

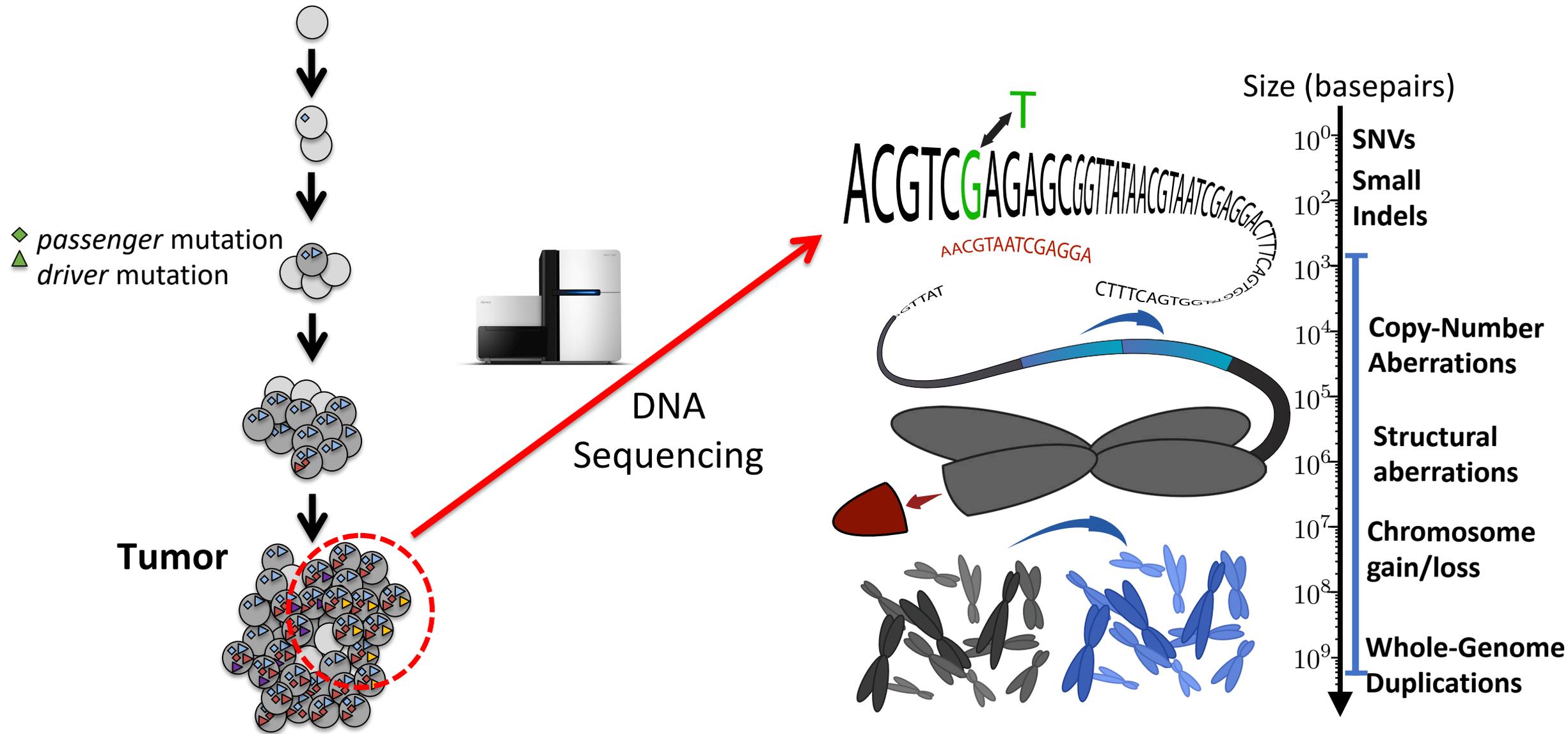
ITCR U24
Comprehensive and Robust Tools for Analysis
of Tumor Heterogeneity and Evolution

PI: Ben Raphael

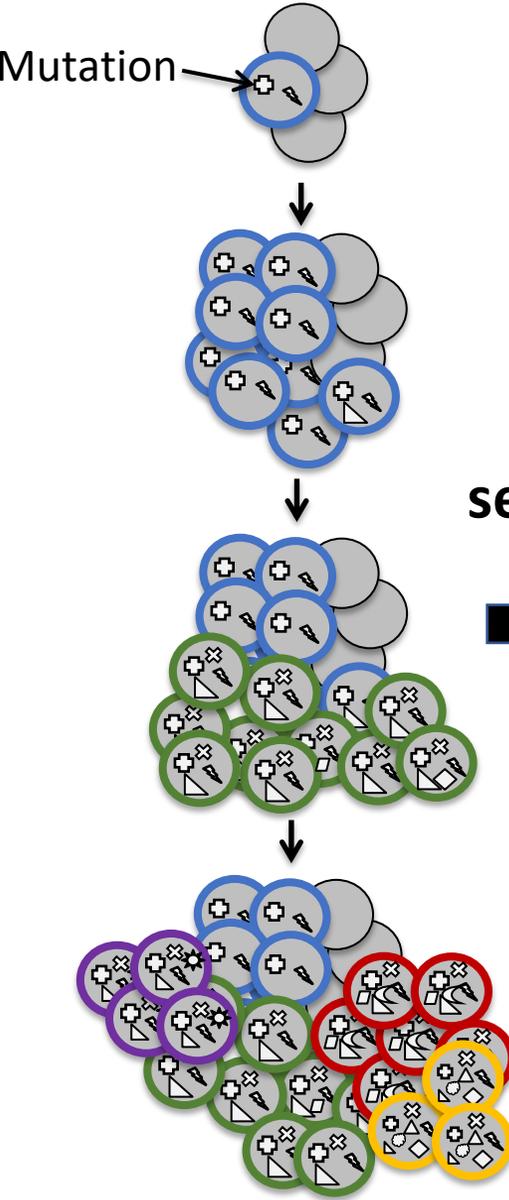
ITCR Meeting 3/5/21



Cancer is an *evolutionary* process driven by somatic mutations over all genomic scales

