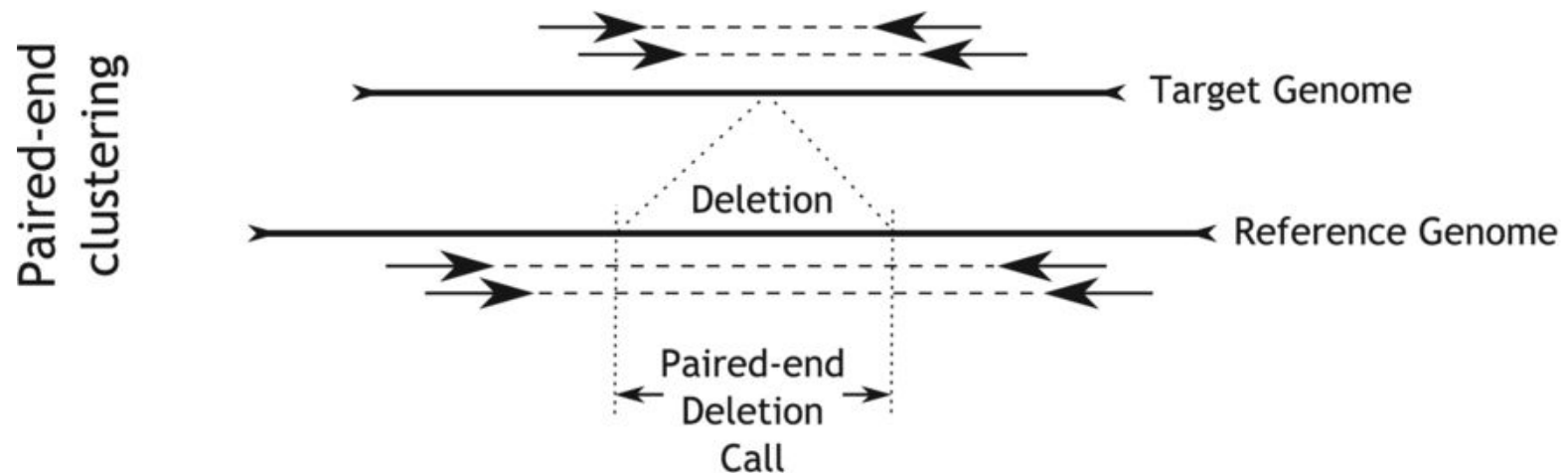
# Read count-based methods for SV detection

- Detect the change of read count/sequencing coverage in a certain region.
- Examples of software tools: CNVnator, BIC-SEQ2, PennCNV-Seq
- Limitation:
  - 1) Only detects unbalanced events (copy number variation).
  - 2) Cannot resolve breakpoints at base pair resolution.



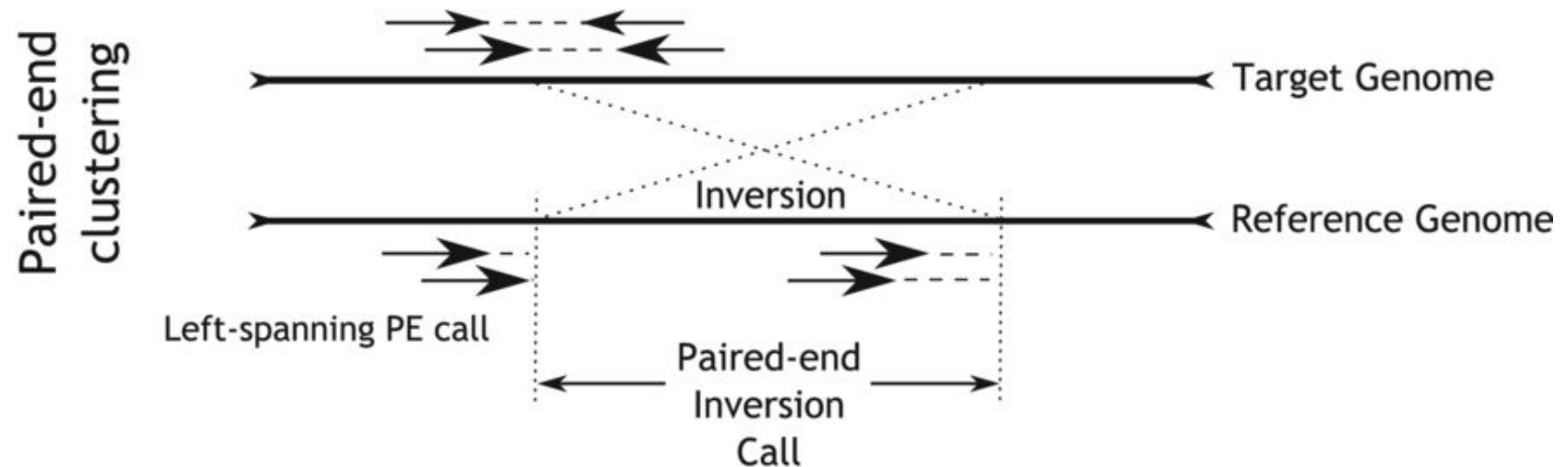
# Detection of SVs from discordant read pairs

