

Somatic Variant Calling

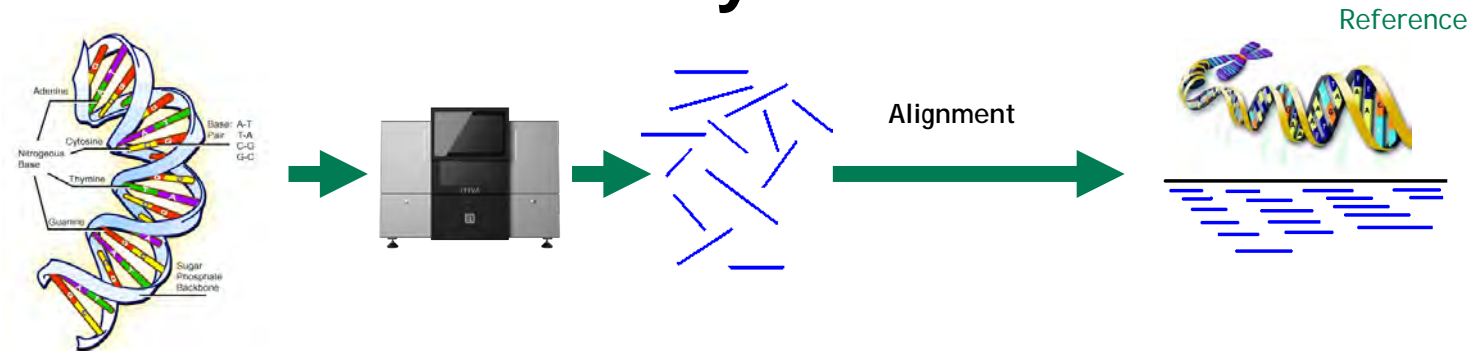
Tobias Rausch

European Molecular Biology Laboratory (EMBL)

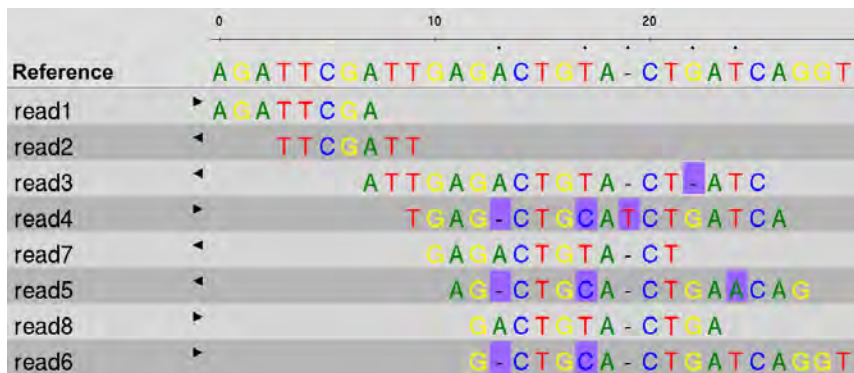
5 February 2026



Genome Variation Discovery



Alignment



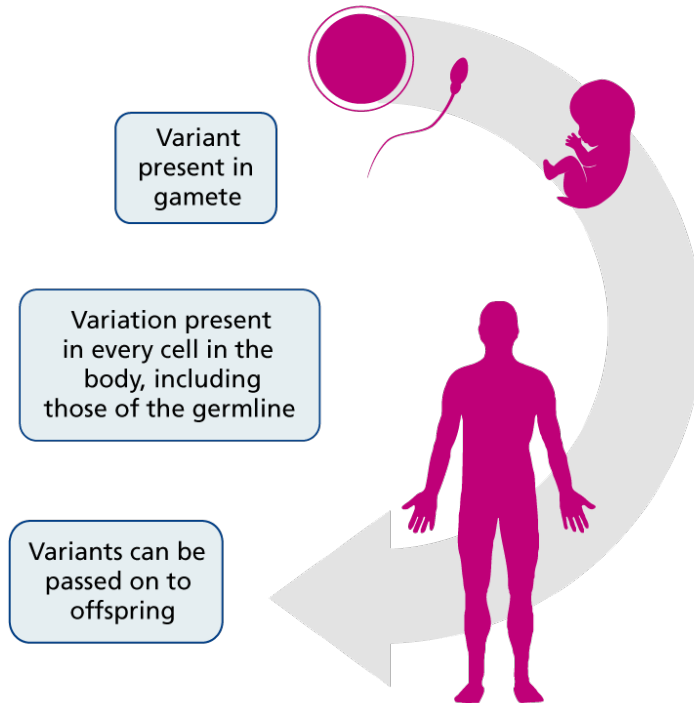
Variants

CHR	POS	ID	REF	ALT	GT
chr1	12	.	GA	G	0/1
chr1	17	rs123	T	C	0/1

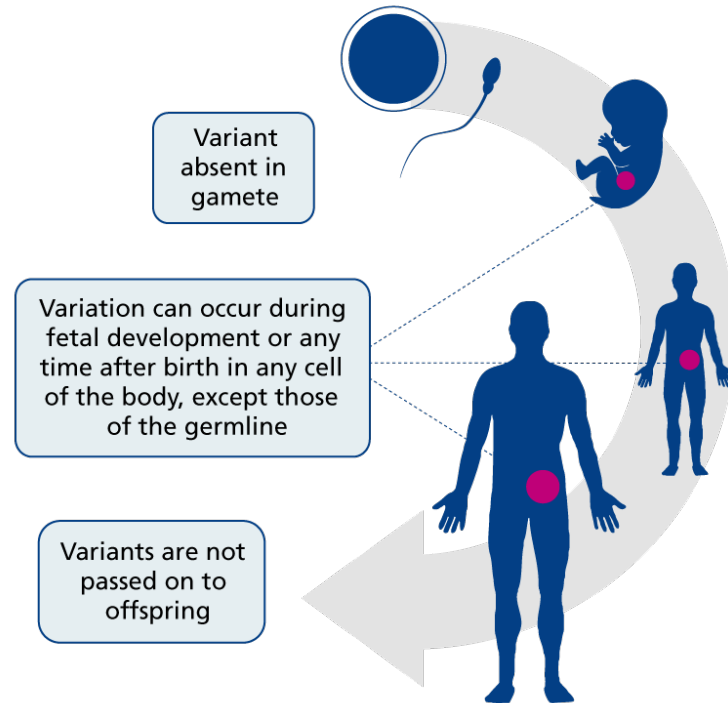
Genotype (GT):
0/0: Homozygous reference
0/1: Heterozygous
1/1: Homozygous alternative

Germline and somatic variants

Germline Variants

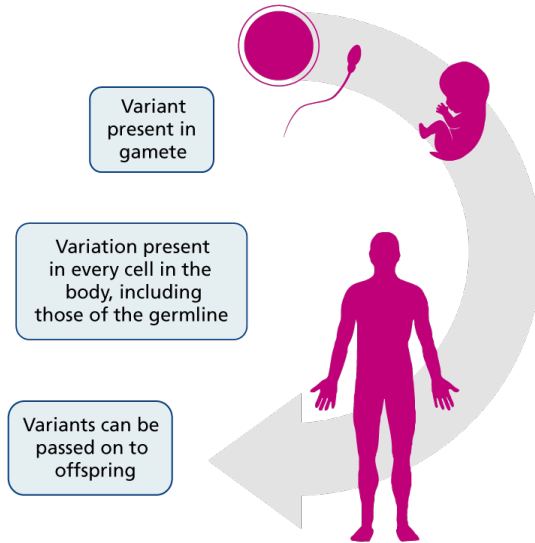


Somatic Variants

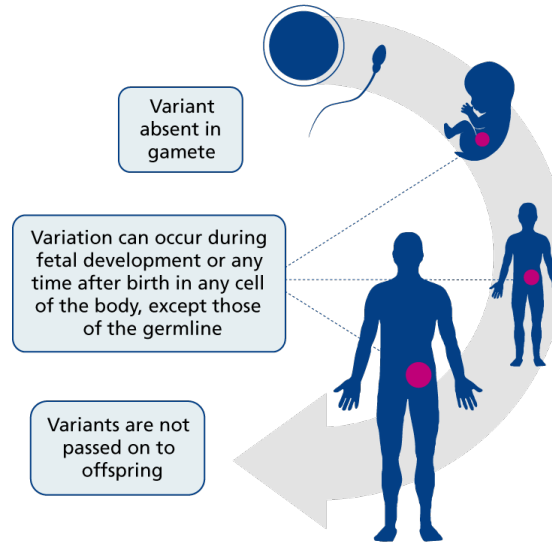


Germline and somatic variants

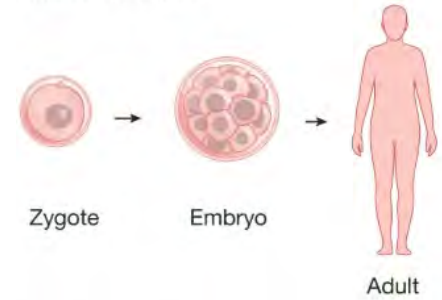
Germline Variants



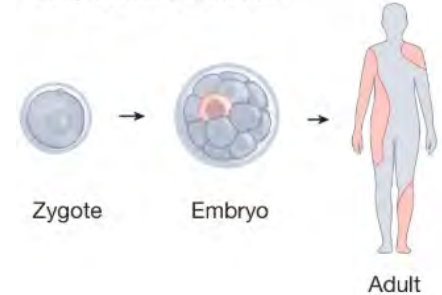
Somatic Variants



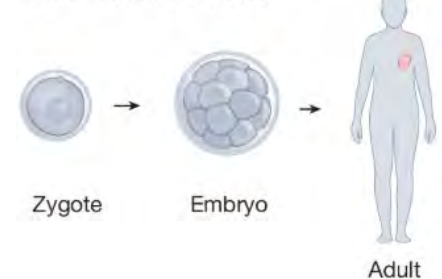
Inherited variant



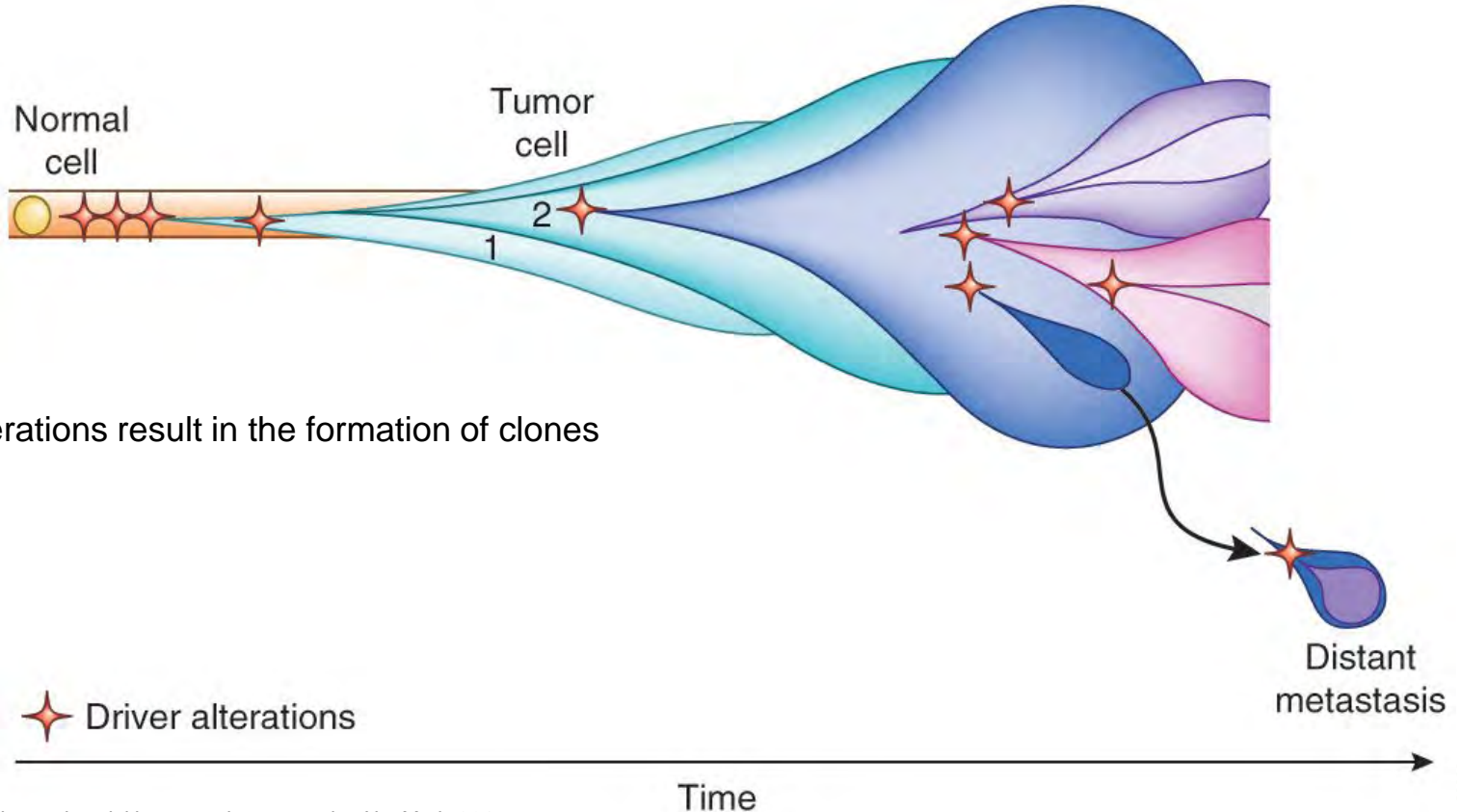
Early somatic mutation



Late somatic mutation



Cancer as a disease of the genome

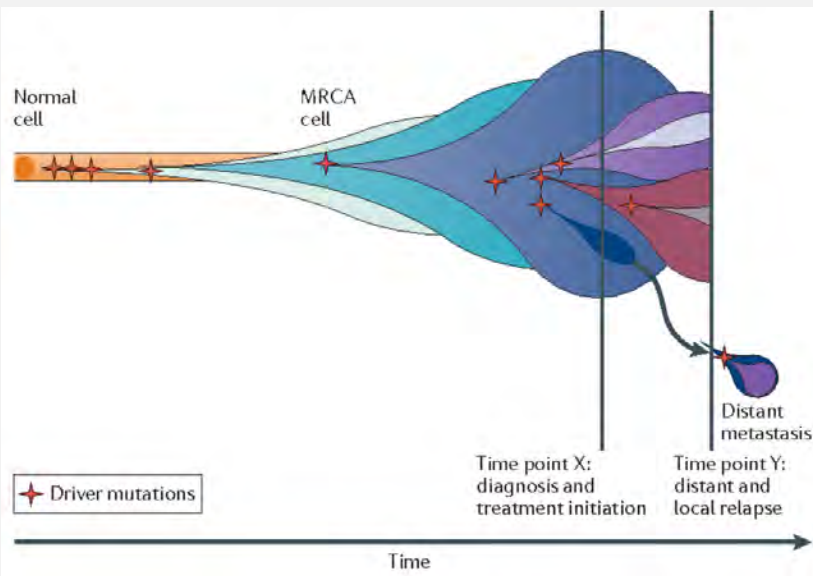


Tumor evolution

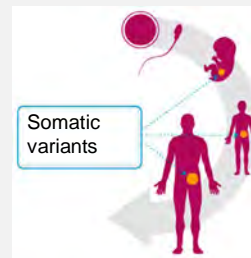
Somatic driver alterations result in the formation of clones

Agenda: Somatic variants as the driver of cancer

Tumor Evolution



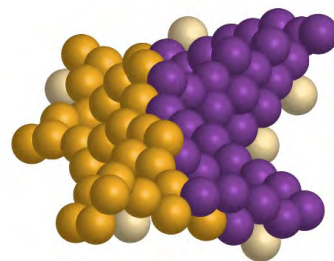
Germline and somatic variants



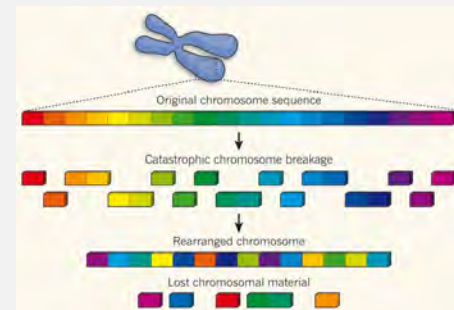
- Per genome
 - ~3-5 million germline variants
 - 100-100,000 somatic variants

Tumor heterogeneity

Schematic depiction of a bi-clonal tumor



Complex Rearrangements



Sources:

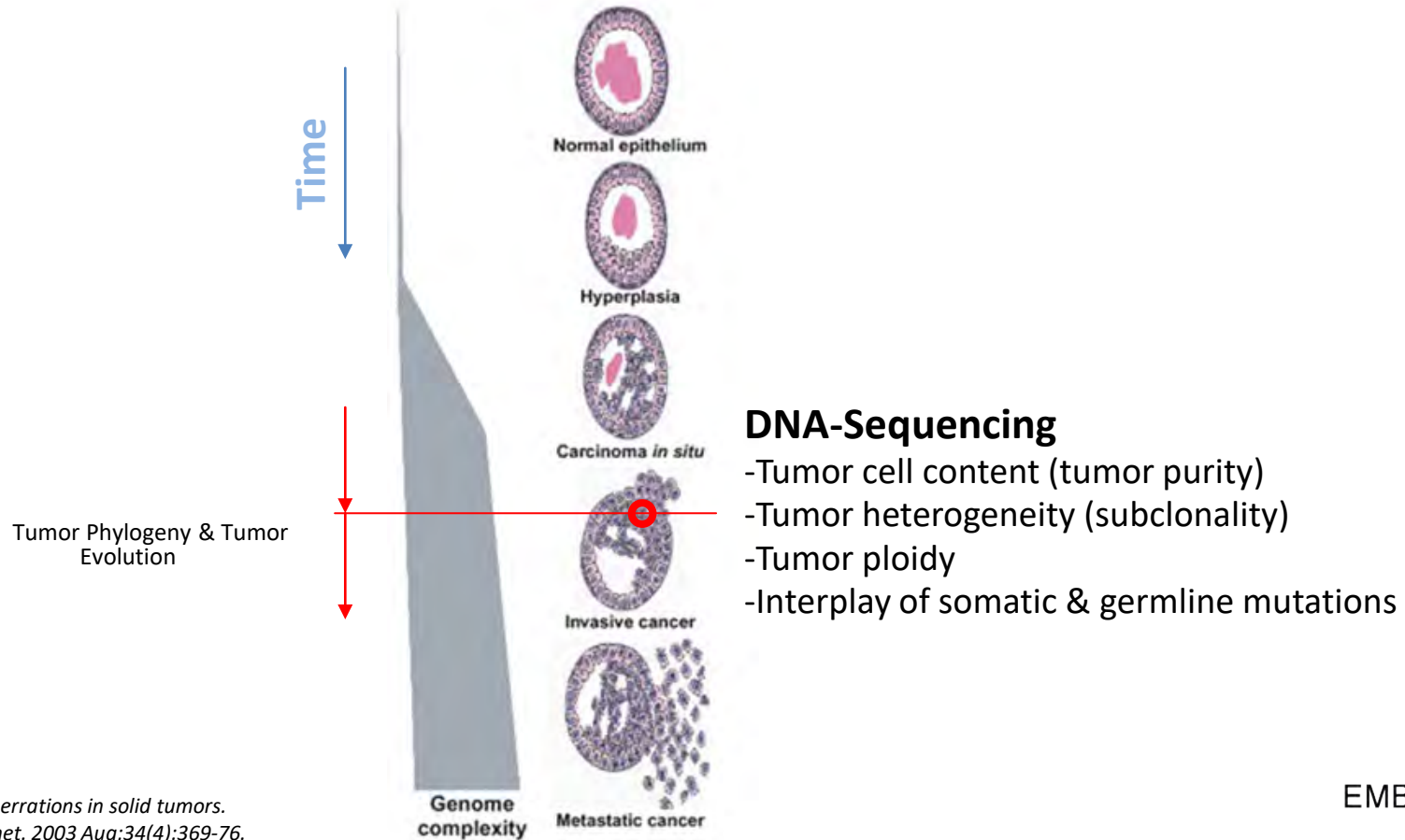
Genomic landscape of non-small cell lung cancer in smokers and never-smokers. Govindan et al., Cell. 2012 Sep 14;150(6):1121-34.

Evolution of the cancer genome. Yates and Campbell, Nat Rev Genet. 2012 Nov;13(11):795-806.

Genome sequencing of pediatric medulloblastoma links catastrophic DNA rearrangements with TP53 mutations. Rausch et al., Cell. 2012 Jan 20;148(1-2):59-71.

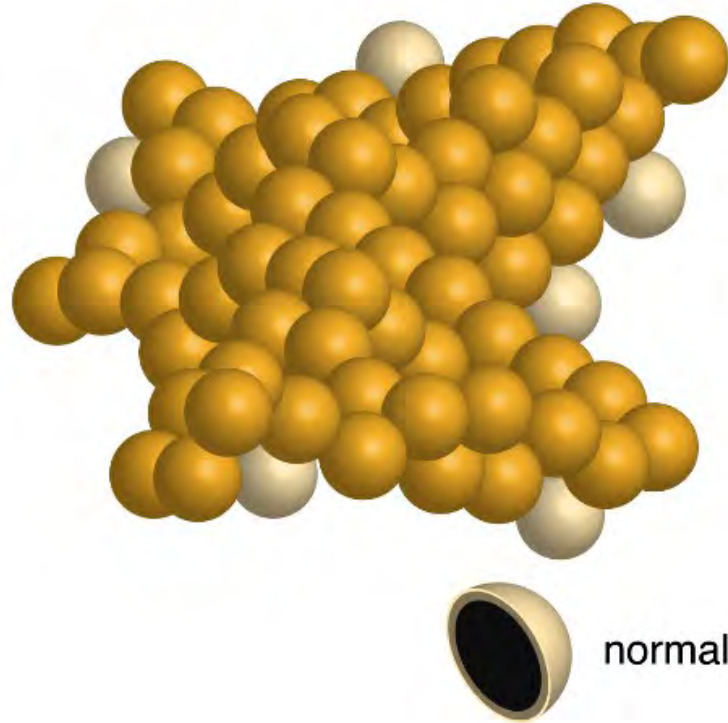
Cancer Genomics

Sequencing provides a snapshot in time and space

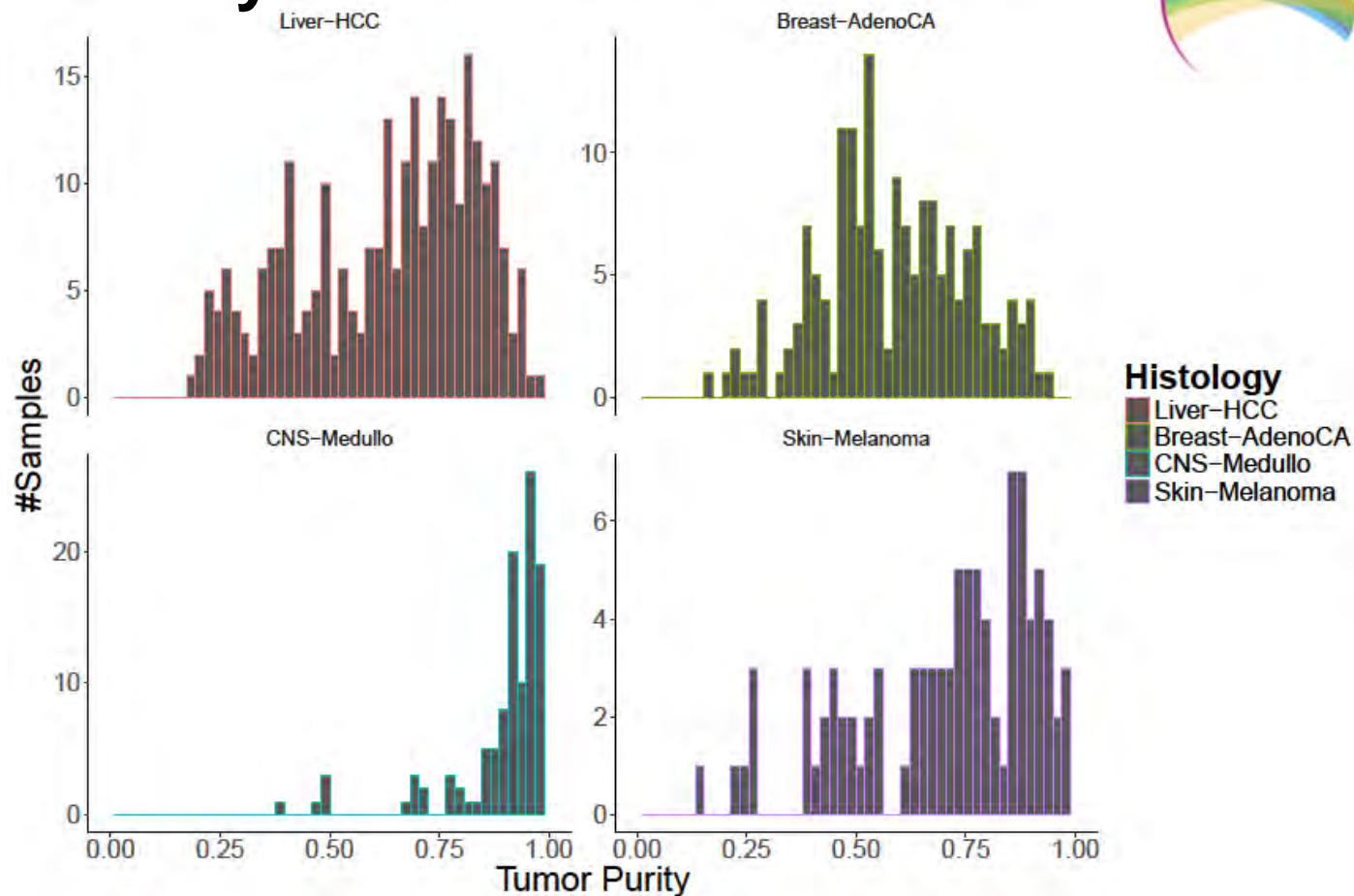


Tumor Purity

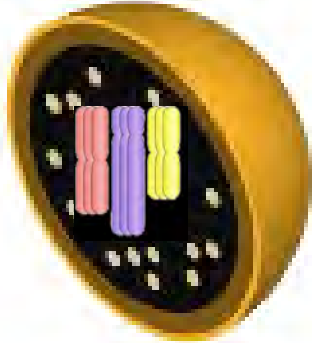
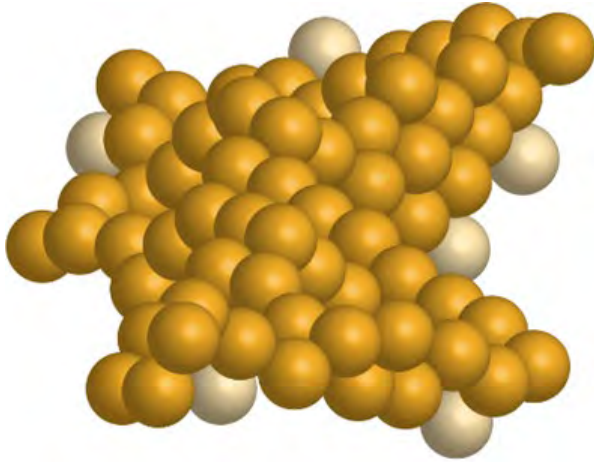
Schematic depiction of a mono-clonal tumor