- Widely used software tools: Delly, Lumpy
- Pattern of deletions: large gaps between read pairs:



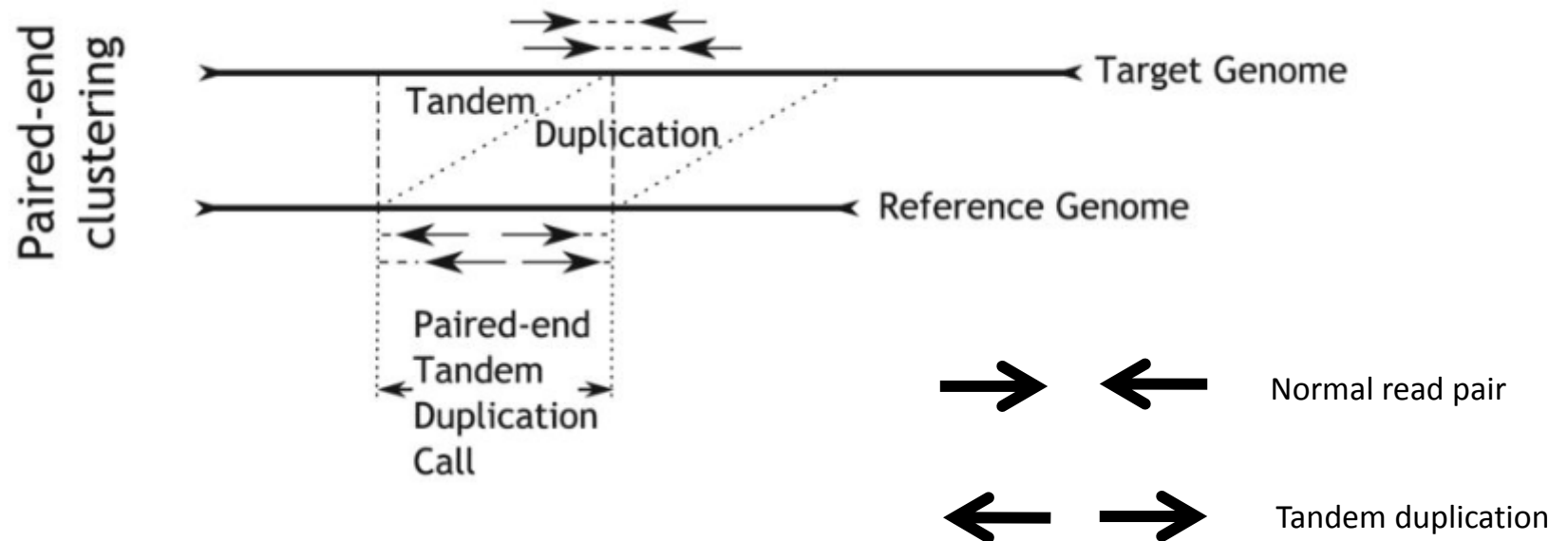
# Detection of SVs from discordant read pairs

- Pattern of inversions: same orientation between read pairs:



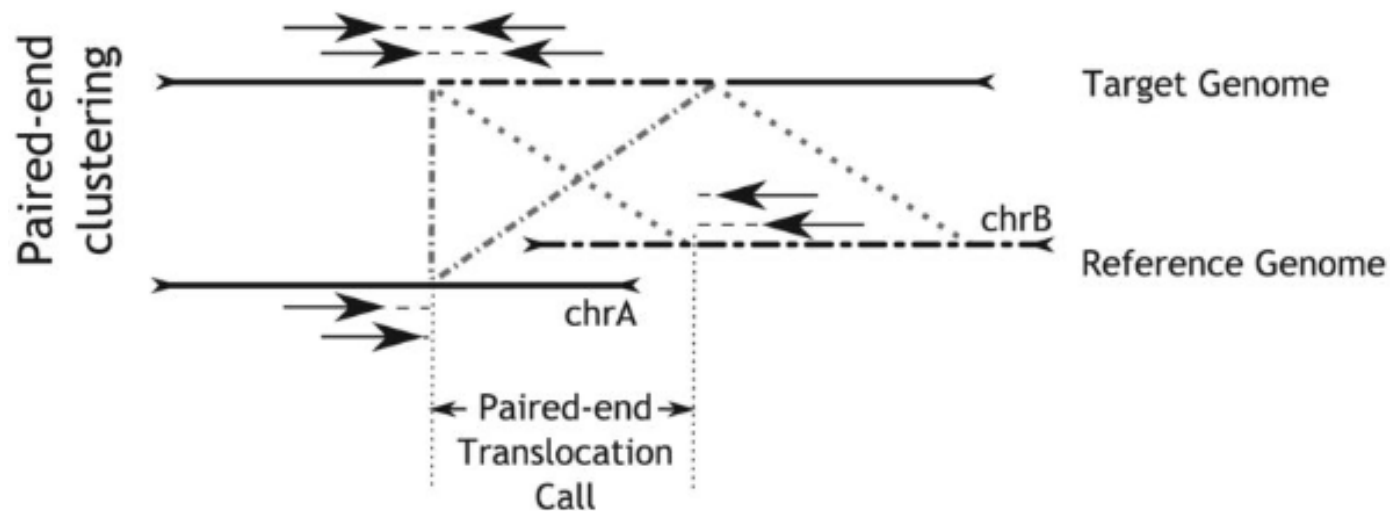
# Detection of SVs from discordant read pairs

- Pattern of tandem duplication: the first and second read changed their relative order



# Detection of SVs from discordant read pairs

- Pattern of translocations: paired-ends mapping to different chromosomes

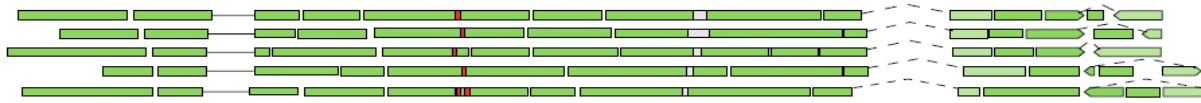


# Detection of SVs using assembly-based methods

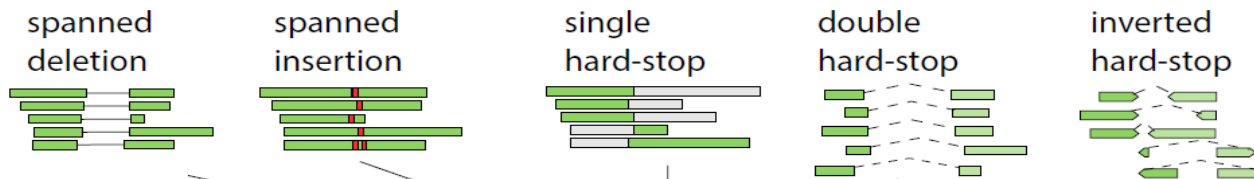
- De novo sequence assembly (AS) enables the fine-scale discovery of SVs, including novel (non-reference) sequence insertions
- Either global or local assembly may be used to discover SVs
- Example tools:
  - SvABA (genome-wide detection of structural variants and indels by local assembly)
  - novoBreak (local assembly for breakpoint detection in cancer genomes)
  - TIGRA (a targeted iterative graph routing assembler for breakpoint assembly)

# Conceptual overview on local assembly

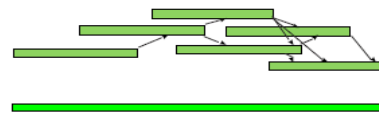
BLASR alignment of reads



Signatures of structural variants



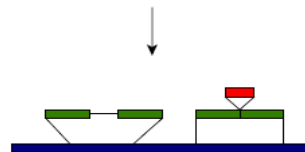
Celera assembly



Remap reads,  
generate Quiver consensus

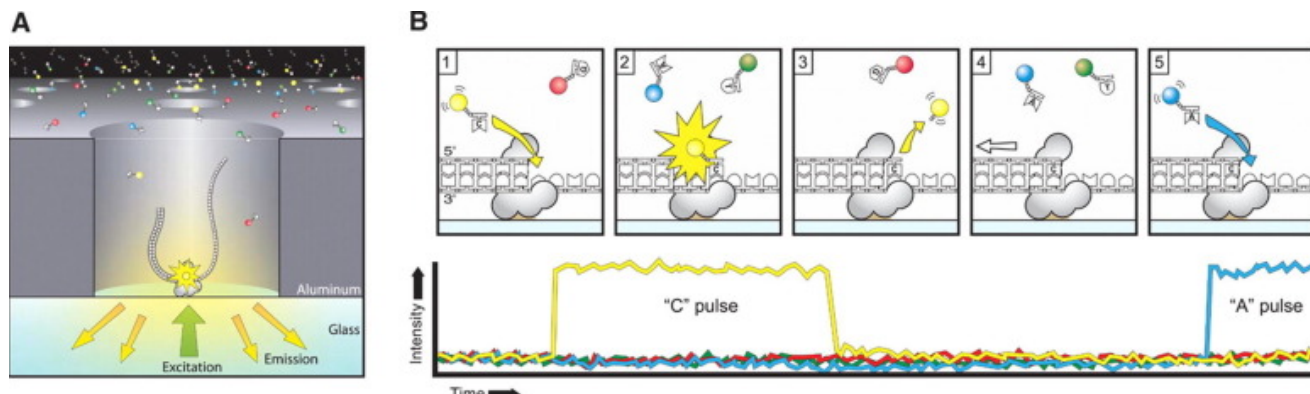


Map consensus,  
structural variant resolution



# Long-read sequencing technologies

- **PacBio (Pacific Biosciences) sequencing:**
- Typically generates reads with N50 read length of >10kb.
- Error rate: about 15% (CLS) or 1% (CCS)



A double stranded DNA diffuses into a unit called ZMW, and the adaptor binds to a polymerase immobilized at the bottom.