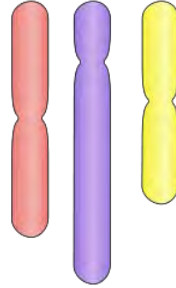
Tumor Purity



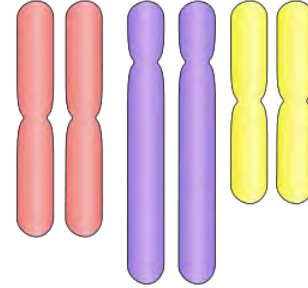
Tumor Ploidy



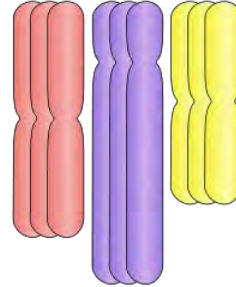
Haploid (N)



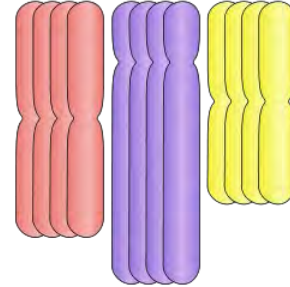
Diploid (2N)



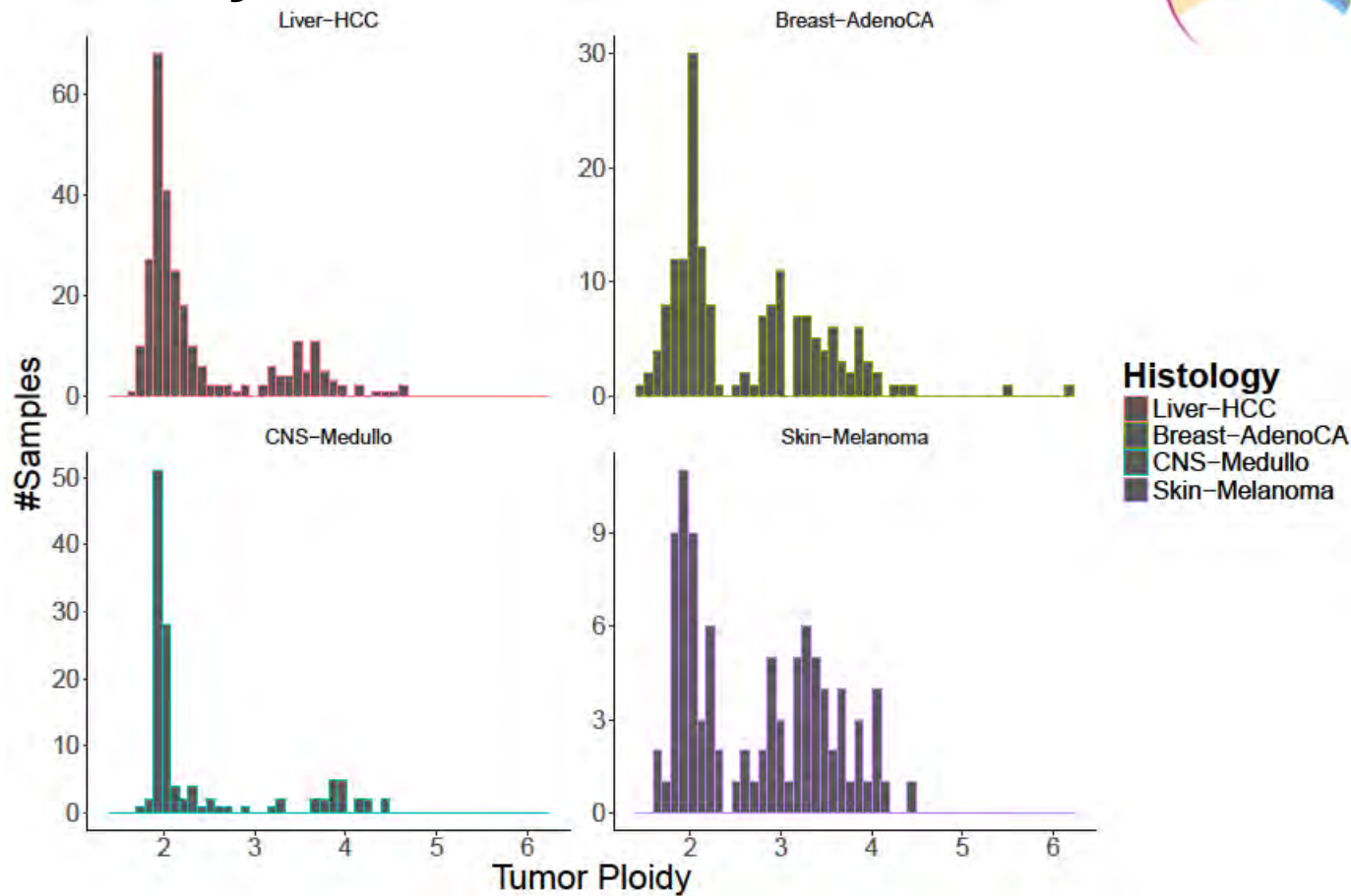
Triploid (3N)



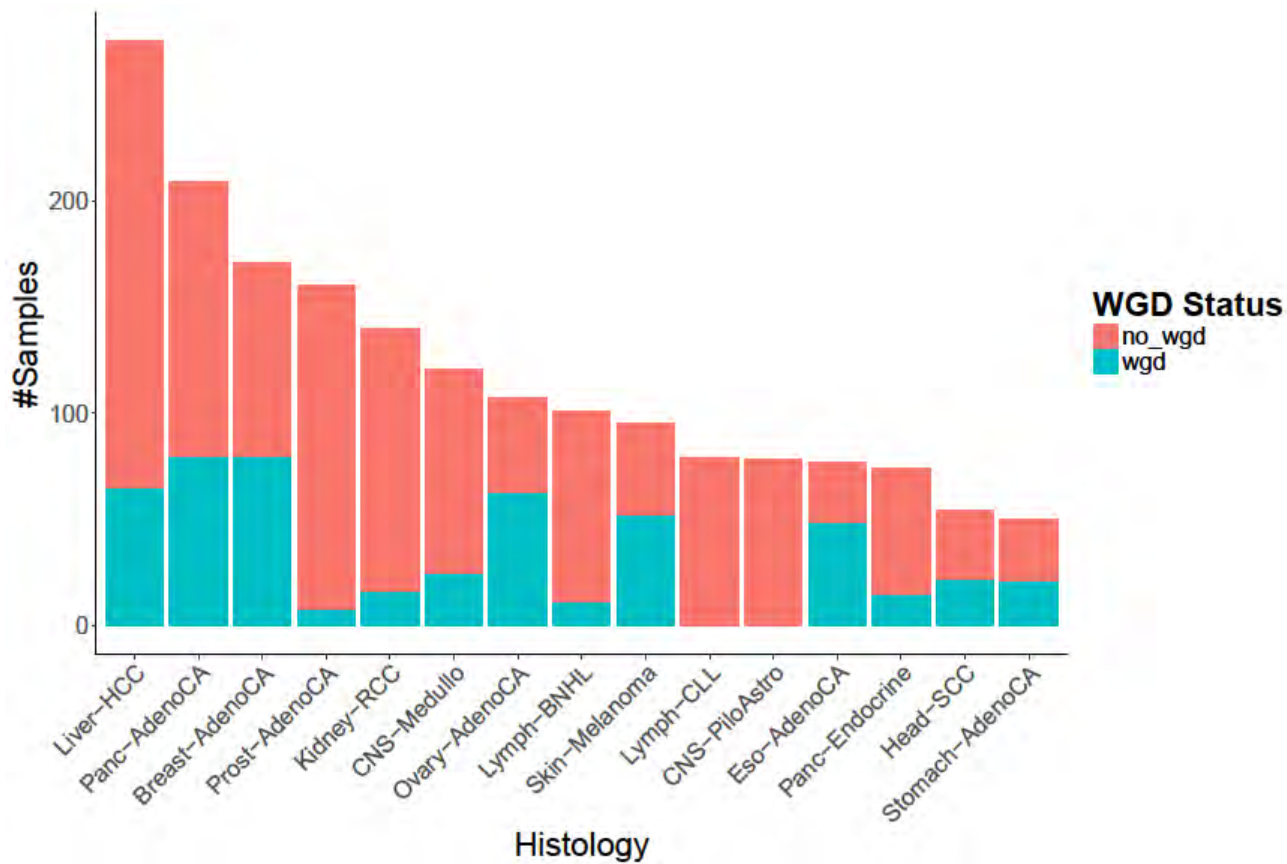
Tetraploid (4N)



Tumor Ploidy

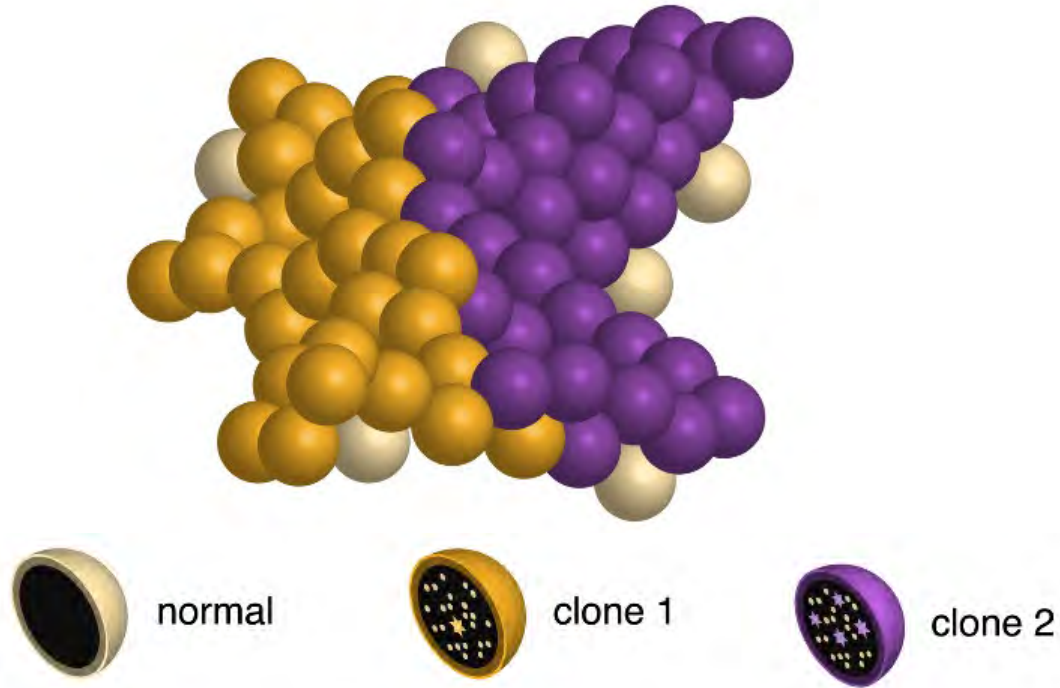


Inferred Whole-Genome Duplication (WGD) Status

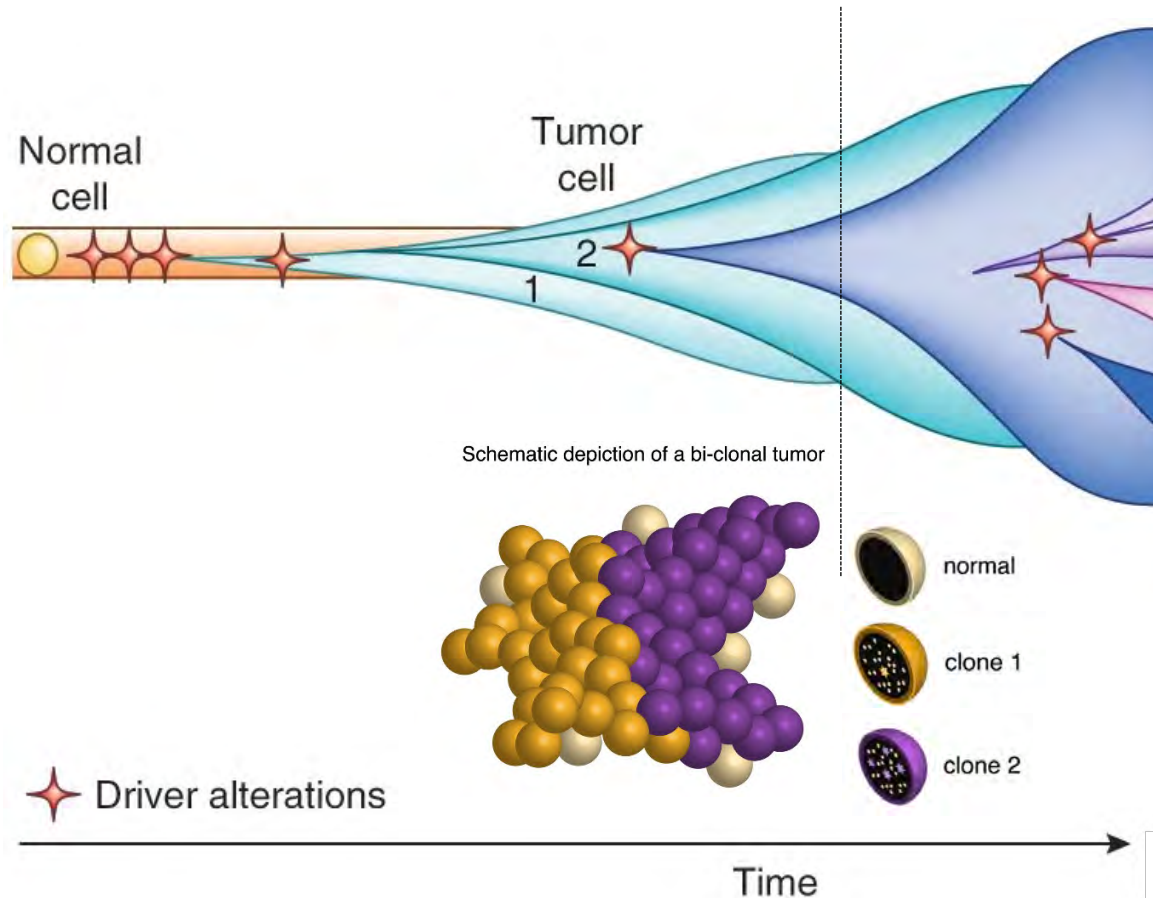


Tumor Clonality/Heterogeneity

Schematic depiction of a bi-clonal tumor

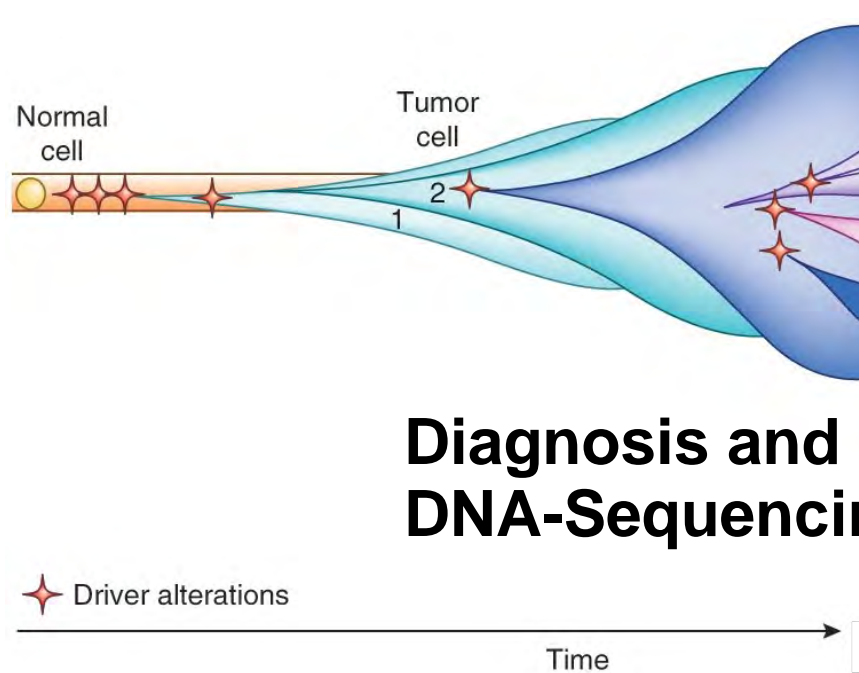


Tumor multi-clonality

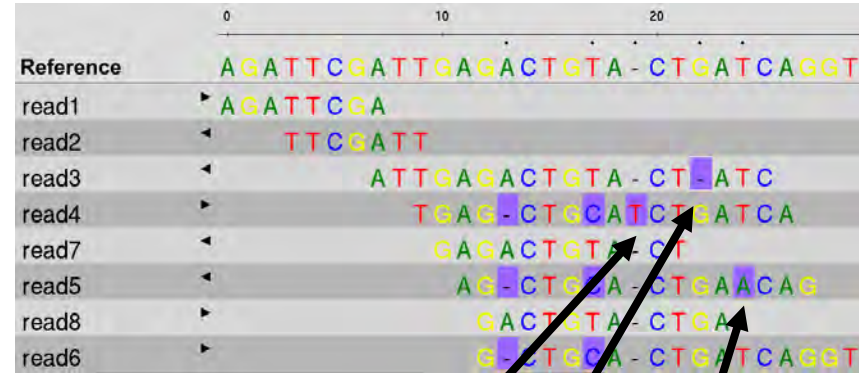


Diagnosis and DNA-Sequencing

Tumor multi-clonality

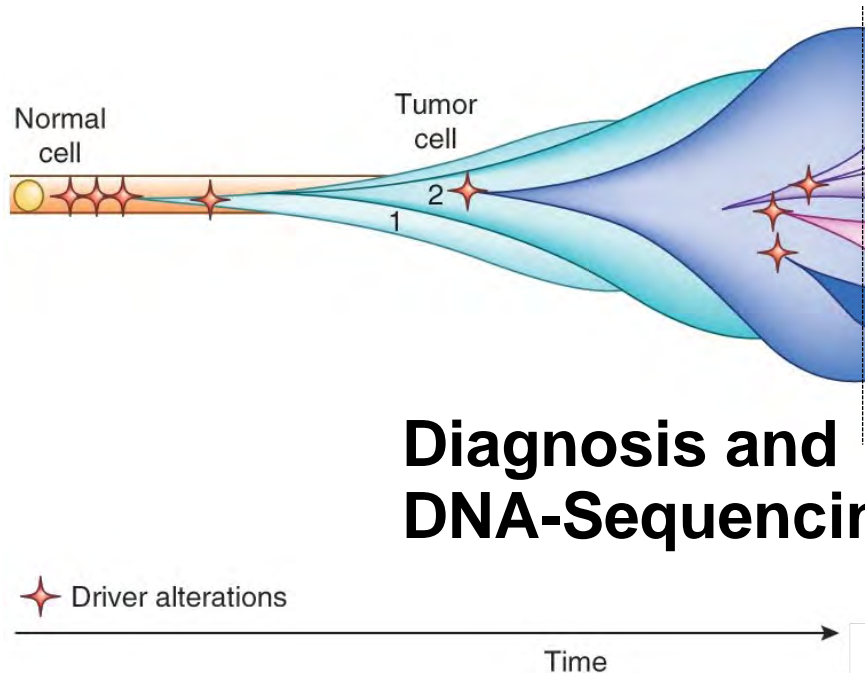


Diagnosis and DNA-Sequencing



Sequencing errors?

Tumor multi-clonality



Diagnosis and DNA-Sequencing

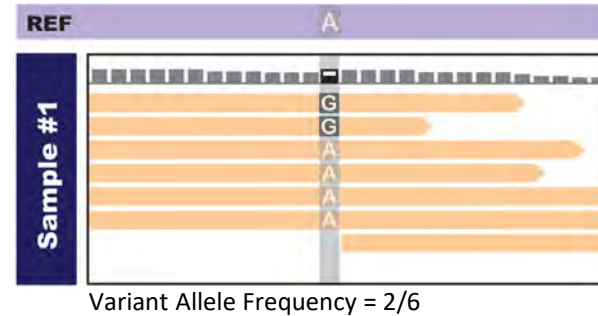
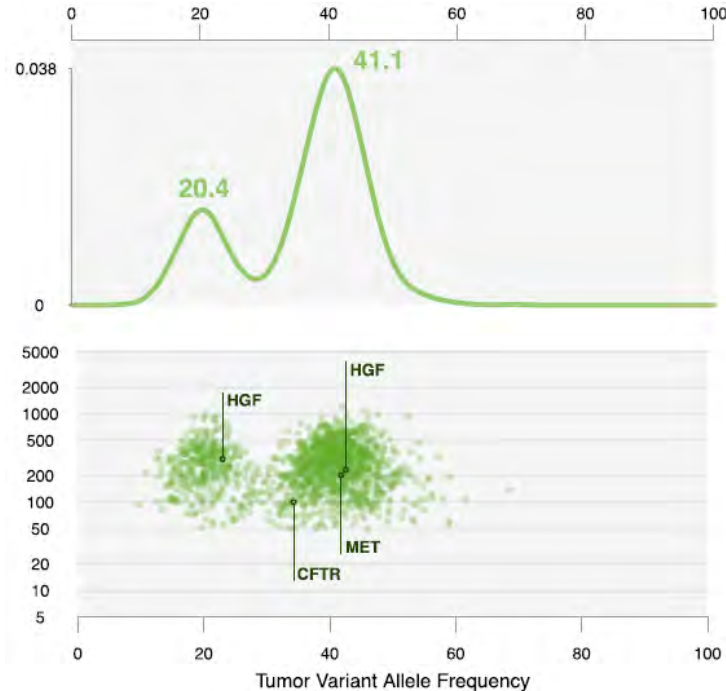


Sequencing errors?