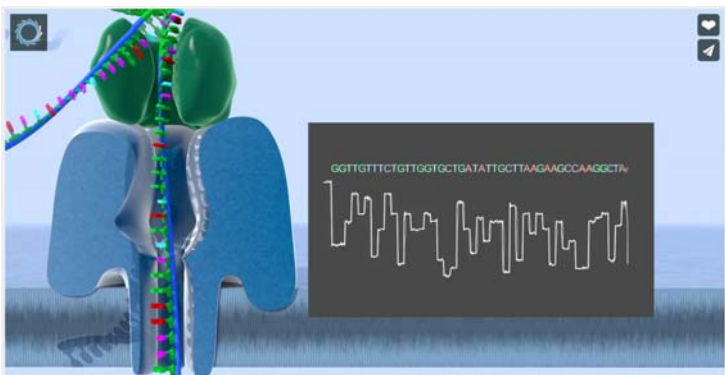
Each of the four nucleotides is labeled with a different fluorescent dye (indicated in red, yellow, green, and blue, respectively for G, C, T, and A) so that they have distinct emission spectrums



# Long-read sequencing technologies

- **Oxford Nanopore Technologies:**

- Regular libraries generate reads with N50 length ~20-30 kb
- Ultra-long libraries generate reads with N50 length to >100 kb but with lower throughput
- Error rate: on average 15%. The error rate in some regions (especially homopolymer regions) could be higher.



The DNA molecule passes through a protein pore bounded in a membrane and the current changes are used to infer the DNA sequence.

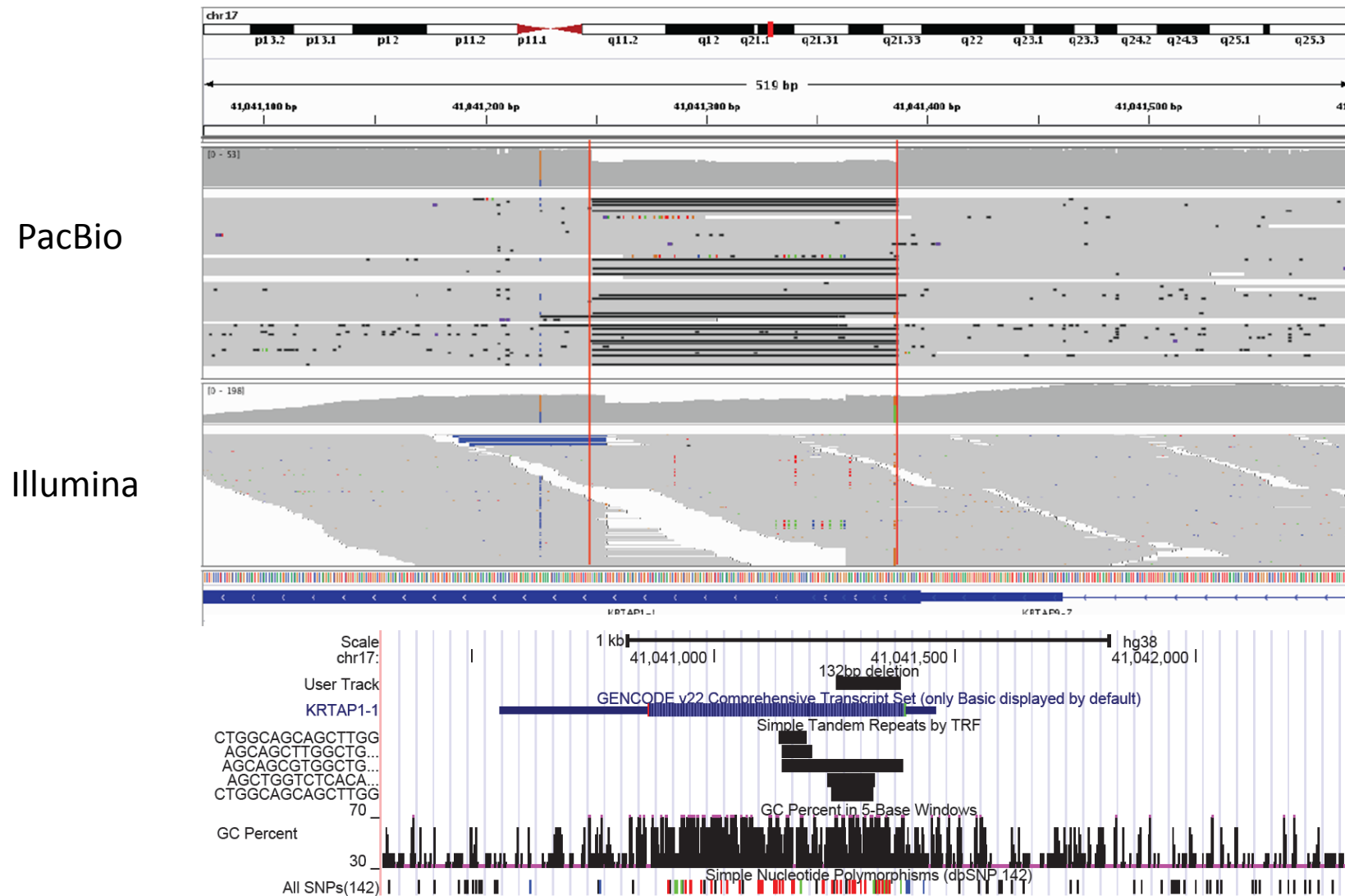
# Mapping long reads to the reference genome