→ Cancer genomes are often sequenced to >60x because of tumor purity, tumor heterogeneity and many chromosomal aberrations

Tumor Clonality/Heterogeneity

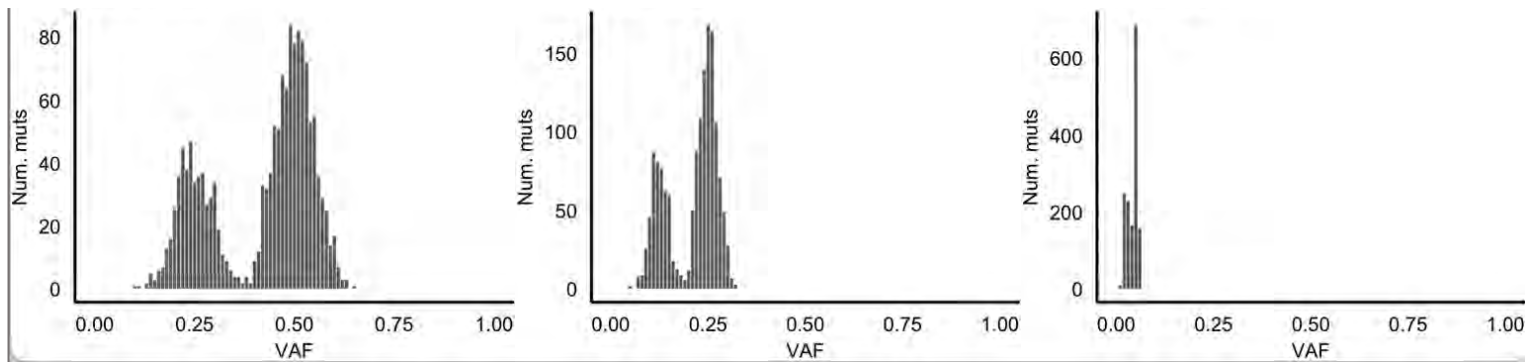
- Requires high sequencing depth
 - Typically done with WES data ($\geq 500\times$ coverage)



Bi-clonal
82.2% tumor purity

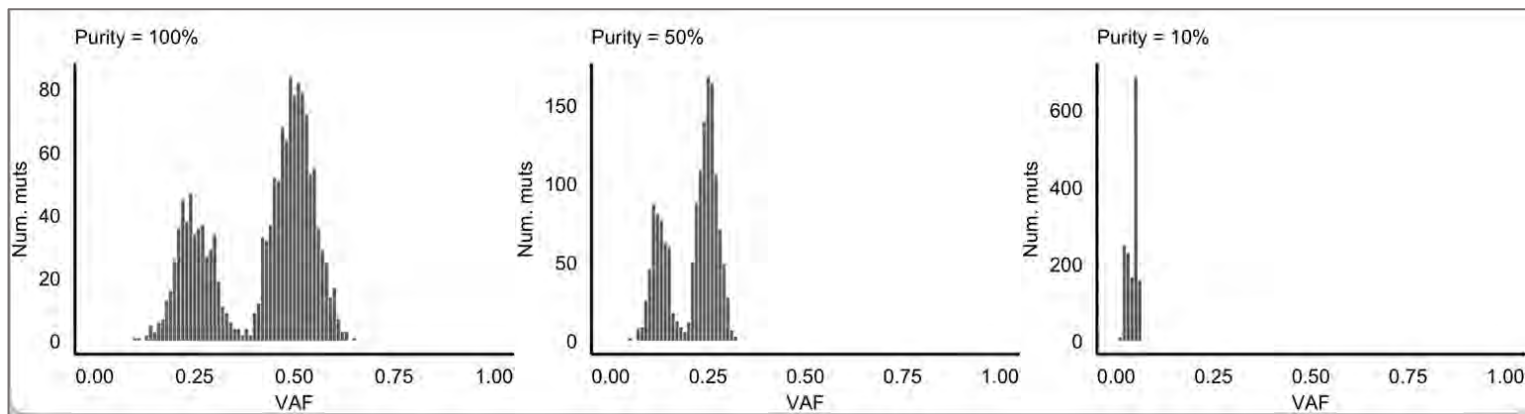
Tumor purity

- Below are 3 tumor samples with varying levels of tumor cell content
- Can you guess the tumor purity based on the somatic VAF?

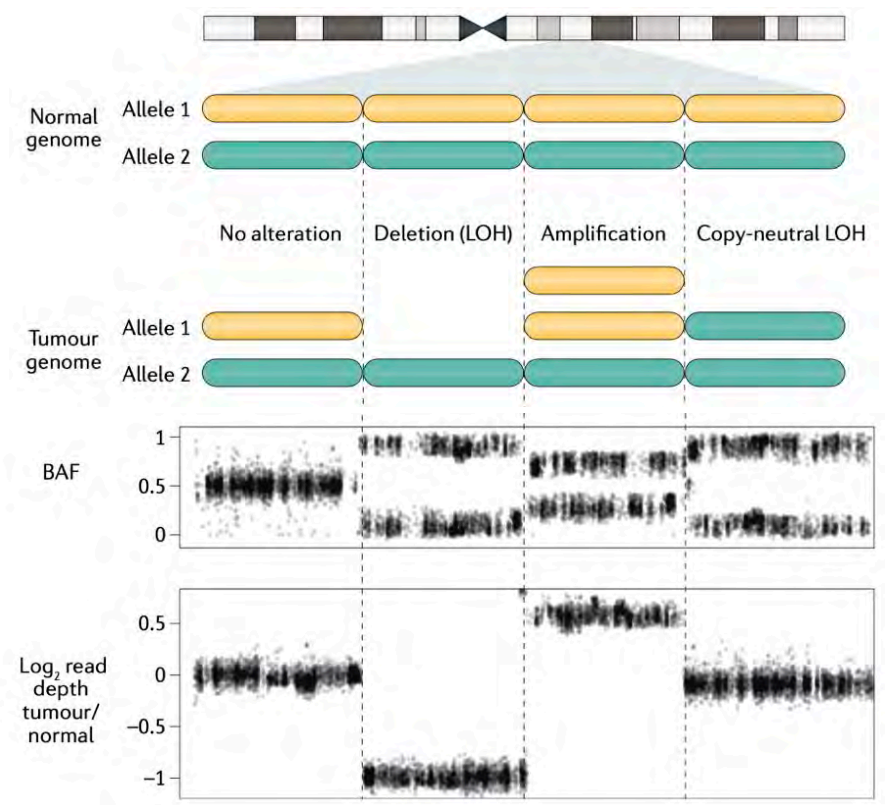
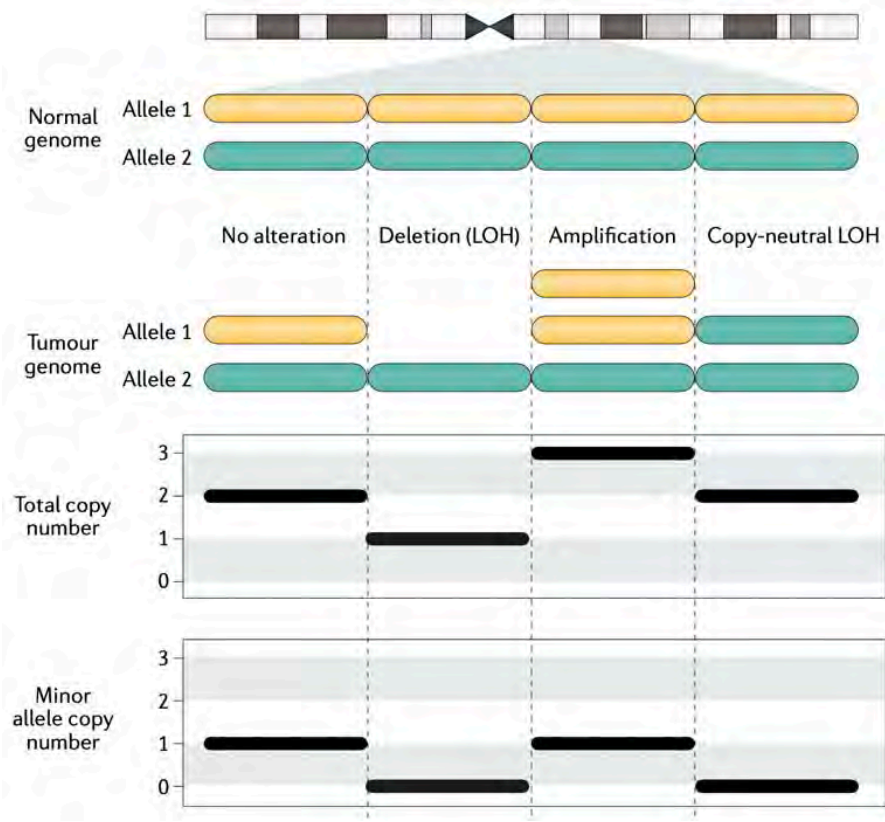


Tumor purity

- Below are 3 tumor samples with varying levels of tumor cell content
- Can you guess the tumor purity based on the somatic VAF?

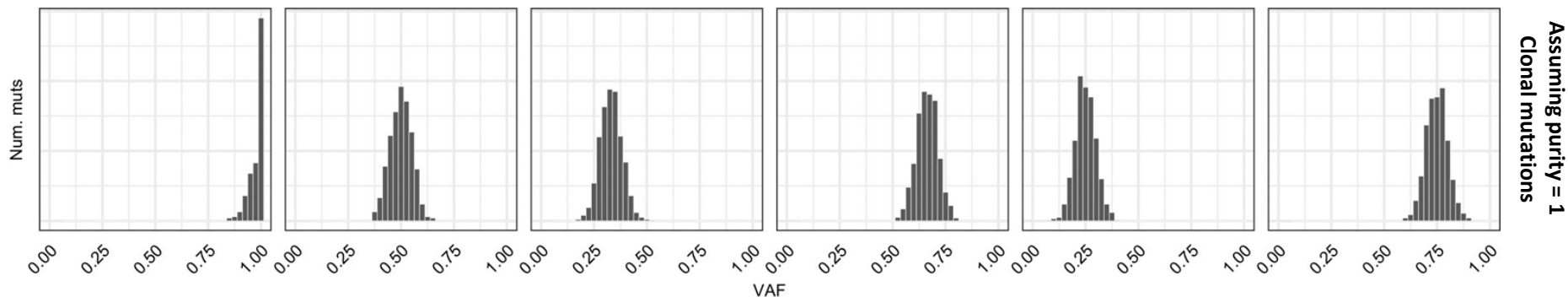


Somatic copy-number variation (SCNA)

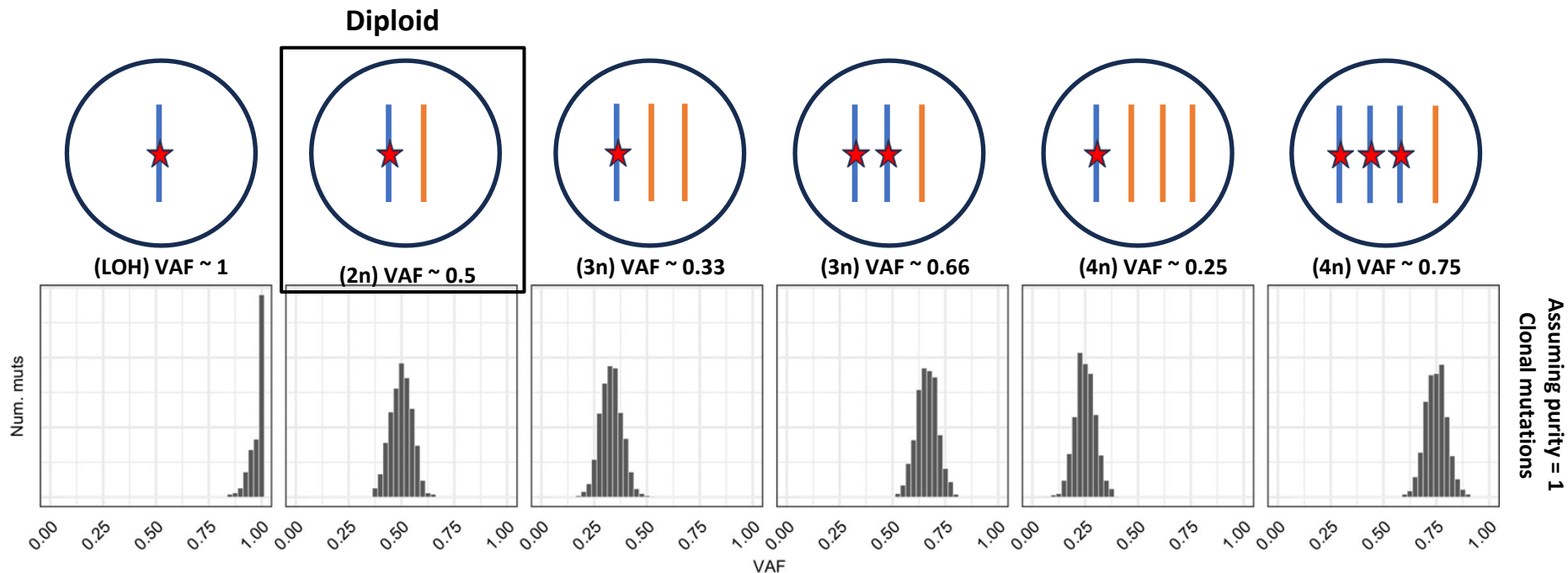


Copy number changes affect the VAF distribution

- Assuming a 100% tumor purity and only clonal mutations
- Can you guess the total copy-number?



Copy number changes affect the VAF distribution

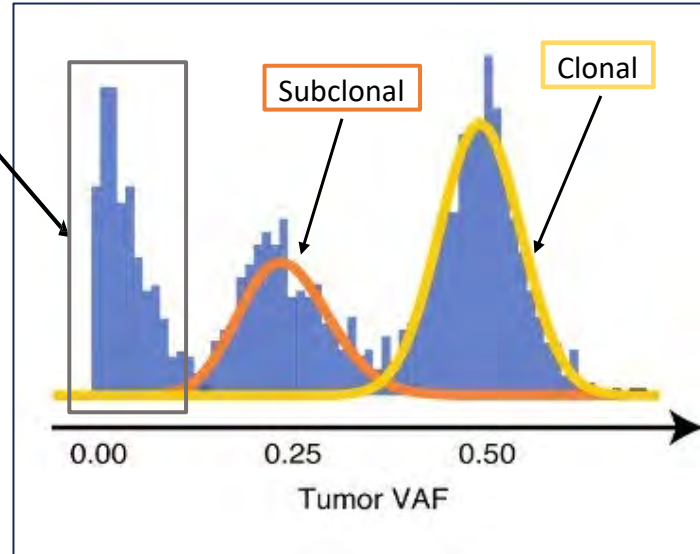


Subclonal heterogeneity

- Bulk sequencing data provides an aggregated view of the genetic information
- Subclonal mutations that are present at low frequencies are difficult to detect
 - → Underestimation of clonal diversity is common

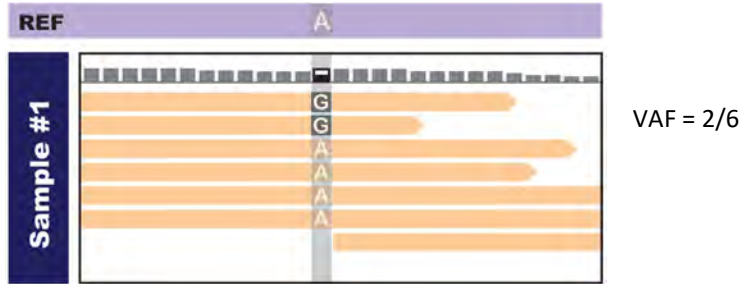
Tail (not all from the same clone)

- Very hard to distinguish clones
- New mutations (majority passenger) occurring in every cell division
- The accuracy of the reconstruction **massively depends on the depth of coverage**
- Subclonal mutations at low VAF **heavily affected by sequencing errors**



Variant vs. Population Allele Frequency

- Somatic variant allele frequency



Clonal mutations



Subclonal mutations

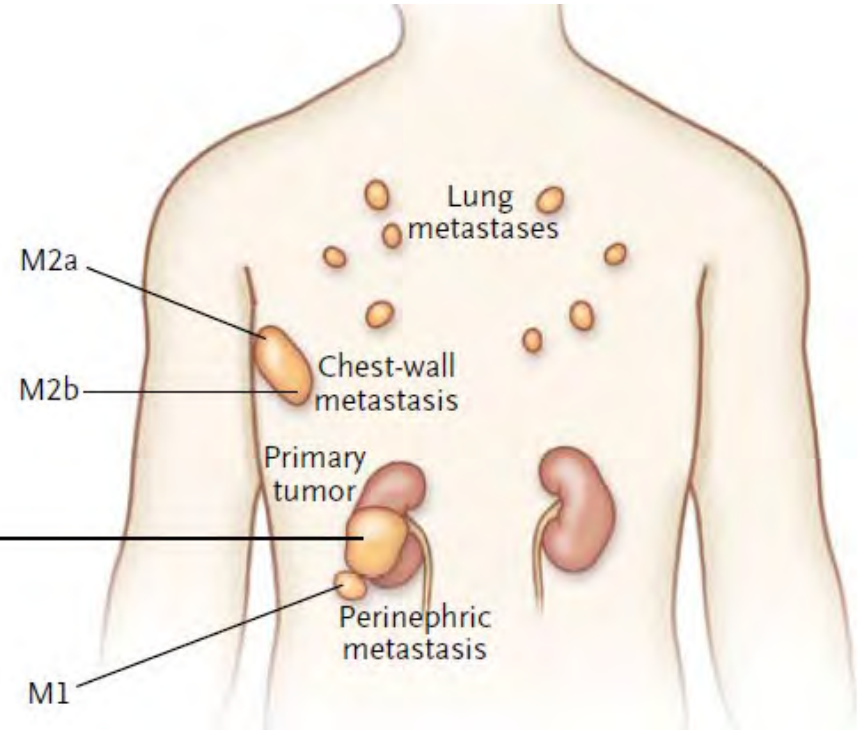
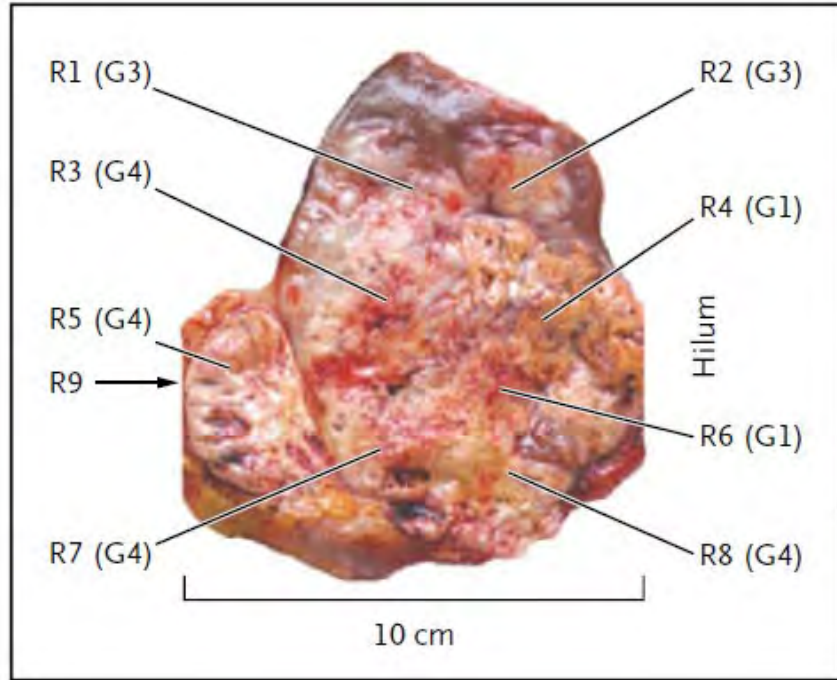


- Population allele frequency of (potentially predisposing) germline variants

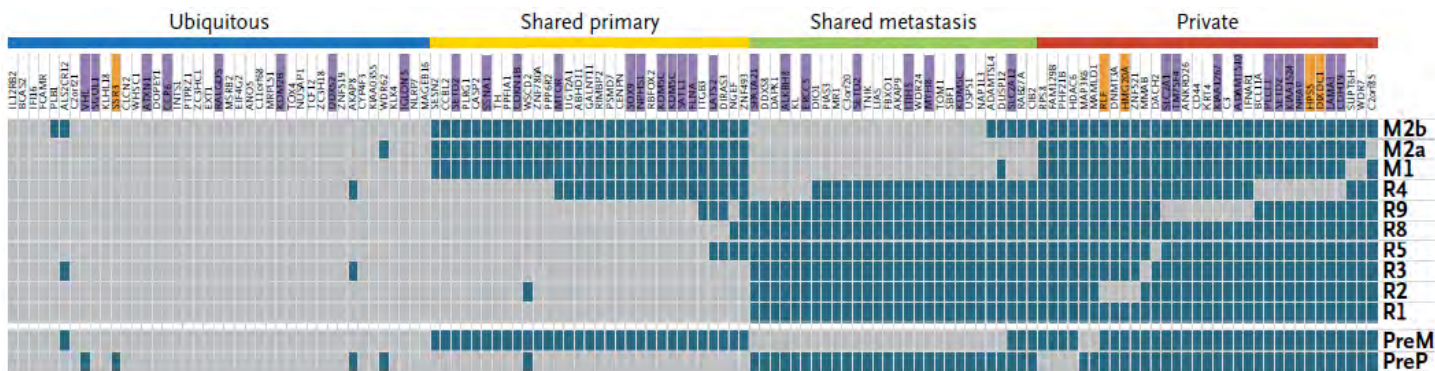
- rs6602666, A>G
 - African: ~26%
 - Finnish: 0%



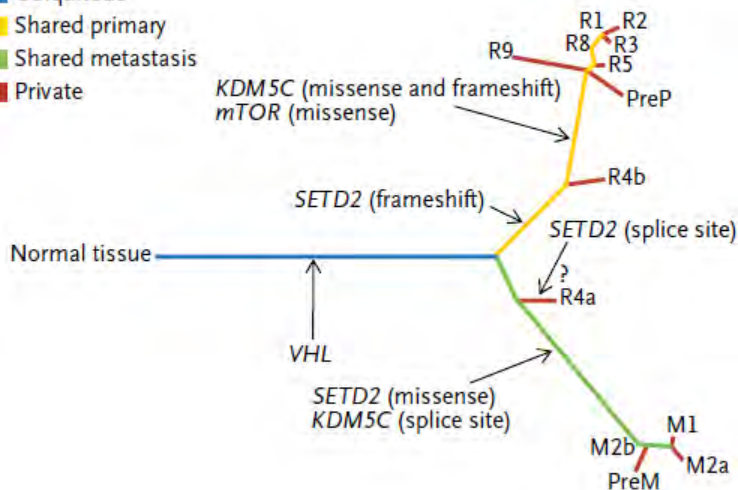
Tumor Heterogeneity & Tumor Evolution



Tumor Heterogeneity & Tumor Evolution

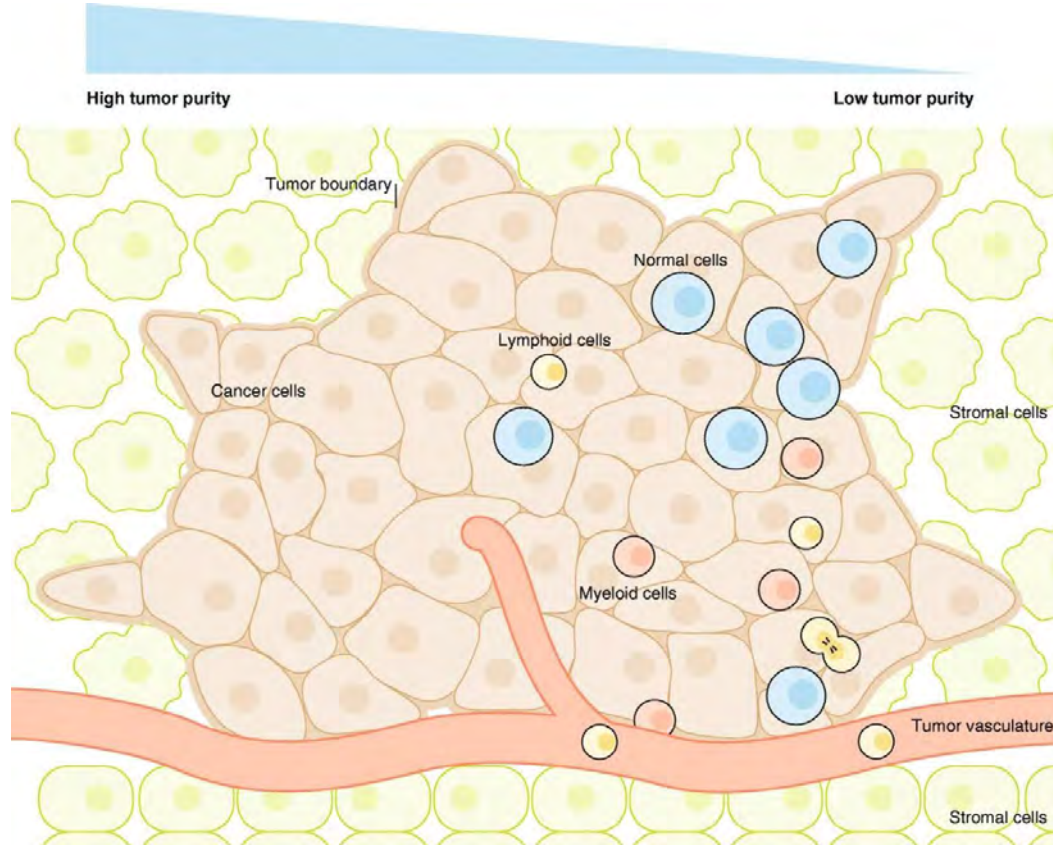


- Ubiquitous
- Shared primary
- Shared metastasis
- Private

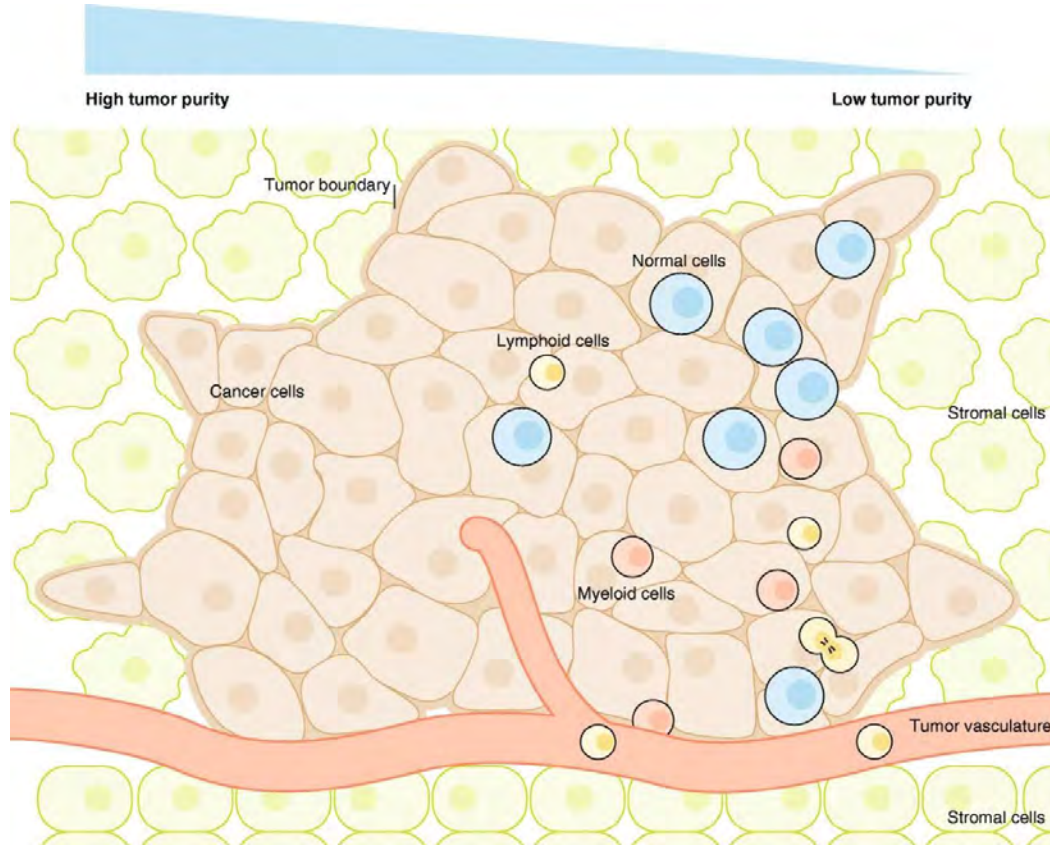


Tumor Phylogeny

The hidden complexity in bulk sequencing



Single-cell sequencing



Bulk RNA-sequencing



Single-cell RNA-sequencing



Single-cell (spatial) transcriptomics

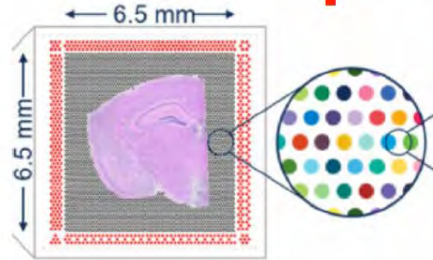
Bulk RNA-sequencing



Single-cell RNA-sequencing

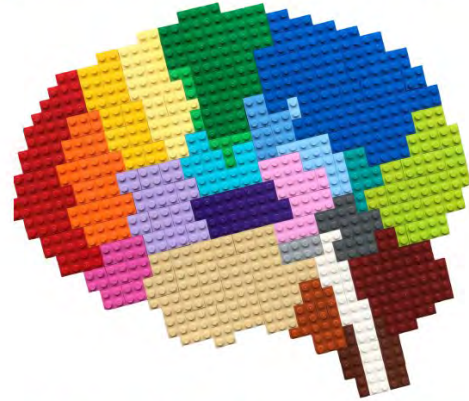


+ =



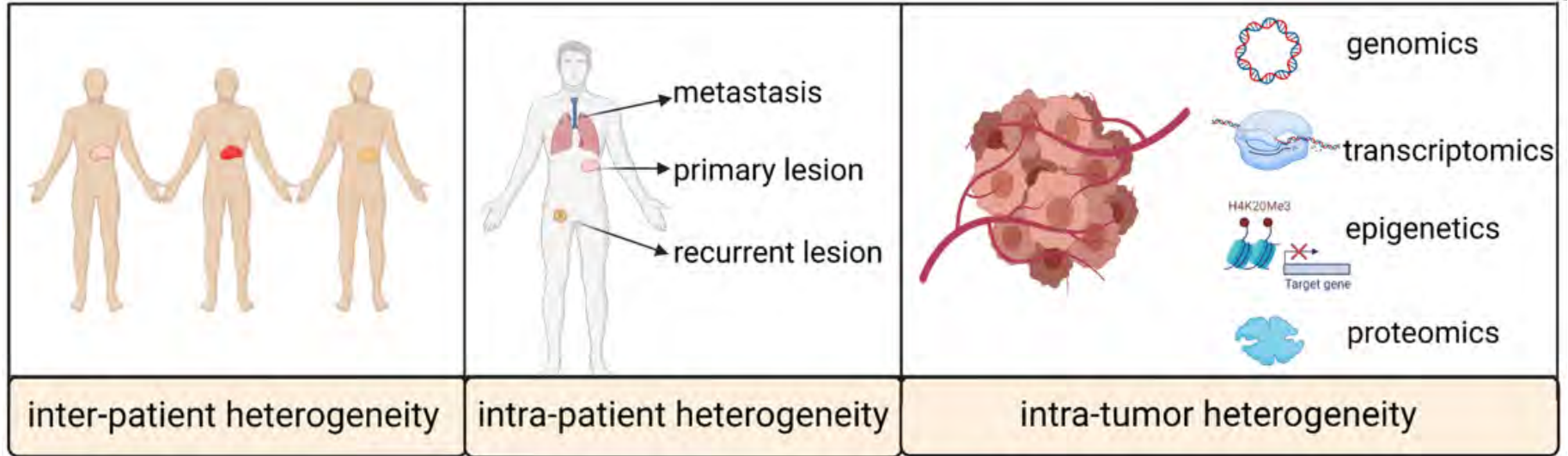
Spatial transcriptomics

Spatial location of all cell types

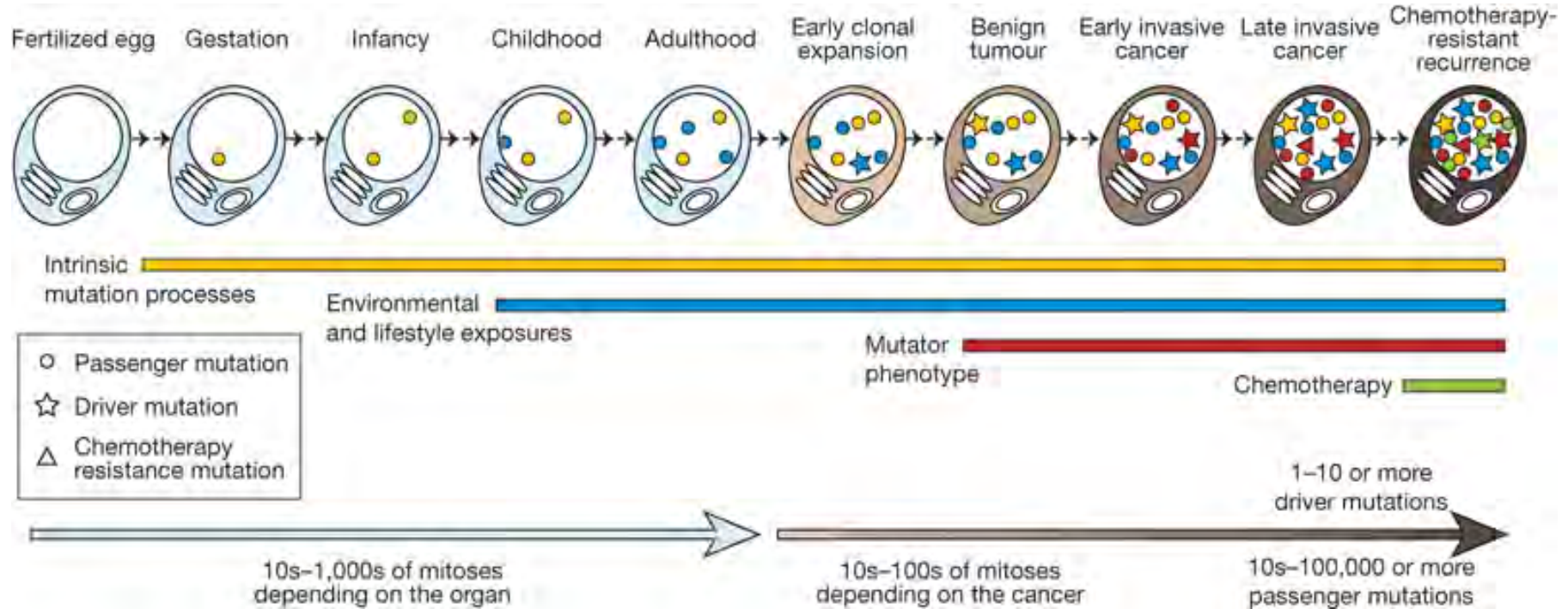


Study cell-cell interactions

Tumor heterogeneity at the patient and tumor level



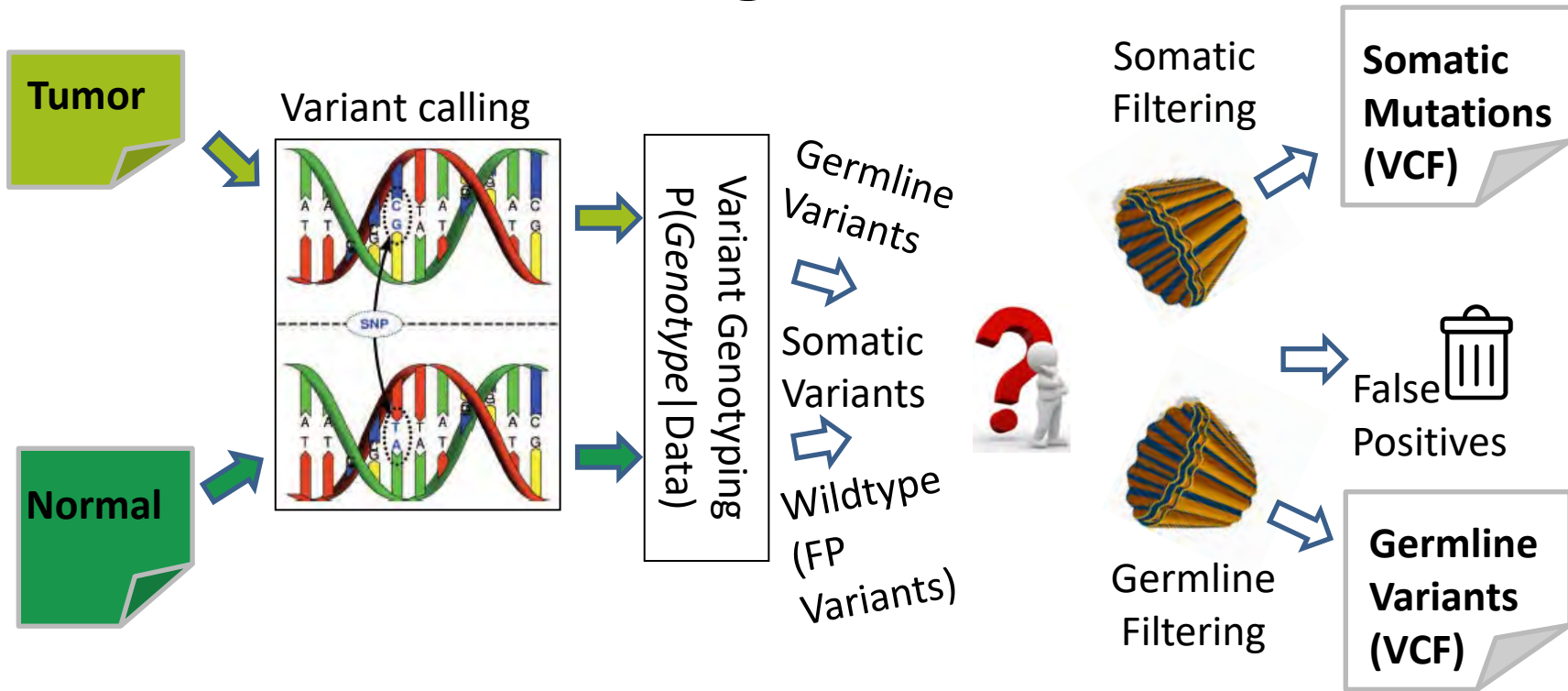
Summary: Cancer as a genetic disease and evolutionary process





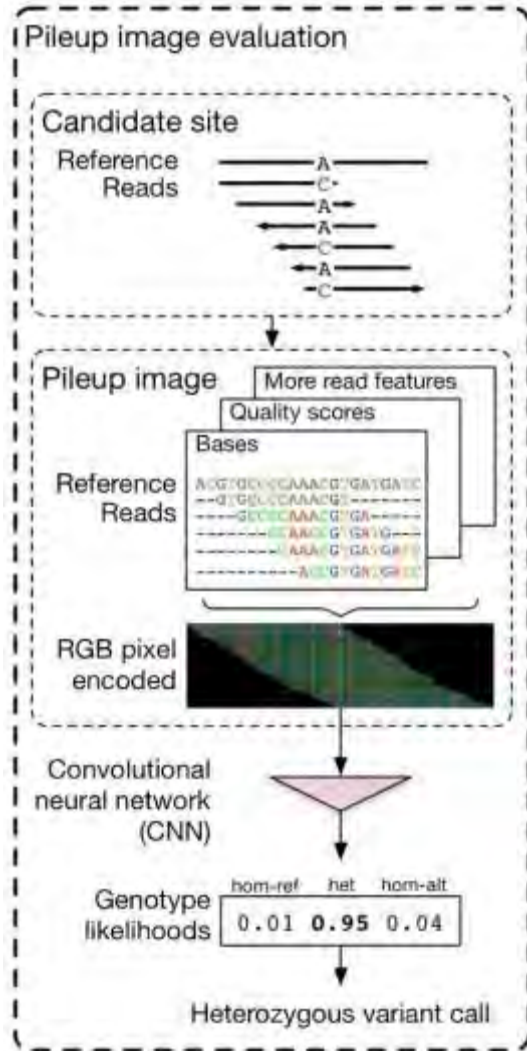
Cancer Genome Data Analysis

Somatic variant calling



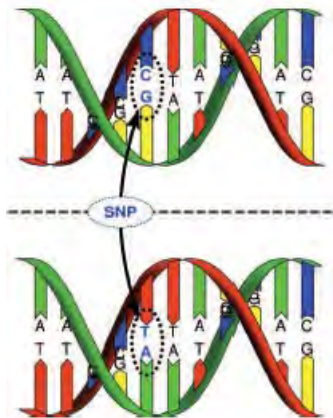
Variant Calling Methods

- Four broad categories
 - Heuristic Methods
 - Hardly used anymore
 - Probabilistic methods
 - Bayesian methods
 - Machine Learning methods
 - Deep Learning methods, e.g., DeepVariant
 - Graph-based methods
 - Pangenome methods



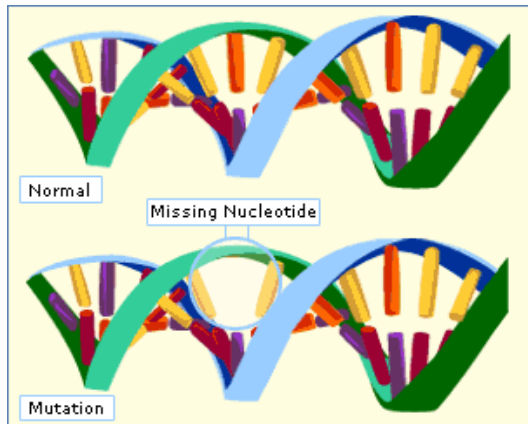
Types of Variants

Single-nucleotide variants (SNVs)



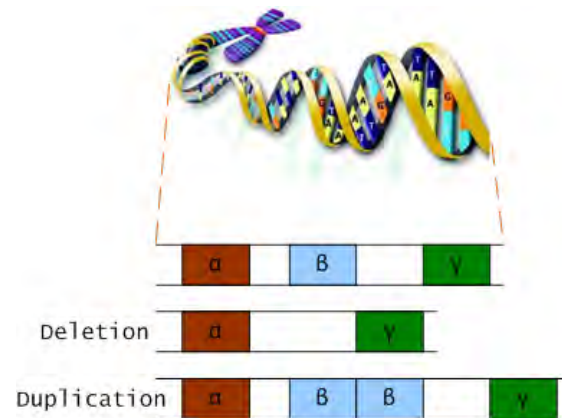
Size: 1bp

Short insertions & deletions (InDels)



1-50bp

Copy-Number Variants (CNVs) & Structural Variants (SVs)



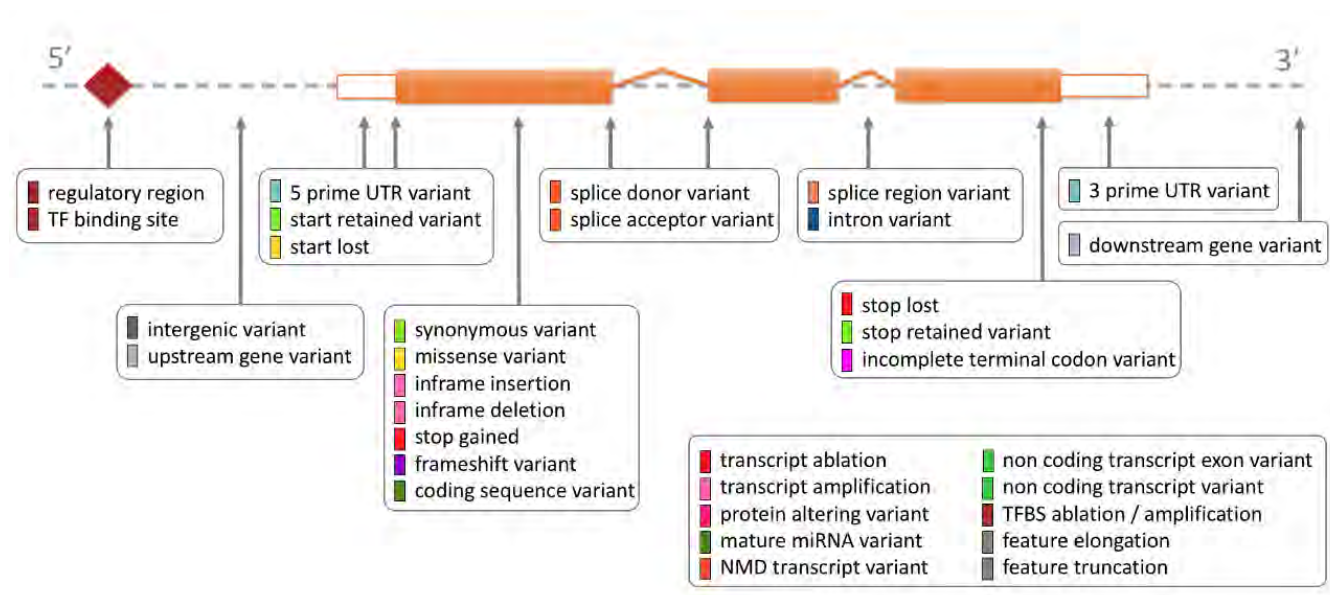
>50bp

Different methods are used to discover and genotype SNVs, InDels, SVs and CNVs.

Further information:

Methods in Genomic Variant Calling: <https://www.youtube.com/watch?v=zO9WCOaq3aQ>

Interpreting Genomic Variants



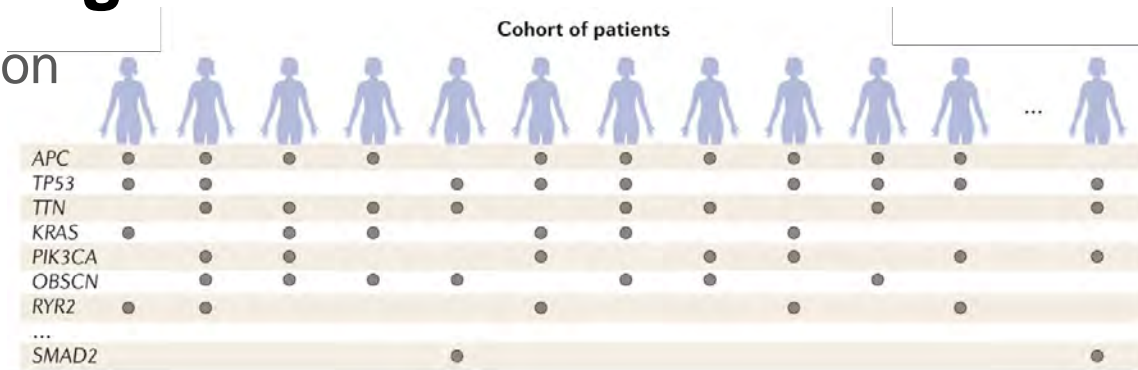
Popular Tools: VEP, Annovar, snpEff

Mediocre support for annotation of copy-number and structural variants

Driver versus Passenger

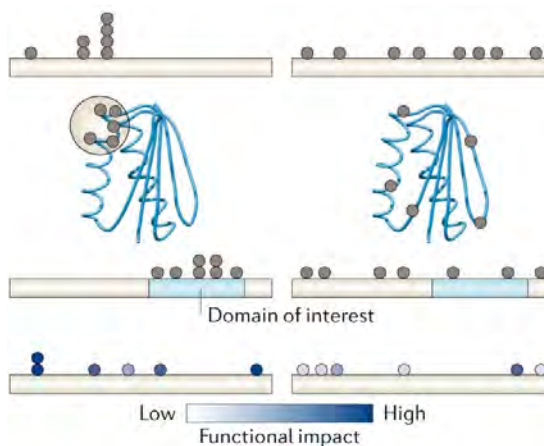
- Signals of positive selection

- Mutation Recurrence



- Hotspot mutations

- Protein domain clustering

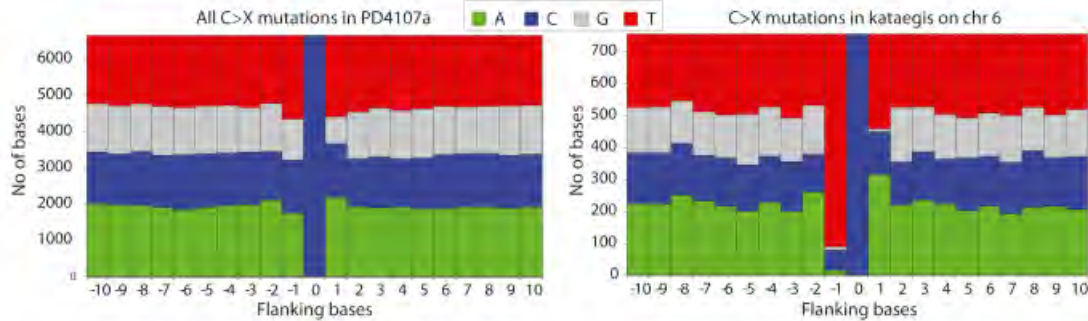
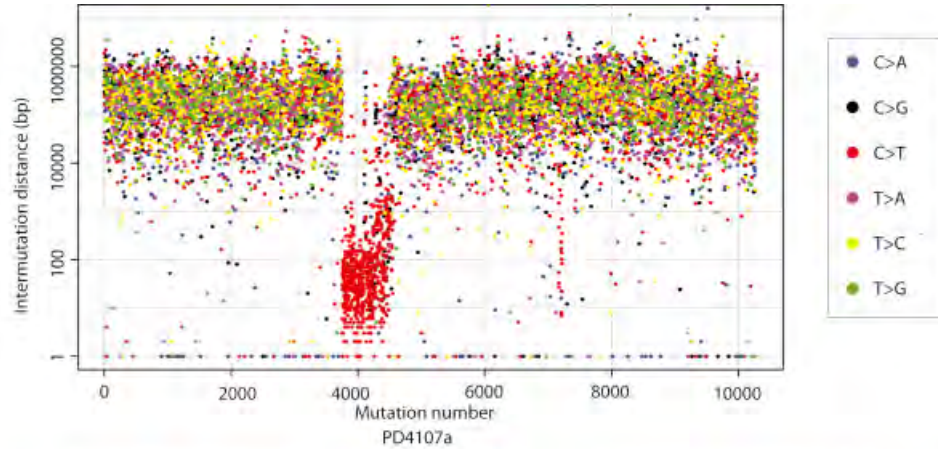