- Multiple alignment tools have been developed to map long reads to the reference genome.
  - **Minimap2**: a ultra-fast long read alignment tool.
  - **NGMLR**: an aligner that is specifically developed for SV discovery.
  - BLASR: a aligner developed for PacBio reads
  - BWA-MEM: an early aligner for long reads, could be replaced by Minimap2

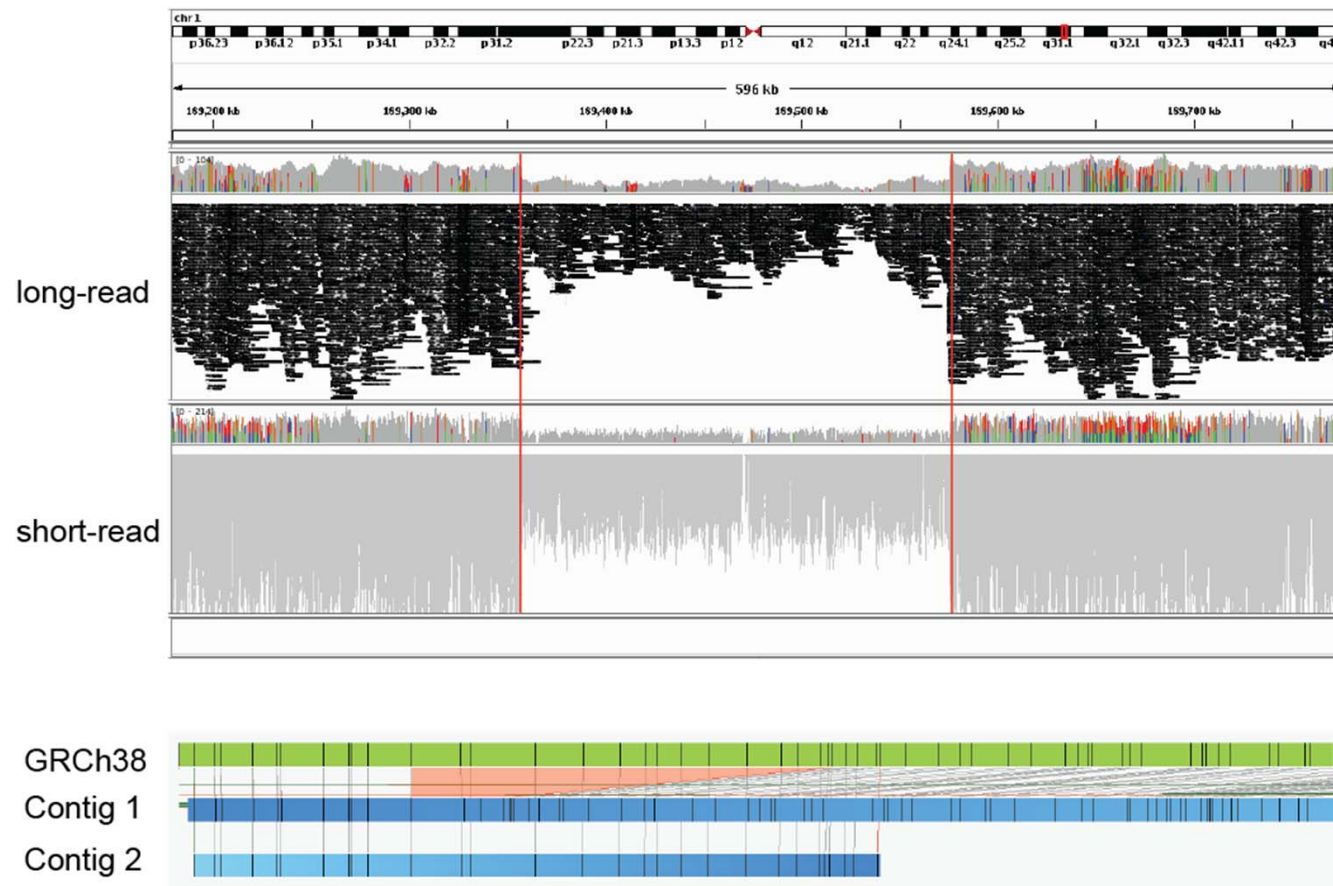
# SV detection from long-read sequencing