- Functional impact bias



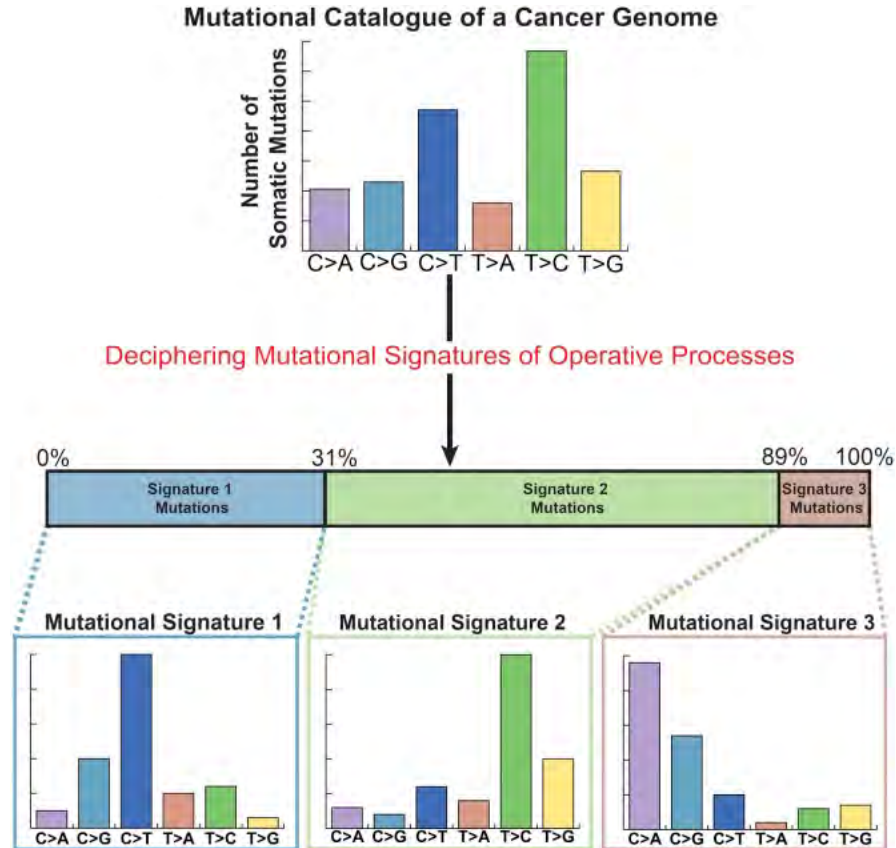
Mutational Signatures

Mutational Signatures

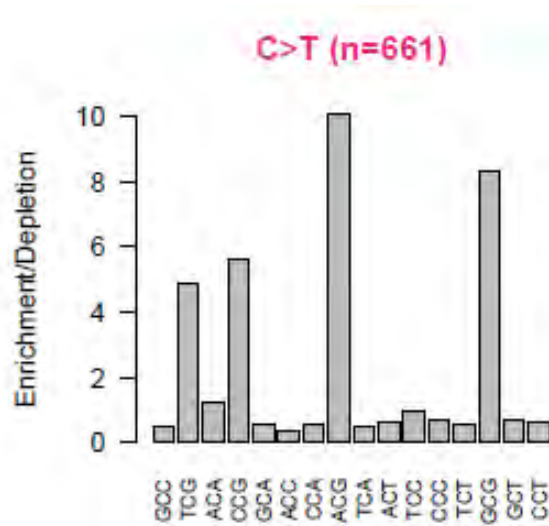


Tri-Nucleotide Context TpCpX

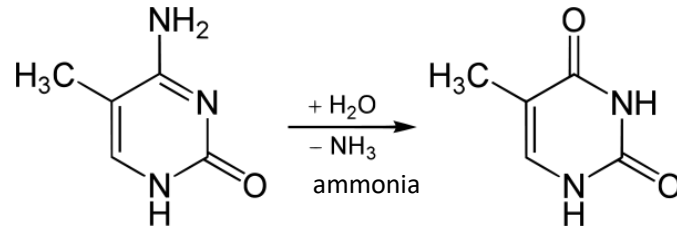
Mutational Signatures



Tri-Nucleotide Sequence Context

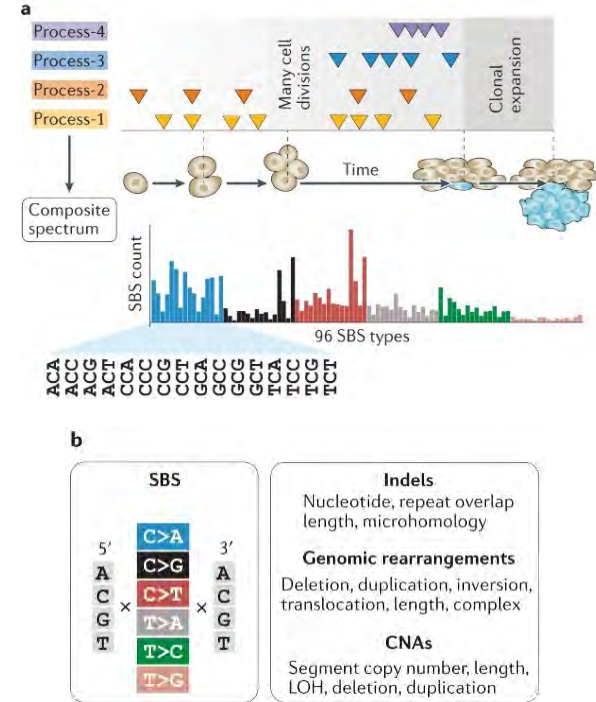


- Elevated **C>T** mutation rate at **XpCpG** trinucleotides
- Deamination of methylated cytosines to thymine (usually at XpCpGs)



Mutational Signature

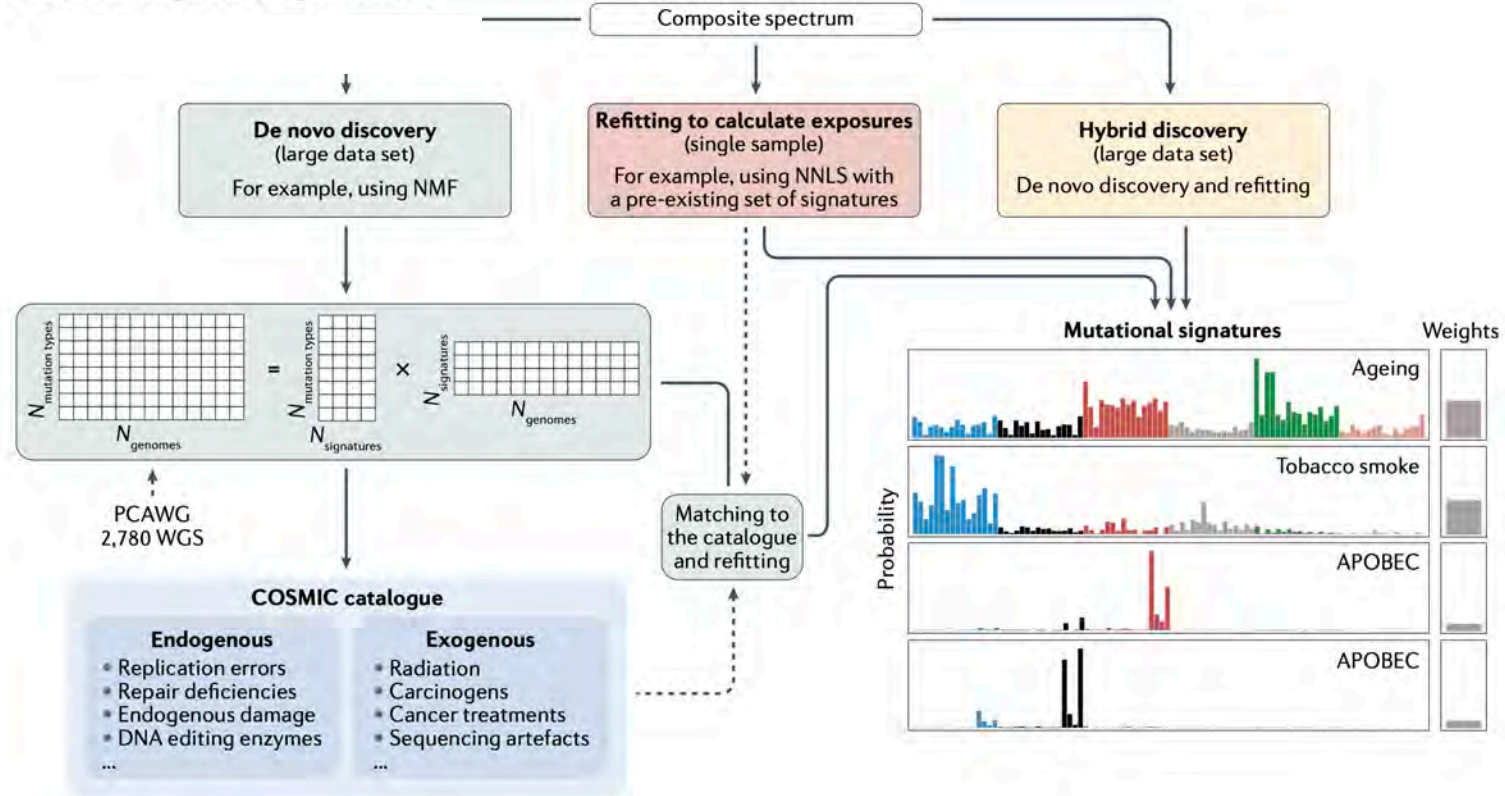
- Characterize patterns of DNA mutations
- These patterns can arise from various mutational processes that lead to changes in DNA sequences
- Mutations can occur due to a variety of factors
 - DNA replication errors
 - Exposure to mutagenic agents (e.g., ultraviolet radiation, chemical carcinogens)
 - Defects in DNA repair mechanisms.



Cortes-Ciriano et al 2022

De novo discovery or re-fitting

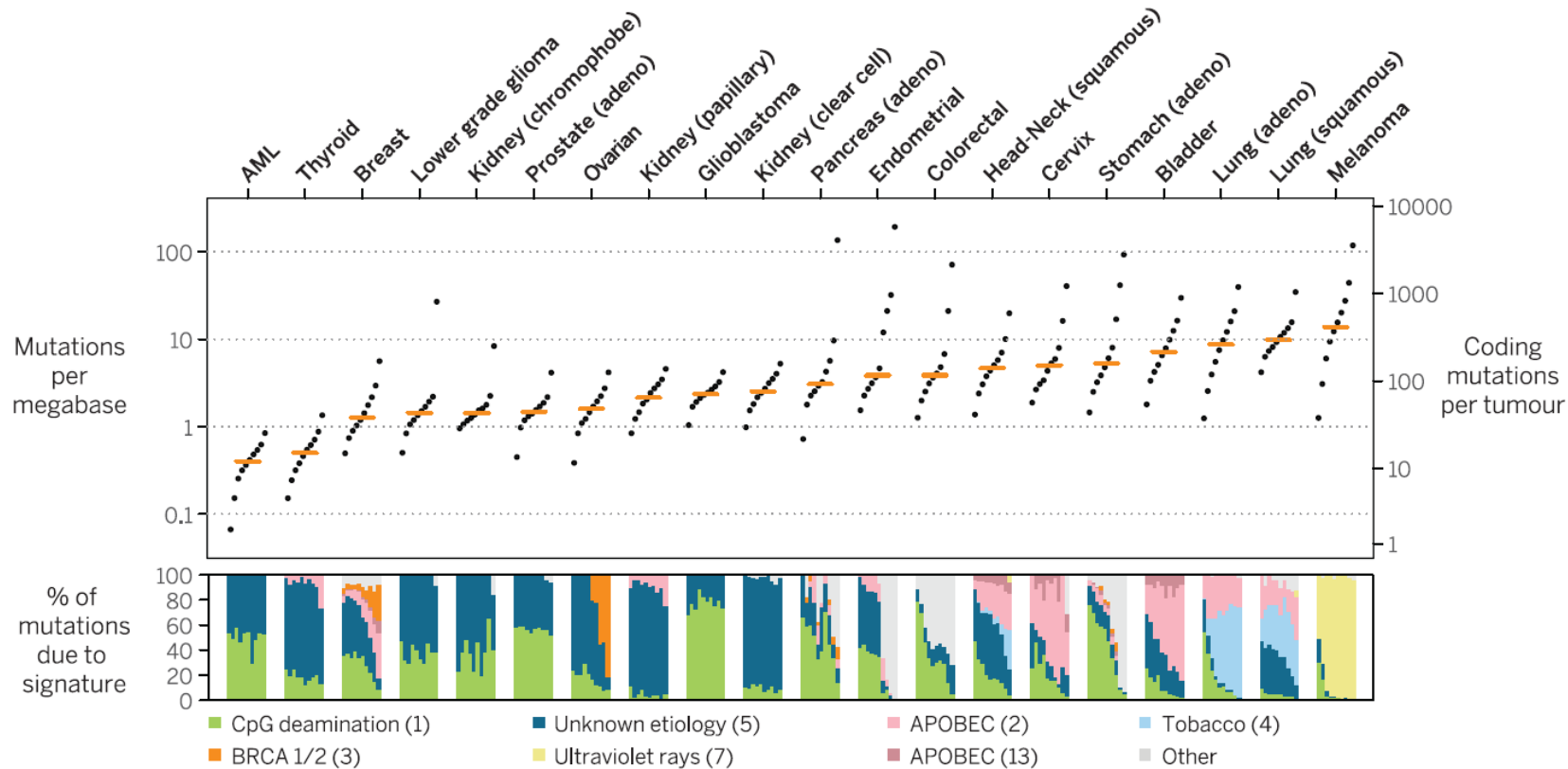
c Mutational signature analysis methods



Mutational signature catalog



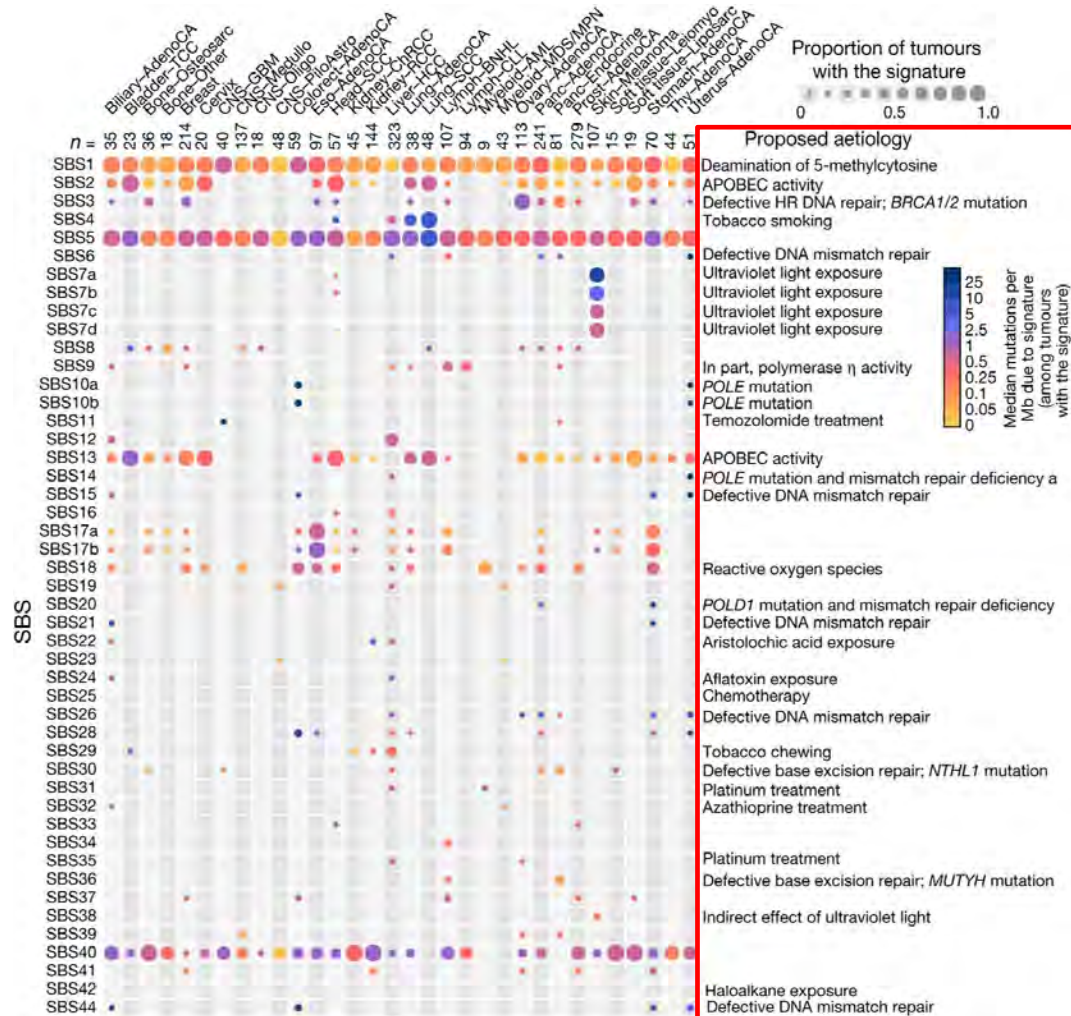
Mutational Signatures across Human Cancer Types



Classification of mutational signatures based on biological processes

• Cancer Aetiology Investigation

- Mutational signatures provide insights into the underlying causes
- <https://cancer.sanger.ac.uk/signatures/>



Recurrently Mutated Cancer Genes

	Endometrial	Melanoma	Thyroid	Kidney (clear cell)	Kidney (chromophobe)	Kidney (papillary)	Prostate (adeno)	Glioblastoma	Breast	Cervix	AML	Lower grade glioma	Colorectal	Stomach (adeno)	Bladder	Ovarian	Head-Neck (squamous)	Lung (squamous)	Lung (adeno)	Pancreas (adeno)	Pan-cancer
ABL1	3.6	4.1	0.2	0.7	1.5	1.8	0.5	0.7	0.6	2.5	0.7	0.5	2.3	3.6	5.8	0	0.3	1.7	1.2	5.3	1.4
ACVR1	4	1.4	0	0	0	0	0	0	0.1	0	0	0.5	0.8	1.8	0	0.9	1.6	0	1.3	0	0.7
ACVR1B	3.2	1	0	0.9	0	0	0.5	0	0.6	2.5	0	0.9	2.3	3.9	0.6	0.4	1.3	1.7	1.7	1.8	1.2
AKT1	3.2	1	0.7	0.5	0	0	0.5	0.3	2.5	0	0	0.5	2.1	1.1	0	0	0.6	0.6	0.6	3.5	1.1
ALK	7.3	8.1	0.2	1.7	1.5	0.9	0	0.3	0.4	2.5	0	0.5	4.1	3.9	1.3	0.4	2.8	2.2	5.8	1.8	2.5
AMER1	7.7	5.7	0	0.7	0	0.9	0	0.3	1	0	0	1.4	8.5	5.7	1.9	0	3.1	4.5	7.3	1.8	3
APC	13.3	8.1	0.5	1.4	1.5	0	0.5	0.3	0.5	7.5	0	0.9	69.4	14.3	5	1.3	4.1	3.9	5.4	1.8	8.4
ARID1A	4.3	4.1	0	3.1	0	4.5	1.6	0.7	2.1	15	0.7	6.4	10.9	23.4	26.4	0.9	4.7	6.7	8.5	10.5	8
ARID2	6.9	13.2	0.2	0.7	0	1.8	2.1	0.7	0.6	2.5	0.7	1.4	4.4	9.3	6.9	1.7	3.4	5.1	5	5.3	3.5
ASXL1	7.3	3.4	0.2	0.9	0	0.9	0.5	0	0.4	0	2.8	0.5	5.4	5.4	5.7	0	3.4	5.6	2.7	1.8	2.3
ATM	15.8	5.1	1.2	3.8	4.5	1.8	5.9	1.4	2.2	5	0	0.5	11.9	10.8	12.6	1.7	2.8	4.6	8.9	5.3	5.2
ATP1A1	3.6	1	0.2	1.7	0	2.7	0	0.3	0.4	2.5	0	0.5	2.1	3.2	1.9	0.4	0.3	0.6	1.3	1.8	1.1
ATP2B3	6.9	3	0	0.2	1.5	0	0.5	1	1.2	0	0.7	2.3	4.4	7.9	0.6	0.4	2.5	1.7	5.2	3.5	2.4
ATRX	11.3	6.4	0.2	2.4	4.5	0	1.1	5.3	1.2	10	0	4.4	6.6	7.9	5.7	0	5.6	6.2	6.9	7	5.9
AXIN1	3.6	3.7	0.2	0.5	0	1.8	0	1	0.1	0	0	0.5	2.3	2.9	1.9	0	1.6	0	1.2	5.3	1.2
AXIN2	4.4	1.7	0.2	0.2	0	0	0	0.3	0.1	2.5	0	0	4.4	3.6	3.8	0	1.6	1.1	1	1.6	1.3
BAP1	4.4	1.7	0.2	10.2	0	3.6	0	0.7	0.4	5	0	0	1	3.6	3.8	0	0.9	0.6	1.2	1.8	1.9
BCOR	14.9	2.7	0.5	0.7	0	0	0	2.7	0.6	2.5	1.4	3.2	4.7	7.2	1.9	0.4	1.9	4.5	3.1	0	2.7
BIRC3	2	2	0	0.7	3	0.9	0	0.3	0.1	0	0	0	0.5	2.5	0.6	0.9	0.3	1.1	0.6	0	0.7
BRCA1	5.2	19.7	0.2	0.7	0	1.8	1.6	2.1	0.4	2.5	0	0.9	10.1	5.7	1.9	0.9	1.3	4.5	7.3	1.8	10
BRCA2	6	3.7	0.2	1.2	0	0.9	0	1.4	1.6	5	0	0	3.4	5.7	3.1	2.2	2.9	5.6	4	3.5	2.5
CACNA1D	13.7	6.8	0.7	2.1	0	0.9	2.7	1.4	1.7	5	0	0.9	7.5	10	8.8	3	3.4	6.2	5.8	1.8	4.2

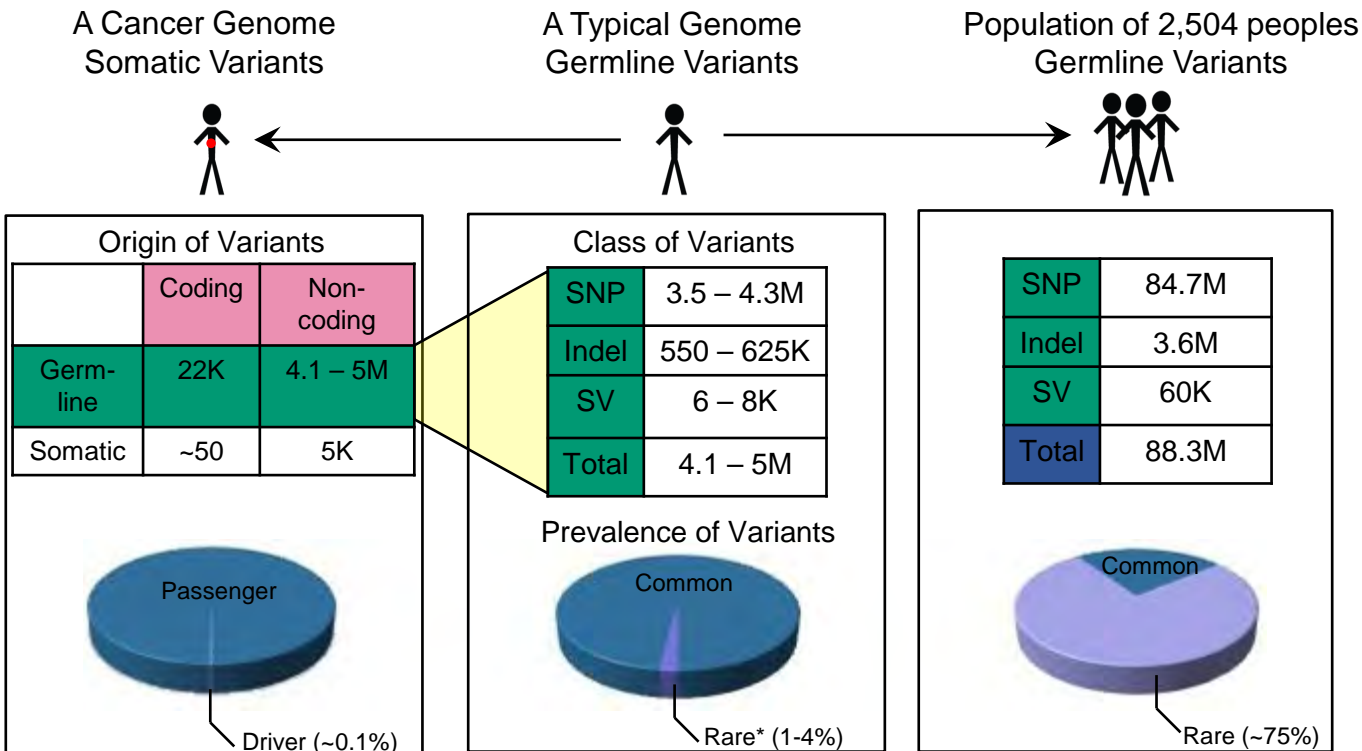
■ ■ ■

HNF1A	4	3.7	0	0	4.5	1.8	0.5	0.7	1.2	0	0	0	3.1	3.6	1.3	0	0	1.7	0.8	1.8	1.3
HRAS	0.4	1.4	3.5	0.2	0	0	1.1	0	0	0	0	0	0.3	0	4.4	0	4.4	2.8	0.2	1.8	1
IDH1	2.8	5.1	0	0.5	0	1.6	5.2	0.3	0	11.3	76.9	1.8	1.1	2.5	0	0.9	1.1	0.6	1.8	4.7	
IDH2	1.6	0.7	0	0	0.9	0	0	0	0	9.9	3.6	1	1.4	0	0	0	0	0.4	1.8	0.8	
IKBKB	4	1.7	0	0.2	1.5	0.9	0	0.3	0.5	0	0	0	1.3	2.9	2.3	0.4	1.9	1.1	1.7	1.8	1.1
IKZF1	2.8	4.4	0	0.5	0	0	1.4	0.3	0	5	0.7	0.5	1.6	1.4	0.6	0	0.8	1.1	2.1	1.8	1.1
IL6ST	6	3.7	0	0.9	0	0.9	0.5	0	0.8	0	0	0.9	1.4	5.7	1.9	0	0.8	0.6	1.2	1.8	1.2
IL7R	3.6	10.6	0.7	0.2	0	0.9	0.5	0.7	0.5	0	0	0	2.3	6.1	0.6	0.9	0.9	4.5	3.9	1.8	2.1
IRF4	3.2	1.4	0.2	0	0	0	0.5	0.7	0	0	0	0.5	0.8	1.4	0.6	0	0.5	1.1	2.1	0	0.8
JAK1	12.1	2	0.2	1.4	0	1.8	1.1	0.7	0.5	0	0	0	2.8	5	1.9	0	1.6	1.1	3.3	3.5	2
JAK2	5.2	3	0	1.4	0	0	0.7	0.6	2.5	0	0.9	2.1	3.6	1.9	0	0.6	2.2	2.7	1.8	1.5	1.5
JAK3	4	2.7	0	0.9	0	0.9	0	0.7	0.6	0	0.7	0.5	2.6	3.6	3.1	1.3	1.6	3.4	1.5	1.8	1.5