- Several tools have been developed to detect SVs from long read sequencing. This is an area under active development, and novel software tools are constantly being developed and published
- SV callers for PacBio reads:
  - PBSV
  - SMRT-SV
  - PBHoney
- SV callers for Nanopore reads:
  - NanoSV
  - Sniffles

# Short/long reads on SV detection

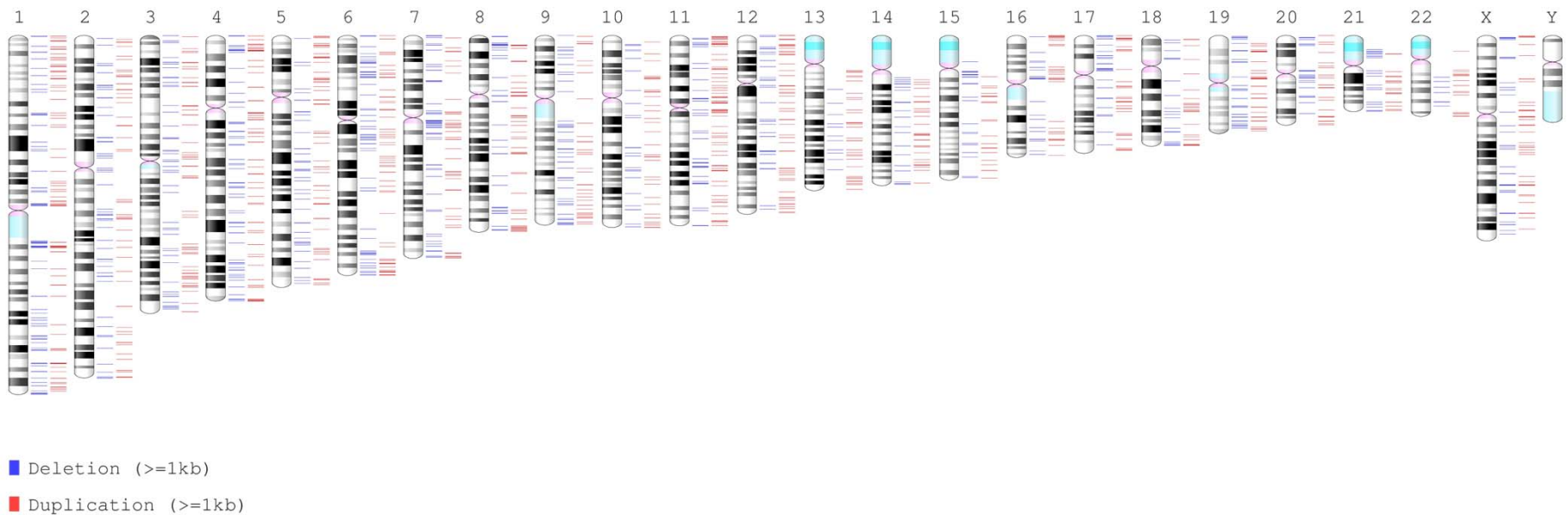


# Short/long reads on SV detection



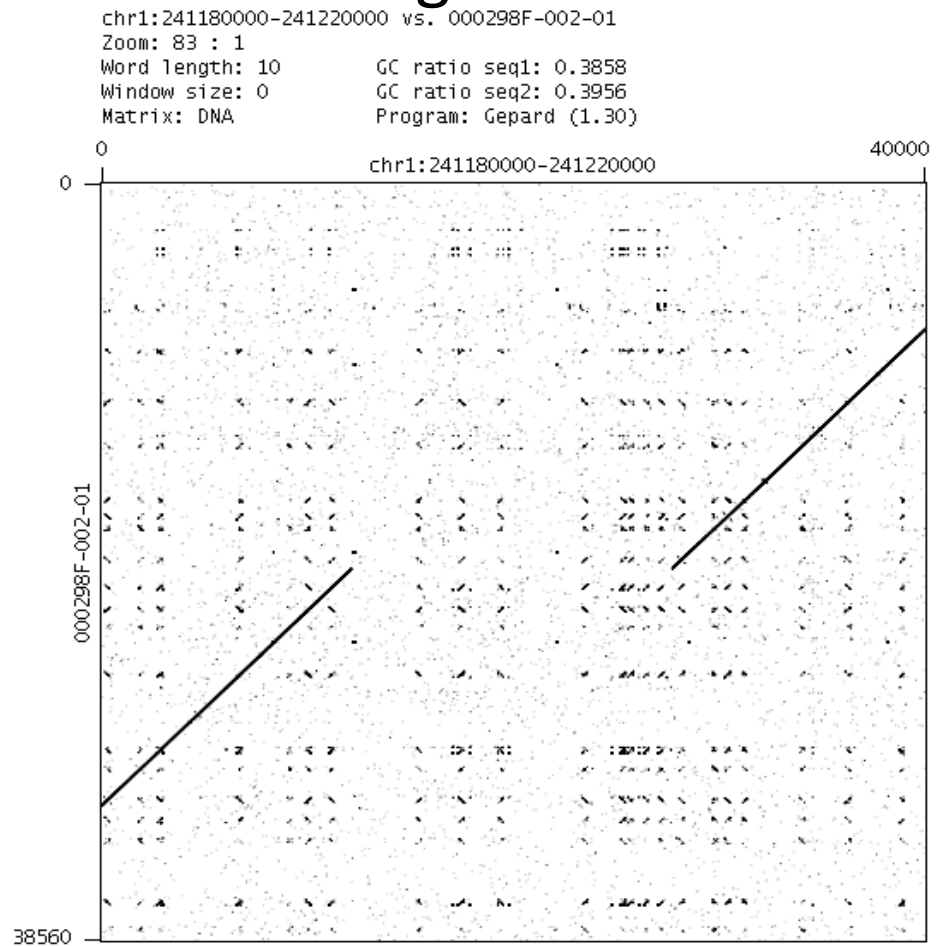
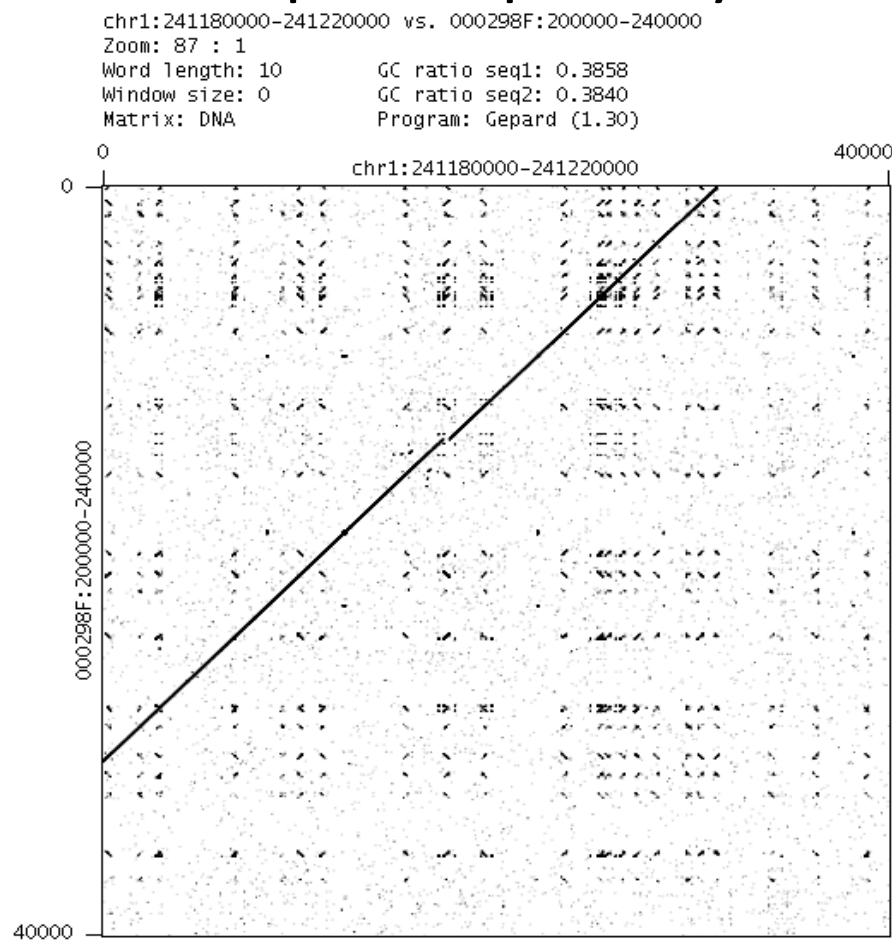
# Example of SV detection from long-read sequencing