■ ■ ■

TNFRSF14	1.2	1	0	0.2	0	0	0	0	0	5	0	0.5	0.3	0.4	0	0	0	0.2	0	0.2		
TP53	29	14.5	0.7	2.6	2.4	1.8	8.5	27.5	33.2	5	5.6	52.7	56.7	48.4	48.4	84.8	69.3	79.2	51.6	64.9	36.1	
TRAF7	2	2.4	0	0.5	1.5	0	0	0.5	0	0	0	0.5	0.5	3.6	0.6	0.4	0.3	0	0.8	1.8	0.8	
TSC1	5.6	1.7	0	1.2	3	1.8	0.5	0	0.5	2.5	0	0.9	2.6	2.9	6.9	0	0.6	2.8	2.1	3.5	1.6	
TSC2	5.2	4.1	0	0.9	3	3.6	0.5	1.4	0.3	2.5	0	0.9	1.8	3.2	1.8	0.9	1.3	2.8	2.1	1.8	1.5	
TSR	3.2	3	0.5	0	0	0	0.5	0.3	0.5	2.5	0	1.4	2.8	3.6	1.9	0.4	0.3	2.8	4	1.8	1.5	
U2AF1	2	0	0	0	0	0	0	0.1	0	4.2	0.5	0.3	1.4	0.6	0	0.6	0	0.6	0	2.3	1.8	0.6
UBR5	10.9	7.4	0.2	2.1	4.5	0	1.1	1	1.2	5	0	0.9	6	15.5	8.7	0.4	3.8	5.6	6	3.5	4	
VHL	1.2	1.4	0	0.6	0	1.8	0.5	0	0	0	0	0	0.5	0.4	0	0	0	0.6	0.2	0	4.8	
WT1	1.2	2.4	0.2	0.7	0	0	0	0.7	0.3	0	0	0.5	2.1	1.4	1.3	0	0	2.2	2.7	0	1.1	
XPO1	5.6	0.7	0	1.9	0	0.9	0	0	0.5	2.5	0	0.5	1.8	1.4	1.9	0	0.9	1.1	1.7	1.8	1.1	
ZRSR2	2.4	0.7	0	0	0	0	0.5	0.7	0.1	0	0	0	0.5	0.3	0.4	1.3	0	0.3	0	1.8	0.4	

Summary: Human Genome Variation

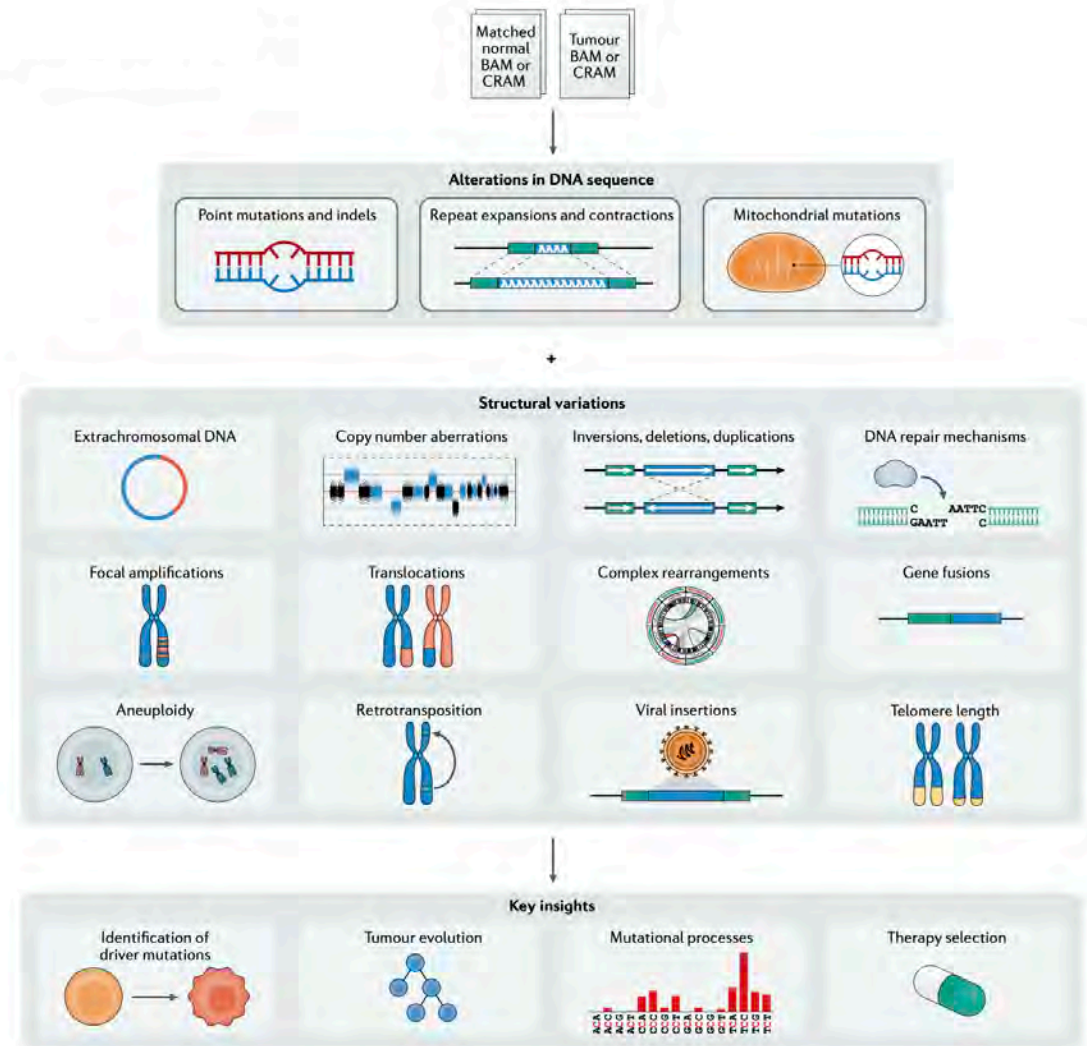


* Variants with allele frequency < 0.5% are considered as rare variants in 1000 genomes project.

Tumor-only sequencing considerations

- Problem: A relatively small number of somatic variants is “hidden” in a large set of germline variants (4-5 Million)
- Study design options
 - Using an unmatched control
 - Rare variants appear as “somatic”
 - Using a panel of normal genomes
 - Fewer rare variants appear as “somatic”
 - Using germline variant catalogs (1000 Genomes, ExAC, gnomAD)
 - Catalogs are often highly curated, i.e., false positive variant calls from your analysis are likely not present and thus, still called as “somatic”
- Tumor-mutational burden (TMB) is often >2-fold over-estimated using tumor-only sequencing

Cancer Genome Data Analysis



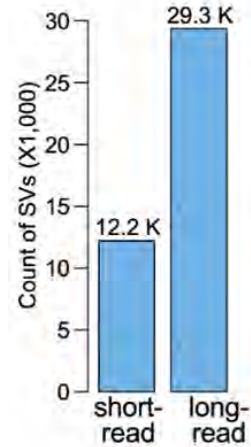
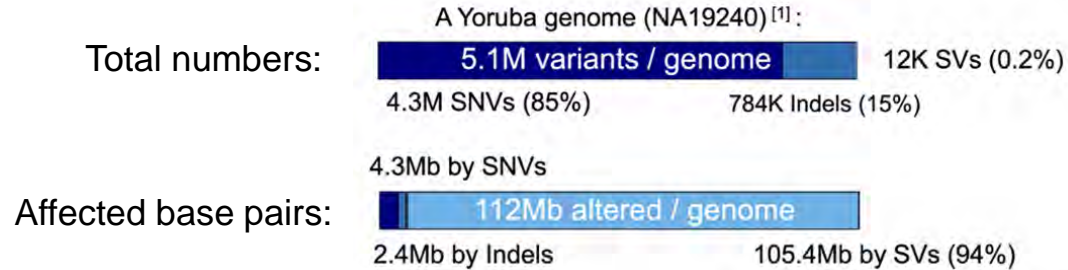
Source: Cortés-Ciriano, I., Gulhan, D.C., Lee, J.J.K. et al. Computational analysis of cancer genome sequencing data. Nat Rev Genet **23**, 298–314 (2022)



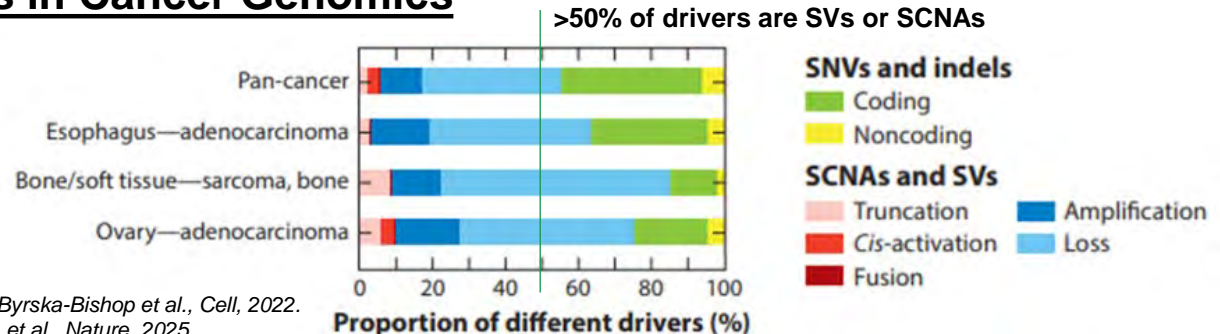
Structural and copy-number variants

Structural Variants in Numbers

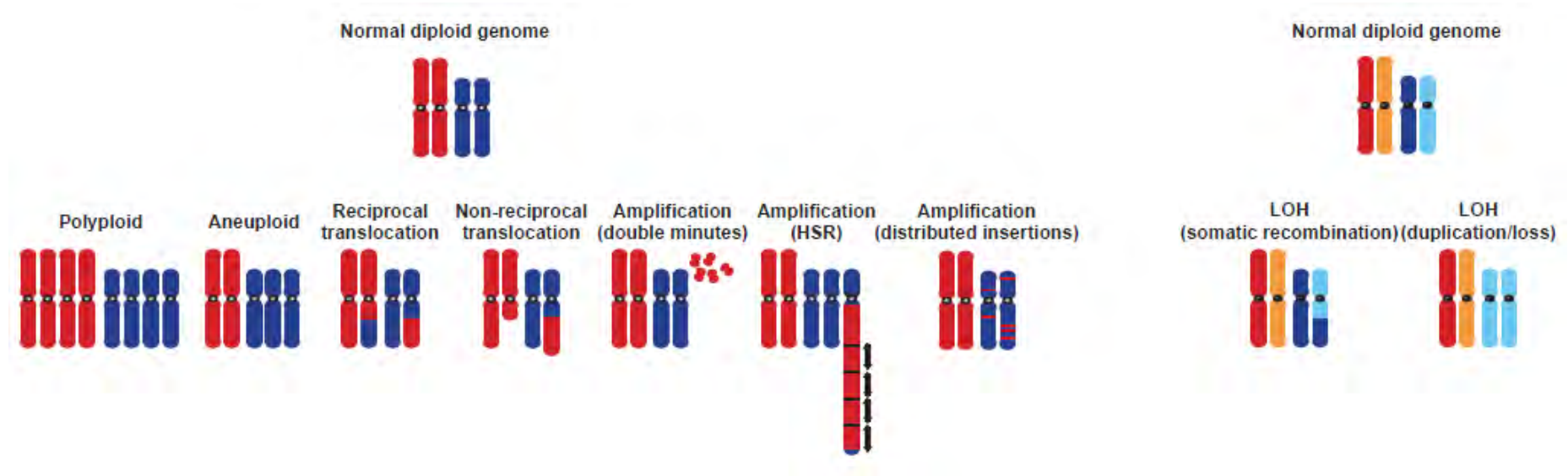
Germline structural variants in Population Genomics



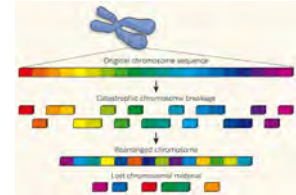
Somatic structural variants in Cancer Genomics



Wide Range of Chromosomal Aberrations in Cancer

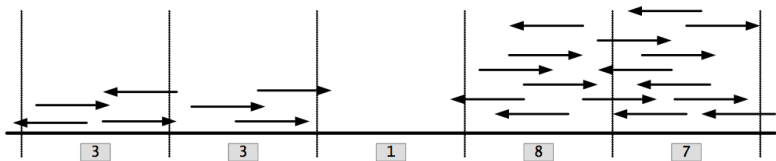


Somatic structural variant calling



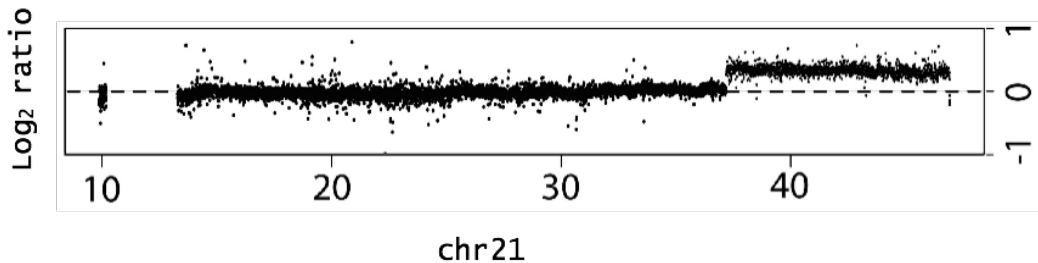
Read-depth

- Read counting in windows for tumor and normal data

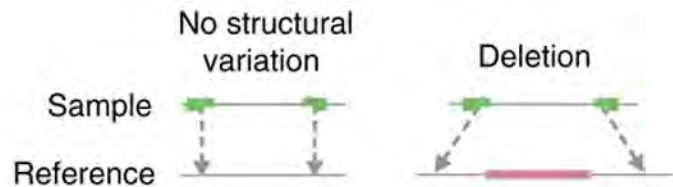


- Log2 ratio for each window
- Chromosome-wide plot

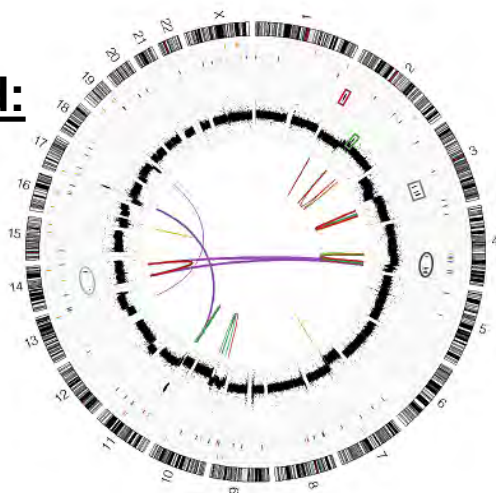
$$\log_2 \frac{\# \text{Reads}_{\text{Disease}}}{\# \text{Reads}_{\text{Normal}}}$$



Paired-end / Split-reads

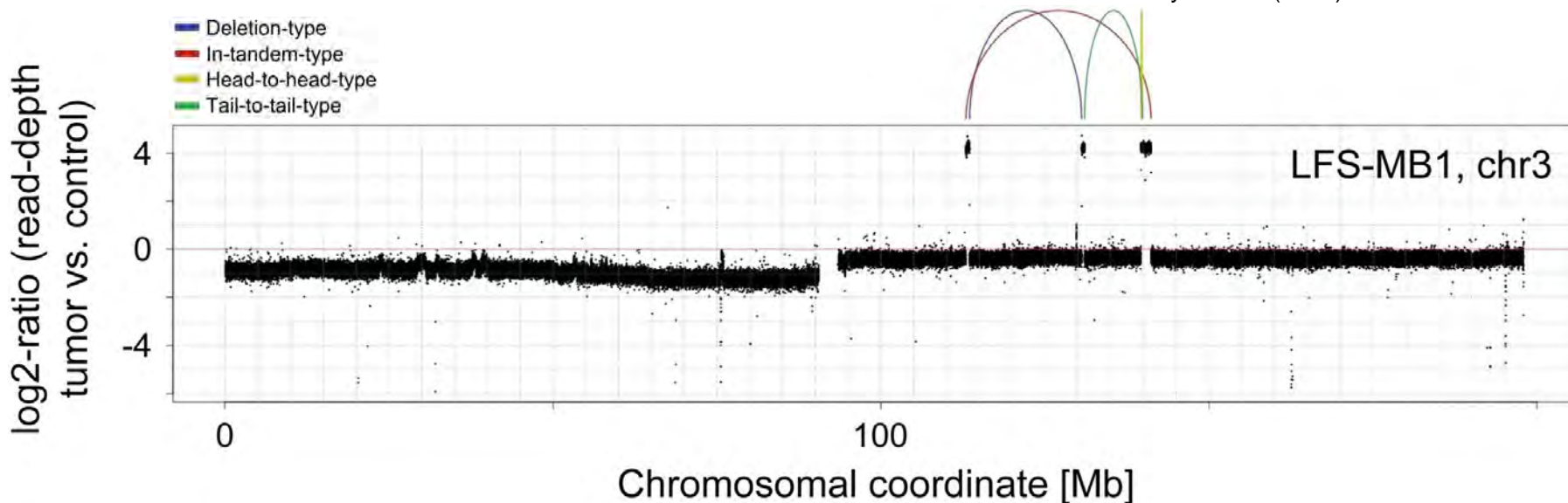
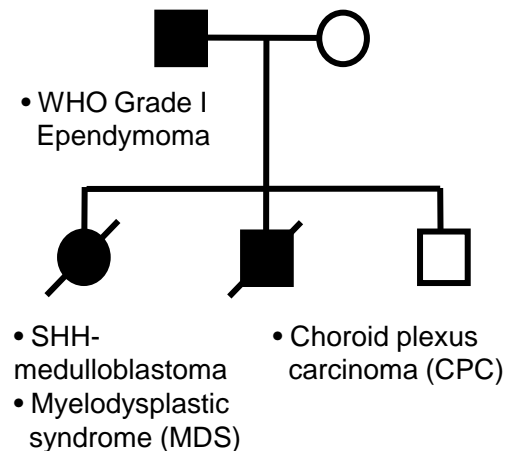


Combined:

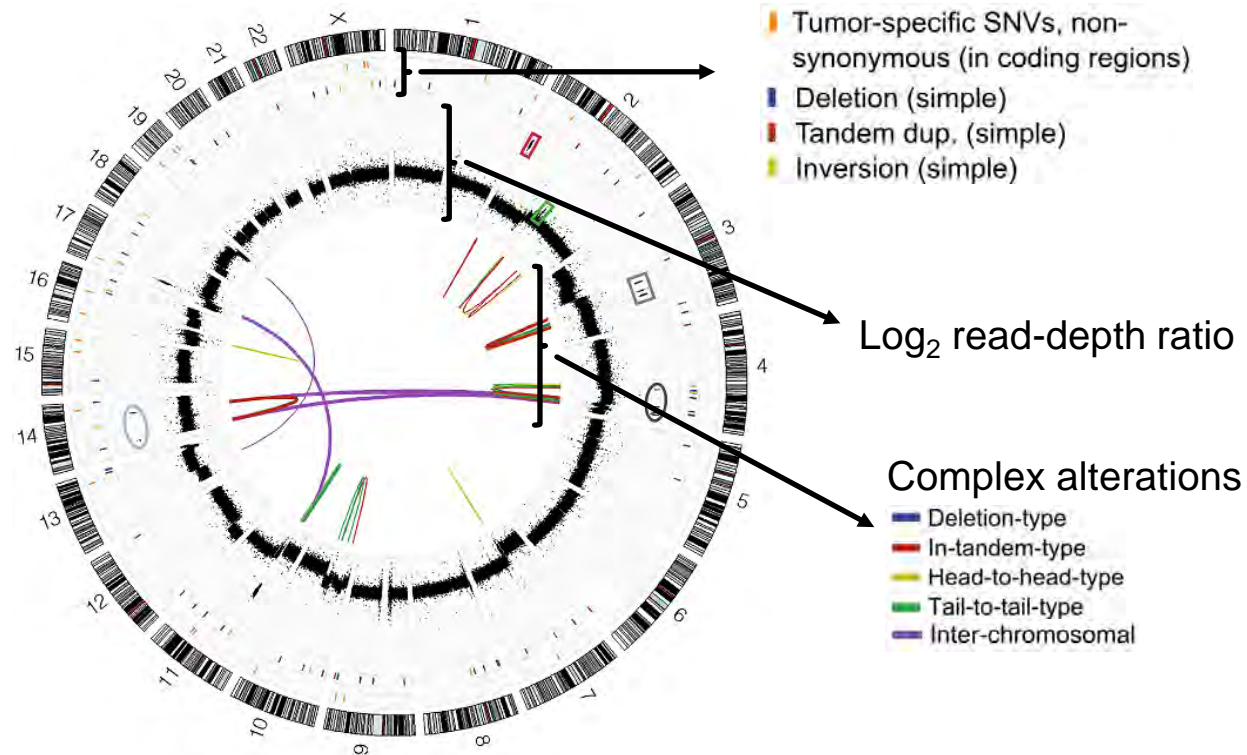


Childhood Brain Tumor Medulloblastoma

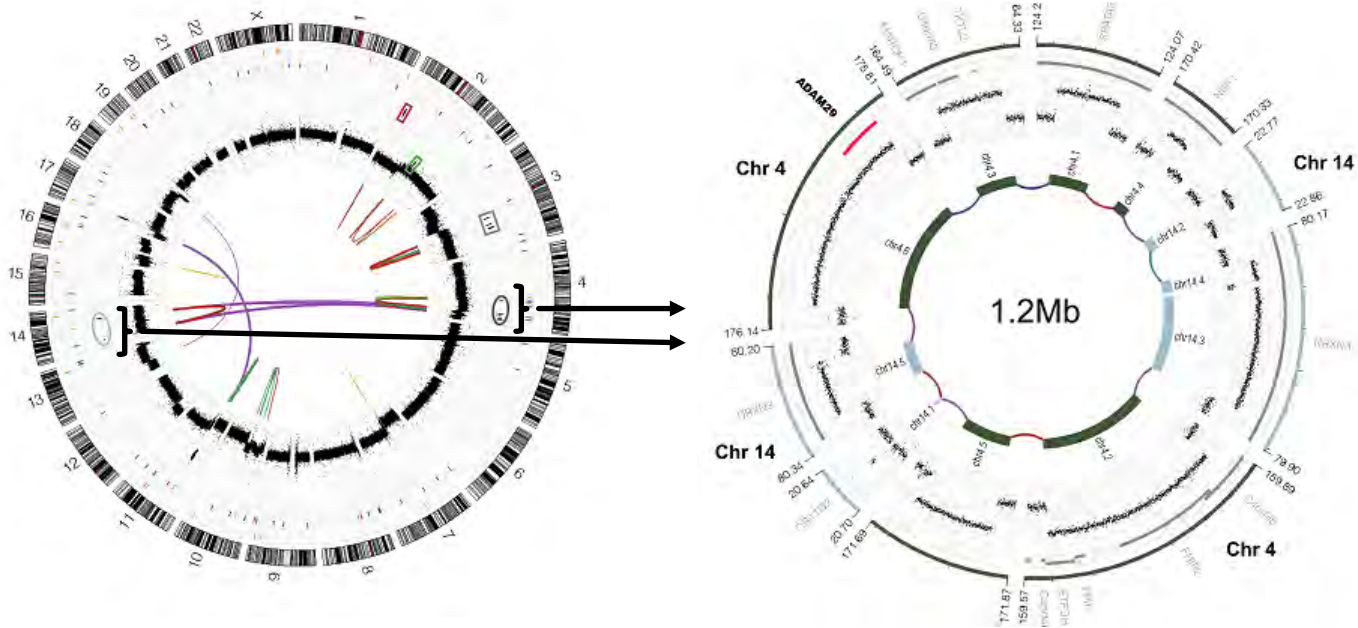
- Li-Fraumeni syndrome
 - Germline TP53 mutation



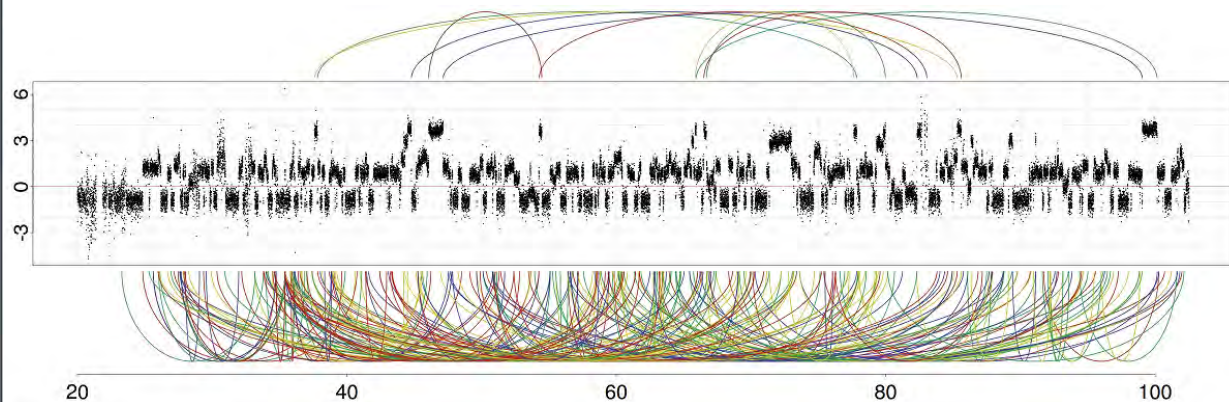
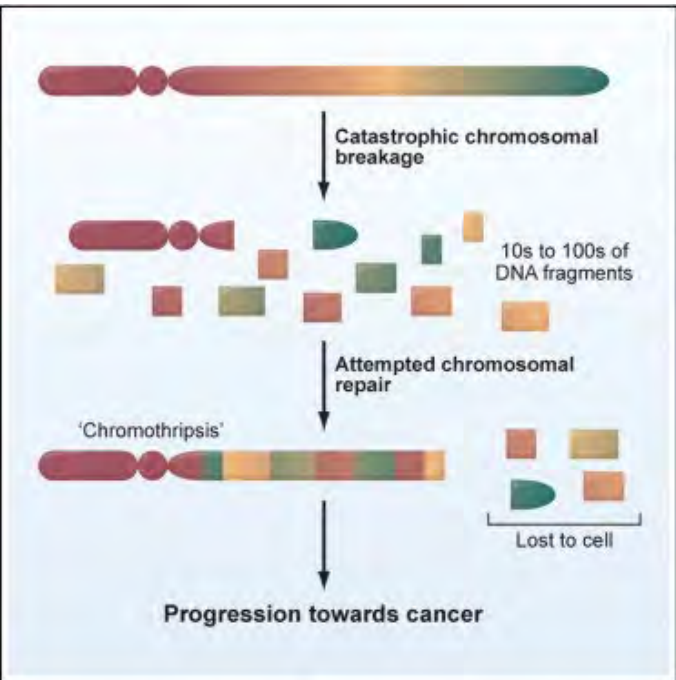
Somatic DNA alterations



Extra-chromosomal DNA (ecDNA)



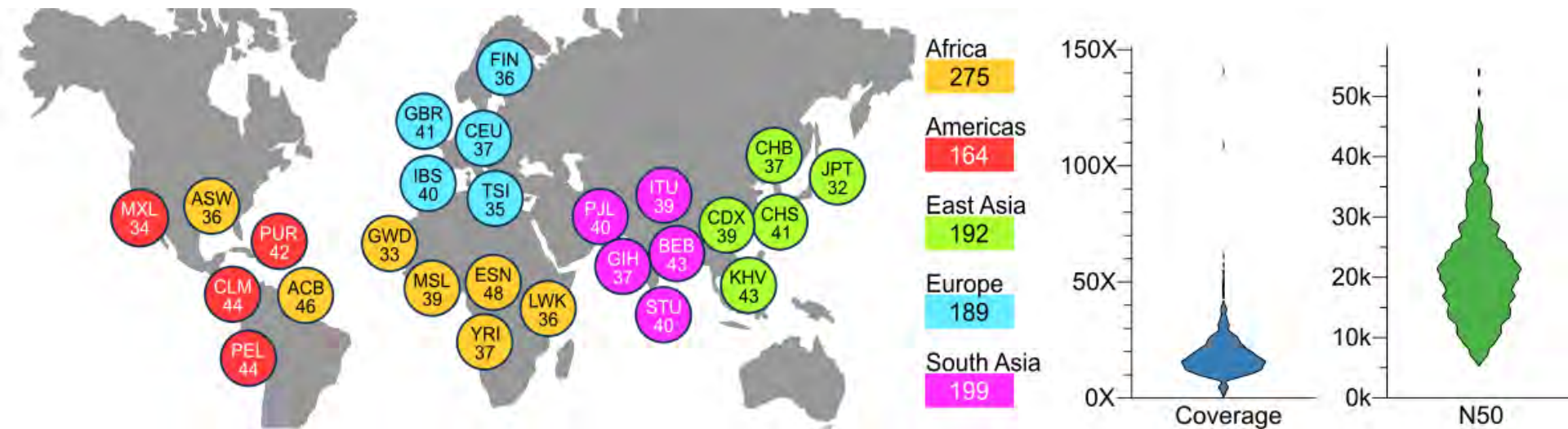
Chromothripsis





Structural variant calling using long-reads

ONT Sequencing of 1,019 samples from the 1000 Genomes Project



1,019 samples sequenced with ONT

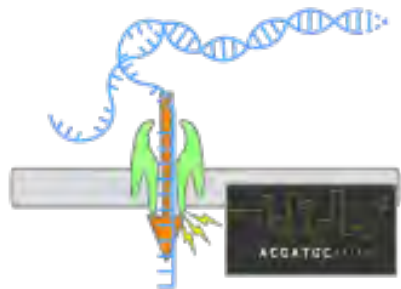
- ~15x coverage
- **Structural variant calling** using long-reads

Pan-genomes and long-reads for SV discovery

Short-reads: 100bp-300bp

↓
2 to 3-fold increase
in detected SVs

Long-reads: N50 read length >15,000bp



Nanopore sequencing

Linear reference genome (GRCh38)

CHM13 (T2T)

Graph pan-genome

↓ + ~200Mbp

↓ + ~100Mbp

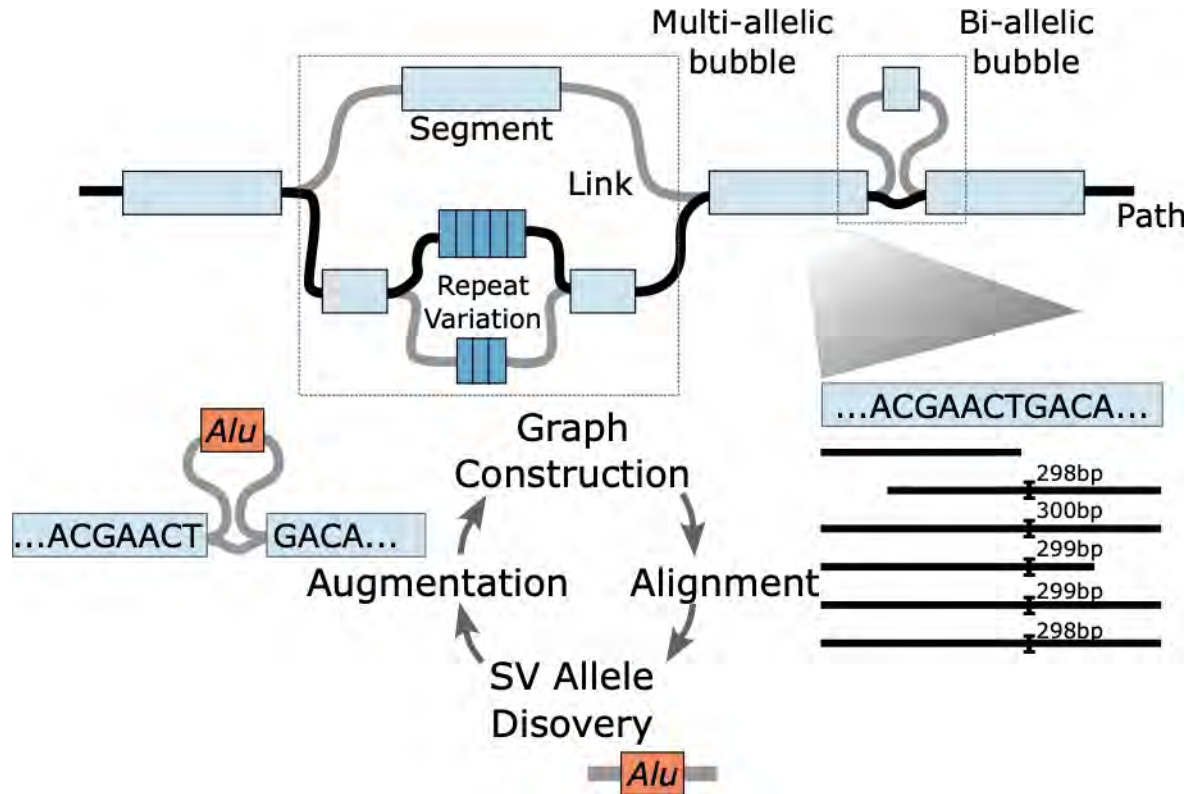


Human Pangenome
Reference Consortium
44 samples

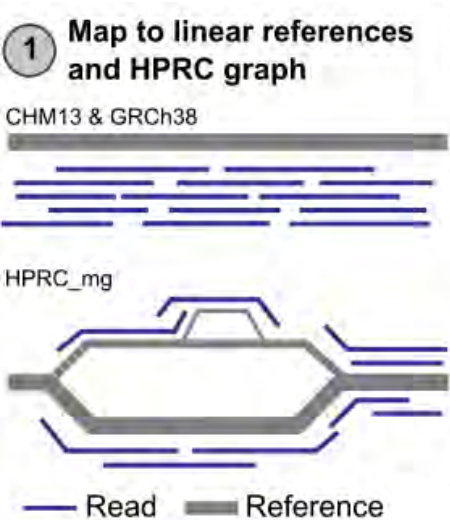
EMBL 

What have we missed with short-reads
and a single reference genome?

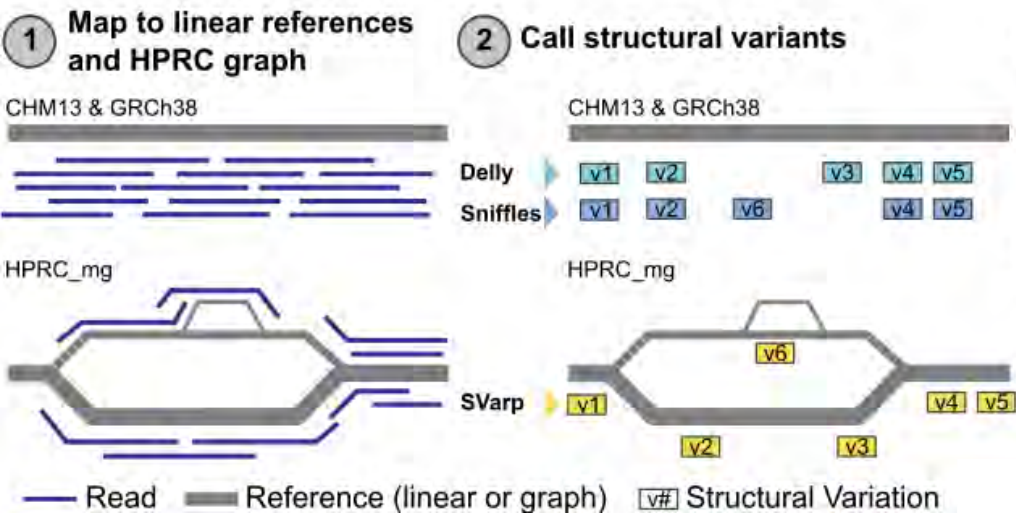
SV Analysis by Graph Augmentation (SAGA)



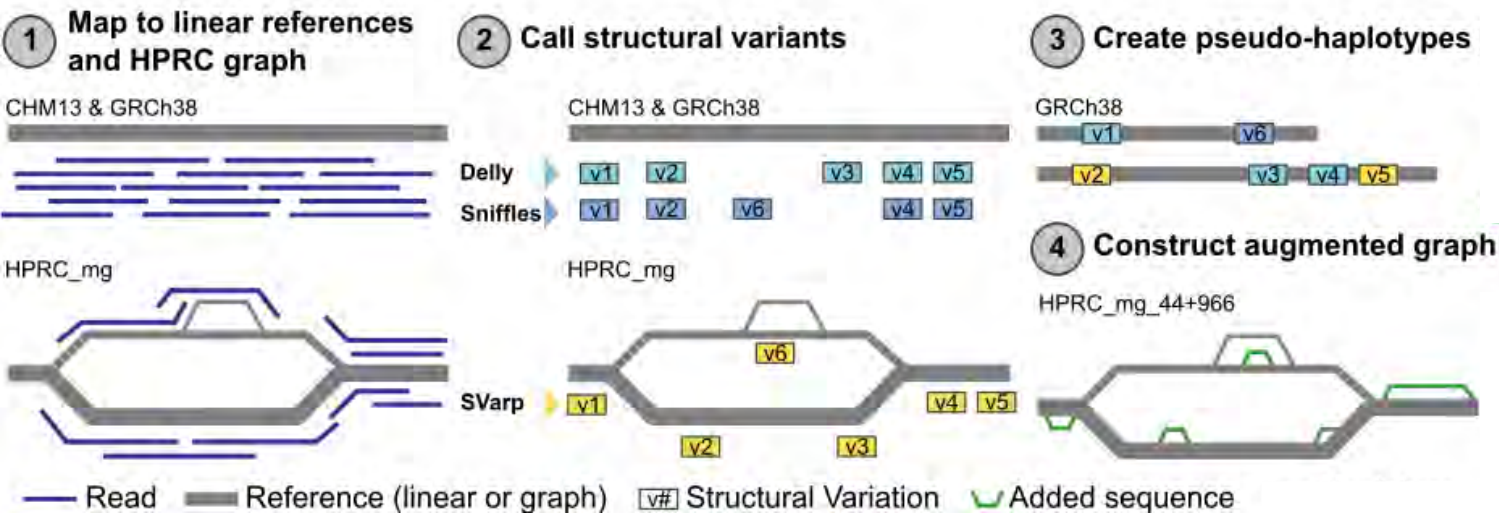
SAGA: SV Analysis by Graph Augmentation



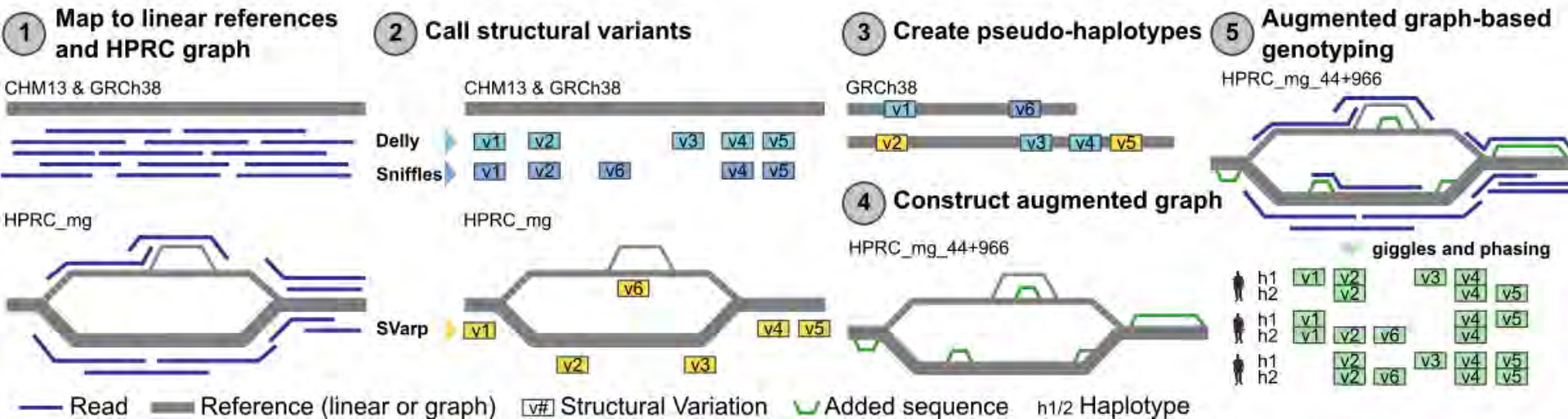
SAGA: SV Analysis by Graph Augmentation



SAGA: SV Analysis by Graph Augmentation

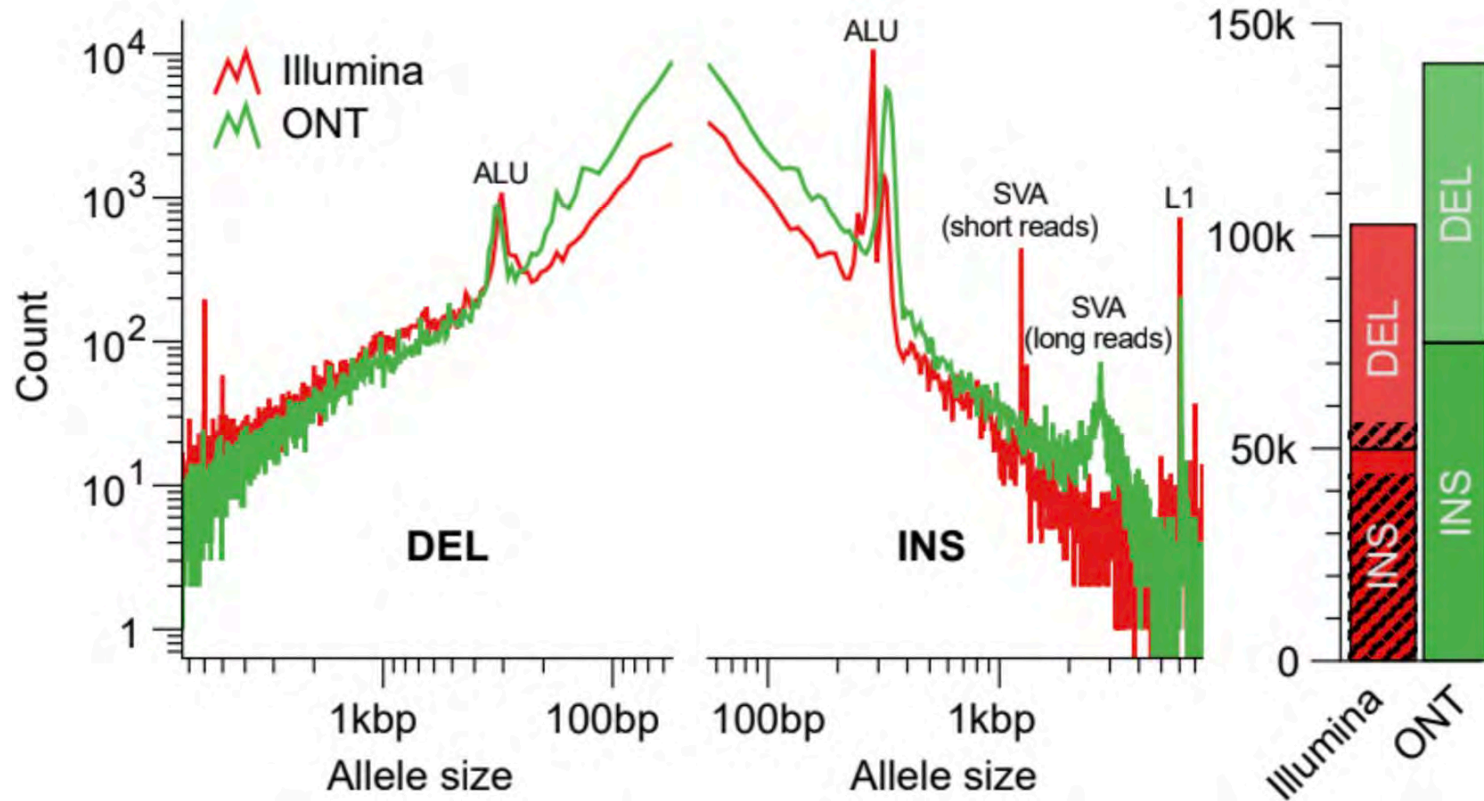


SAGA: SV Analysis by Graph Augmentation



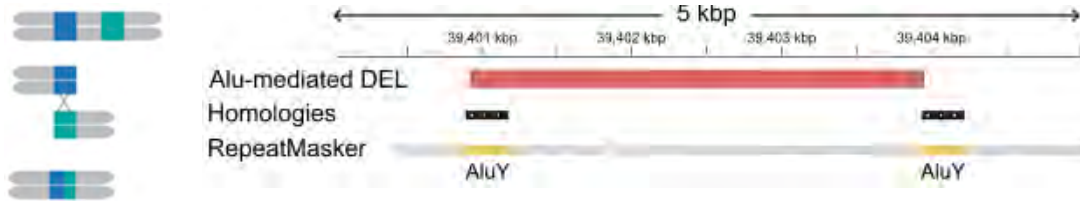
Long-reads facilitate the discovery of sequence-resolved insertions

Byrska-Bishop et al. Cell 2022
for comparison

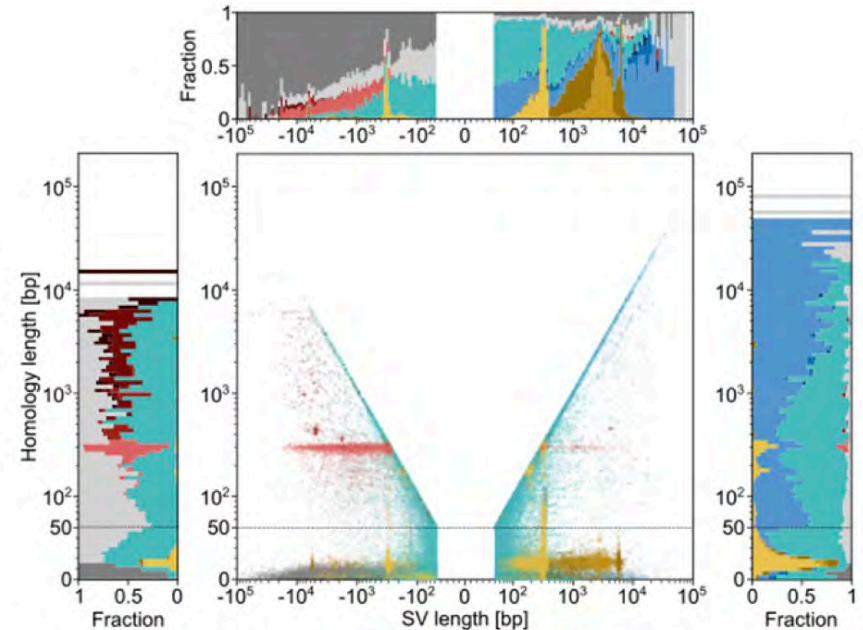


Repeat mediated SVs

- NAHR – Non-allelic homologous recombination



Repeat-mediated	Duplications	Mobile Elements	
Alu-mediated	Tandem	Alu	VNTR
LTR-mediated	Interspersed	SVA	NHEJ
L1-mediated	Complex	L1	Other
SD-mediated	Inverted		All

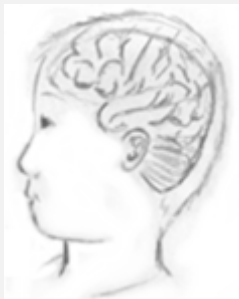


Cancer Genomics using long-reads

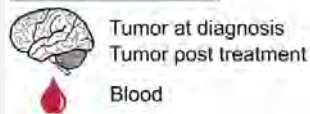
Deciphering haplotype-resolved complex rearrangements

Sample

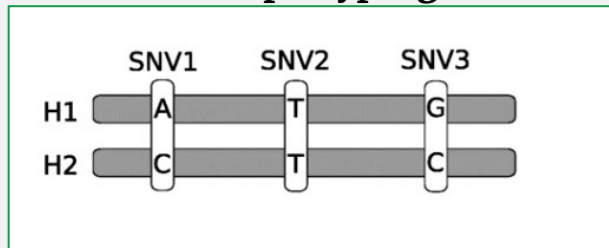
Li-Fraumeni syndrome
Sonic Hedgehog
Medulloblastoma patient



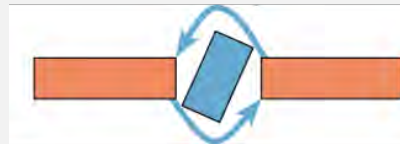
Tissues



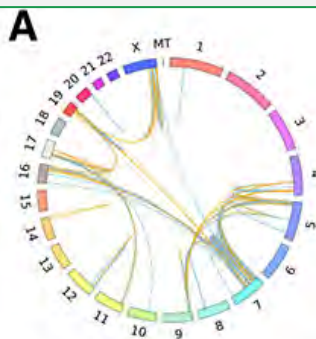
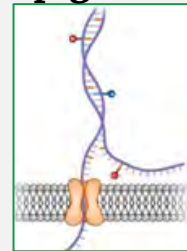
Haplotyping