- 9,643 deletions and 10,022 insertions



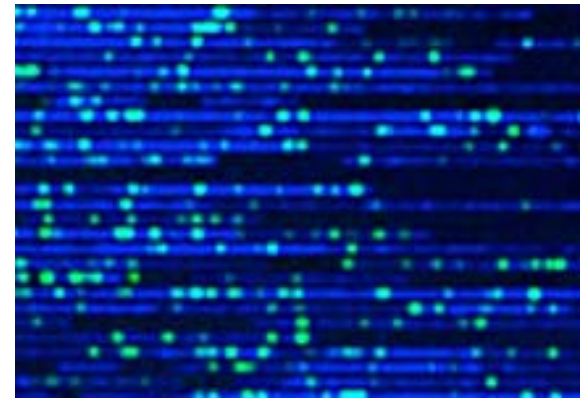
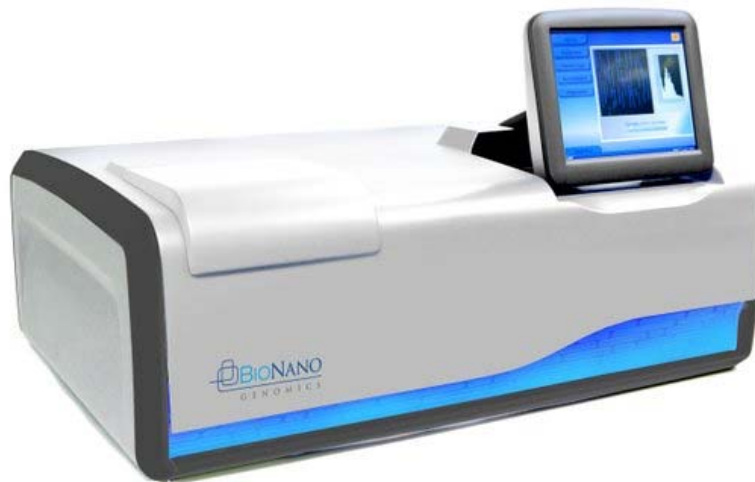
# Assembly-based SV detection

- Dot plot of primary and associate contig



# Bionano optical mapping

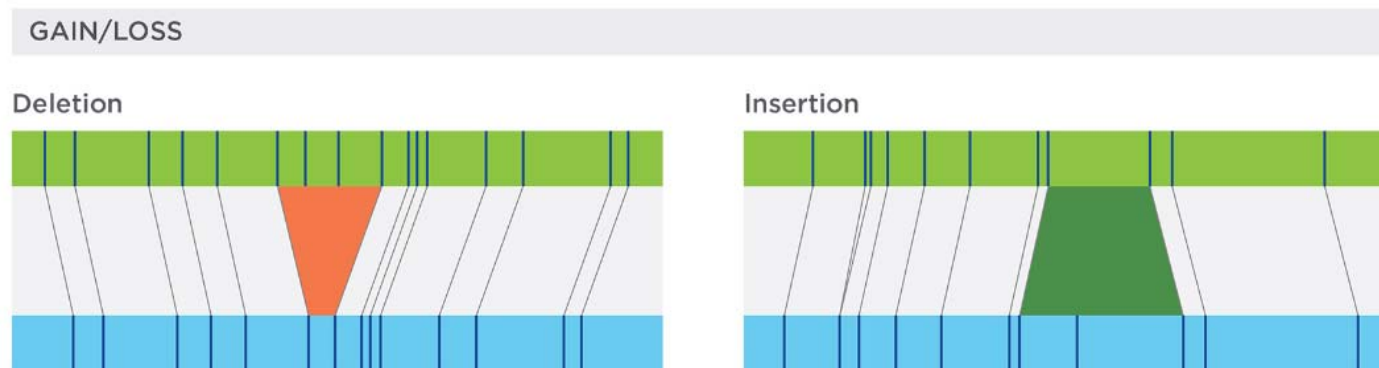
- A nanopore array that detects a characteristic 6 or 7-nucleotide sequence along very long genomic segments





# SV detection from Single-molecule optical mapping

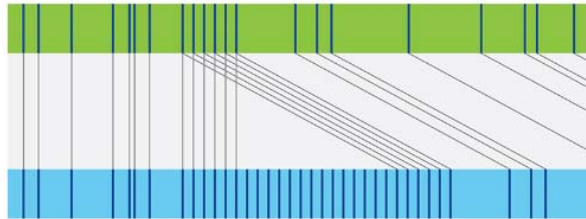
- To identify a structural variation, a *de novo* genome map assembly can be aligned to a reference genome.
- By observing changes in label spacing and comparisons of order, position, and orientation of label patterns, SVs can be detected.



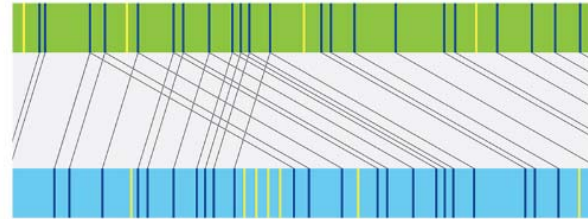
# SV detection from Single-molecule optical mapping

## COPY NUMBER CHANGE

Repeat array expansion

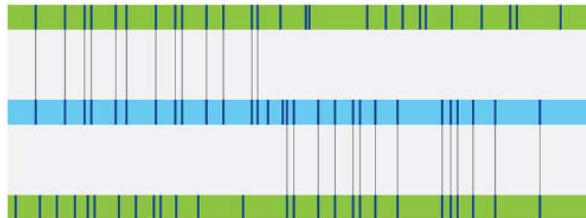


Tandem duplication



## BALANCED

Translocation



Inversion