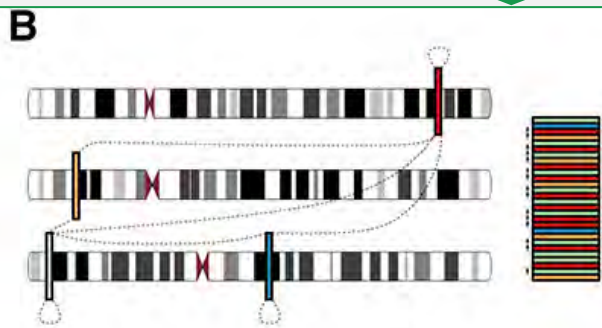
Genetics



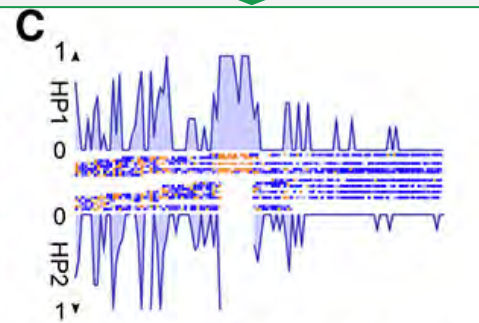
Epigenetics



Structural variants

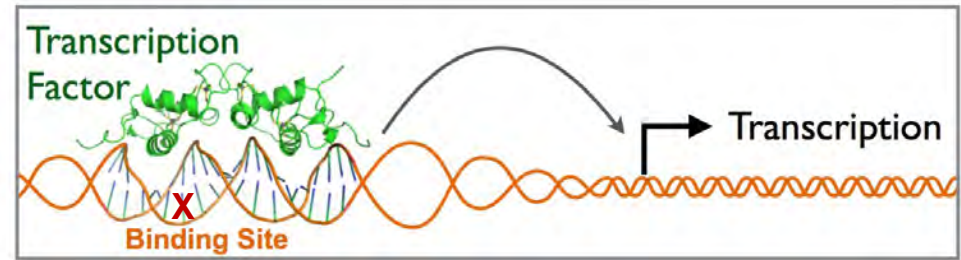
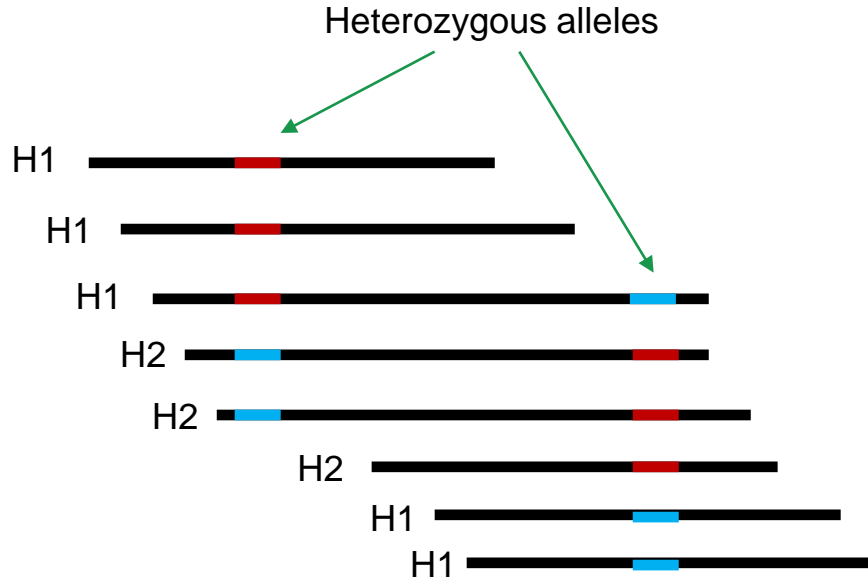


Templated insertion threads



Tumor differential methylation
Allele specific methylation

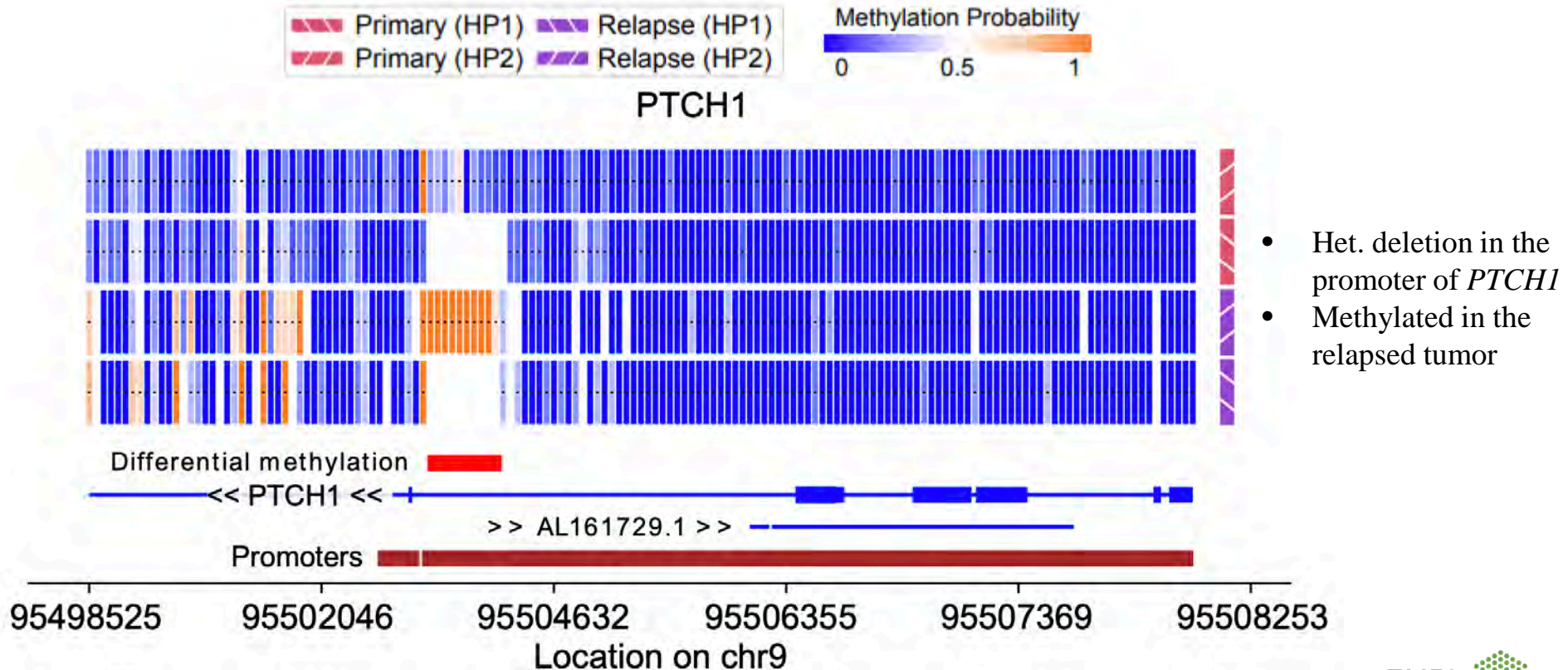
Haplotype-resolved genome analysis



- Applications

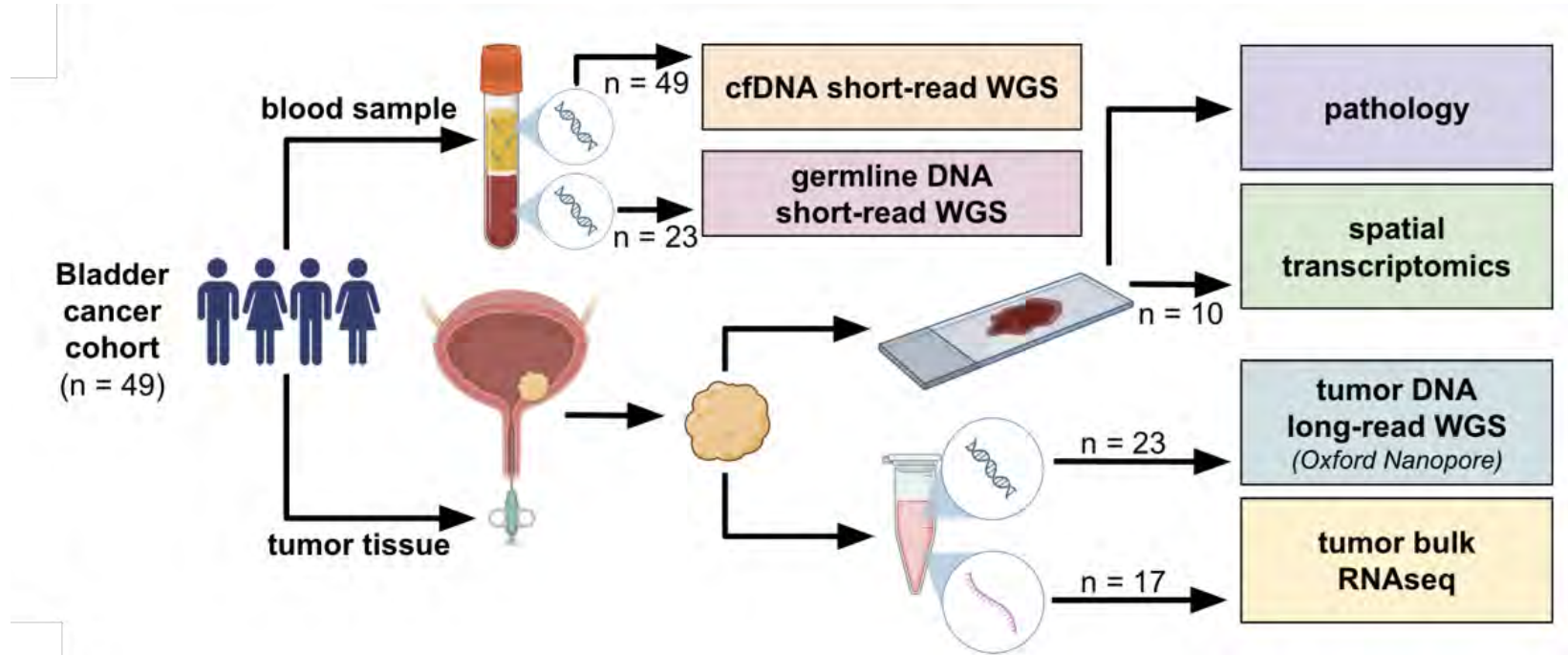
- Analyze compound heterozygotes in rare diseases
- Measure allele-specific expression, methylation, TF binding, etc.
- Determine how combinations of variants uniquely situated on each haplotype may affect gene function

Allele-specific methylation (ASM)



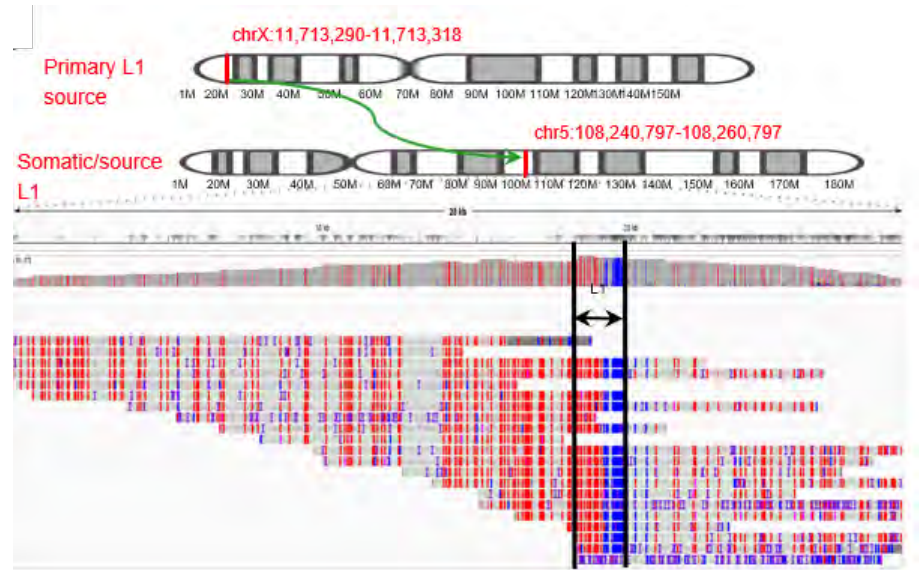
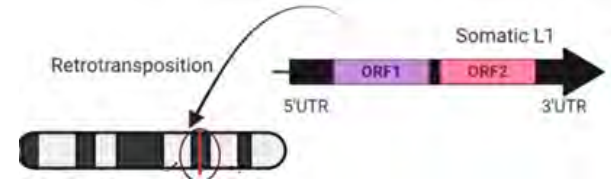
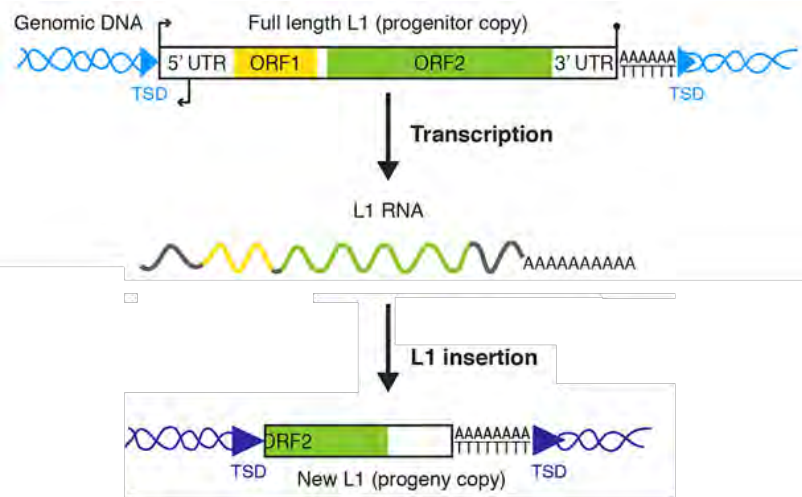
Long-read WGS in bladder cancer patients

- Multi-omics and spatial analyses



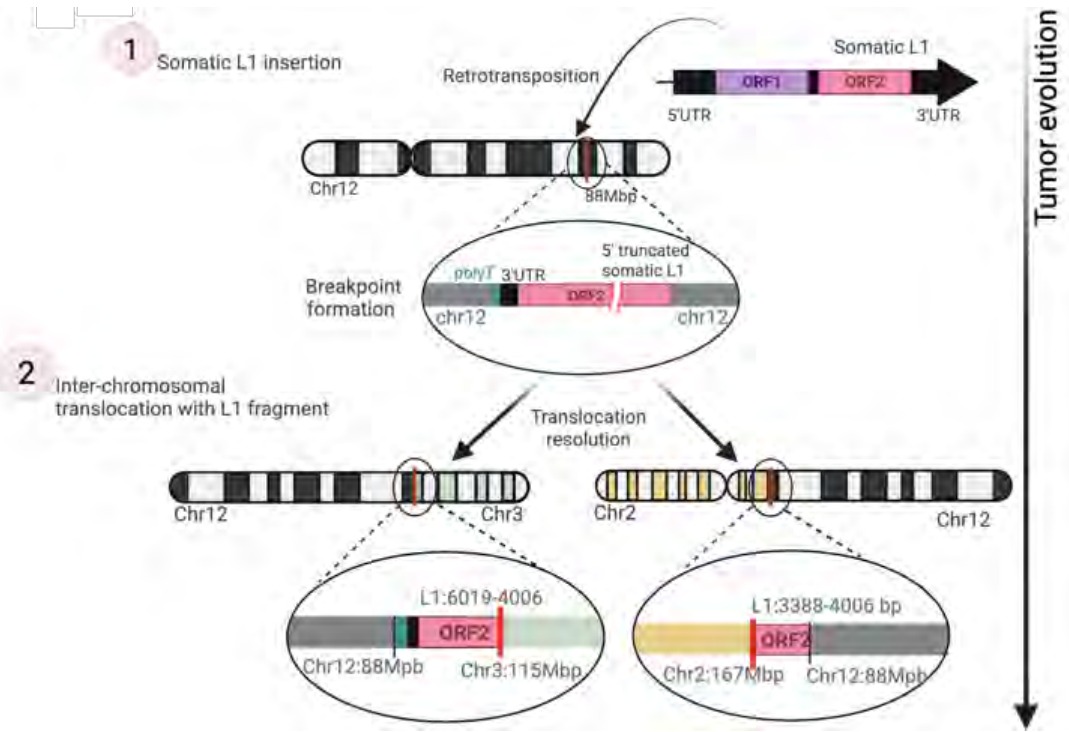
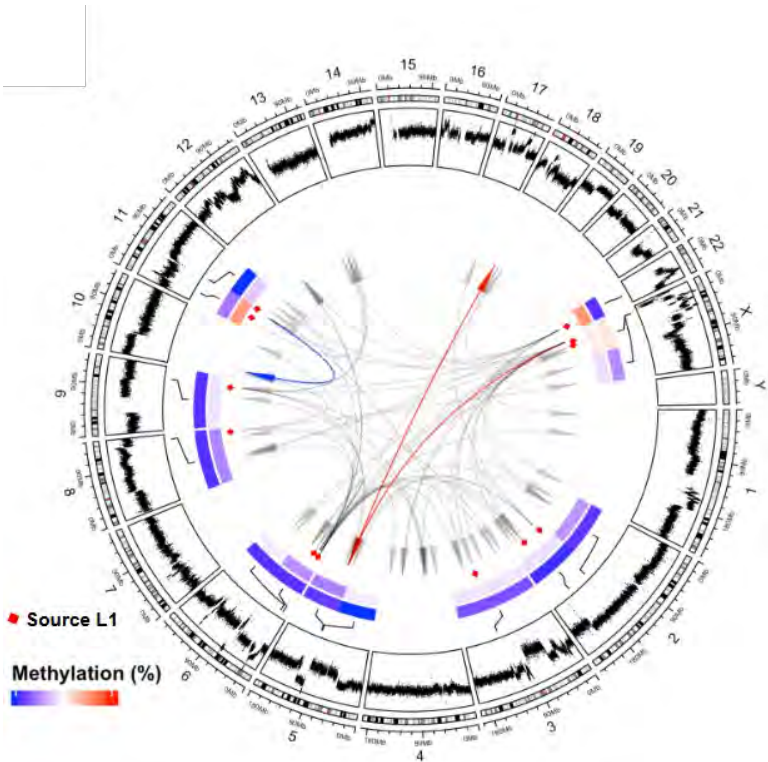
Frequent somatic LINE-1 (L1) insertions

- Up to >500 somatic L1 insertions per tumor
- Evidence in some samples for L1 multi-jumps

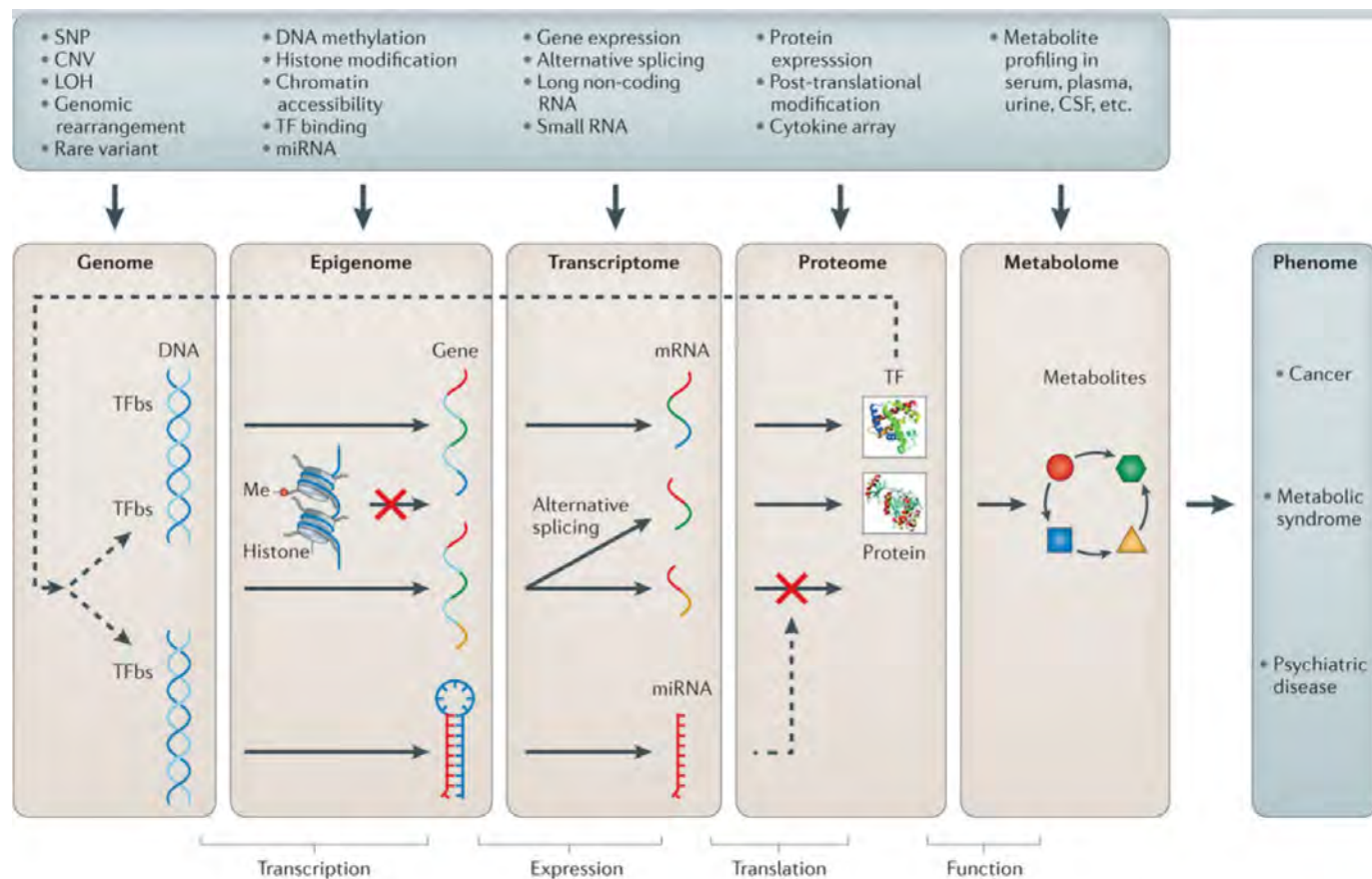


Unmethylated L1 promoter

Somatic L1s are linked with downstream genomic rearrangements and chromosomal instability



Beyond somatic driver variants

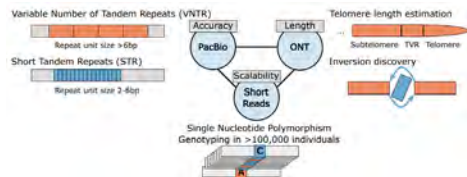


Thank you!

Review > *Genome Res.* 2025 Apr 14;35(4):593-598. doi: 10.1101/gr.280120.124.

The impact of long-read sequencing on human population-scale genomics

Tobias Rausch¹, Tobias Marschall^{2,3}, Jan O Korbelt¹

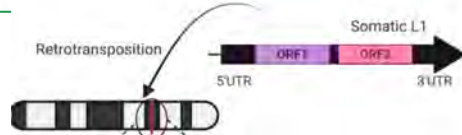


bioRxiv

THE PREPRINT SERVER FOR BIOLOGY

Integrative spatial and multi-omic profiling in bladder cancer links L1 retrotransposition to extrachromosomal DNA, genomic instability, and viral mimicry response

Sophia J. Pribuc, Ivana Oredok, Jan Otonari, Milena Simovic-Lorenz, Michael Scherer, Sergio Manzano-Sanchez, Andreas Kierulff, Urja Parekh, Vladimir Benes, Pooja Sant, Philipp Mallin, Karsten Brand, Angelika B. Riemer, Holger Sultmann, Christoph Plass, Mladen Stankovic, Jan O. Korbelt, Tobias Rausch, Aurélie Ernst



Article | [Open access](#) | Published: 23 July 2025

Structural variation in 1,019 diverse humans based on long-read sequencing

Nature 644, 442–452 (2025) | [Cite this article](#)

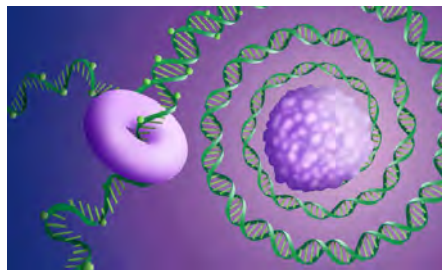
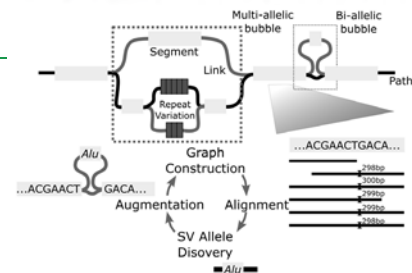
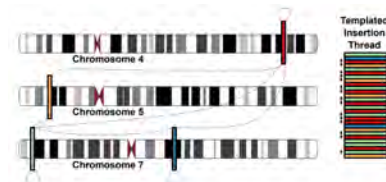


Image: Joana Carvalho/EMBL



> *Cell Genom.* 2023 Mar 22;3(4):100281. doi: 10.1016/j.xgen.2023.100281. eCollection 2023 Apr 12.

Long-read sequencing of diagnosis and post-therapy medulloblastoma reveals complex rearrangement patterns and epigenetic signatures