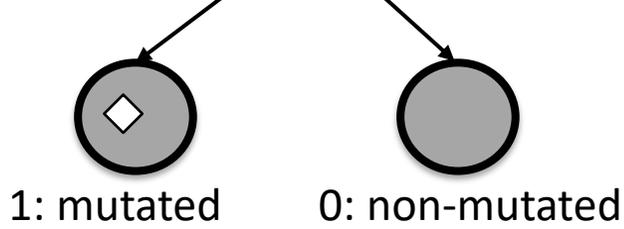


Cancer evolution is described by phylogenetic tree

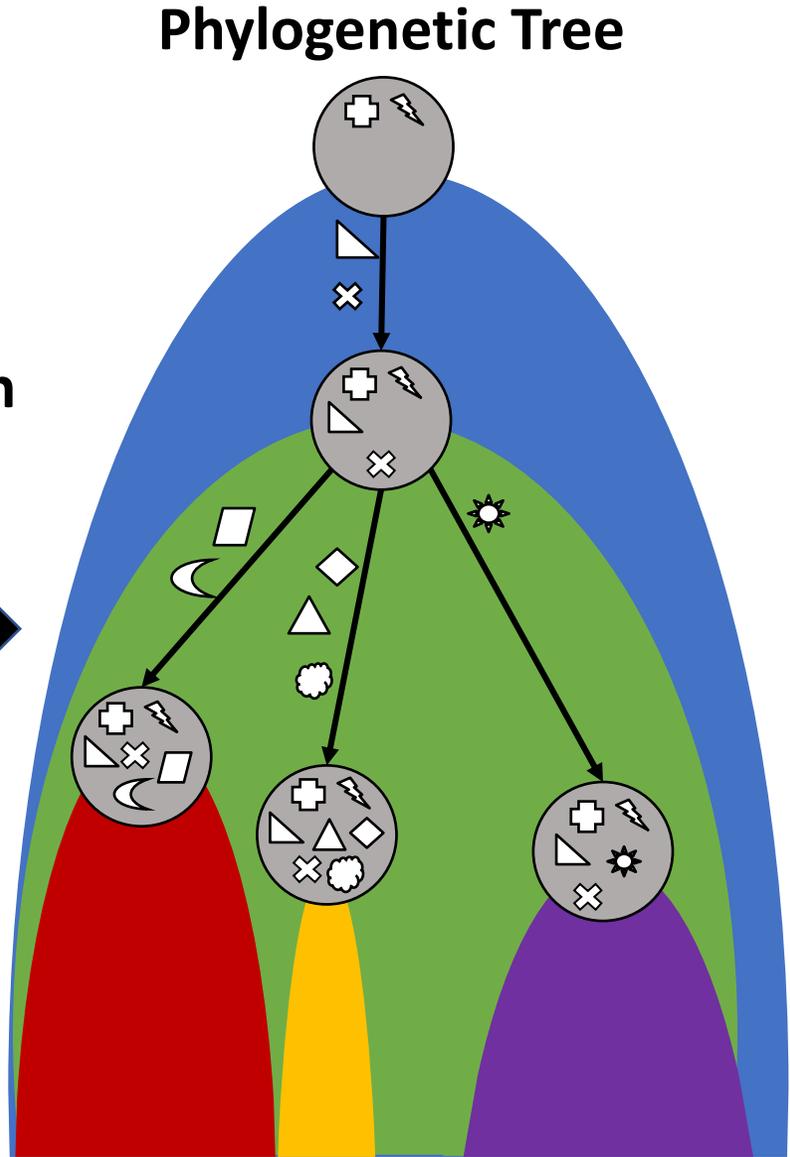


DNA sequencing

	+	⚡	△	×	▭	◐	◇	△	☁	☀
Cells/clones	1	1	0	0	0	0	0	0	0	0
	1	1	1	1	1	1	0	0	0	0
	1	1	1	1	0	0	1	1	1	0
	1	1	1	1	0	0	0	0	0	1

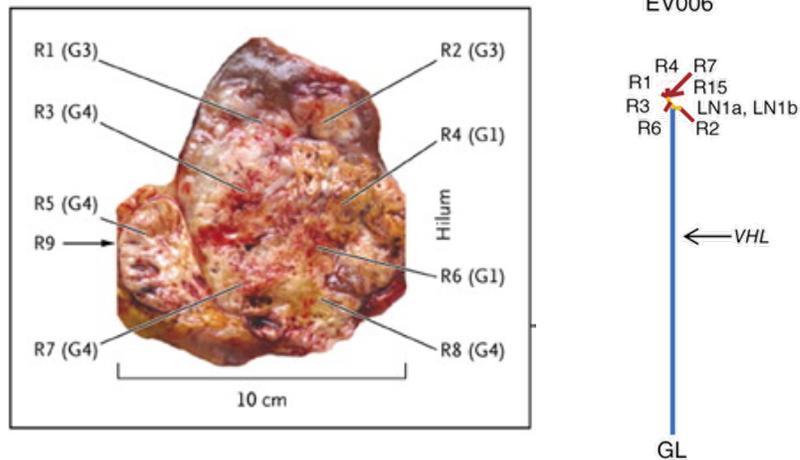


Phylogeny construction algorithms



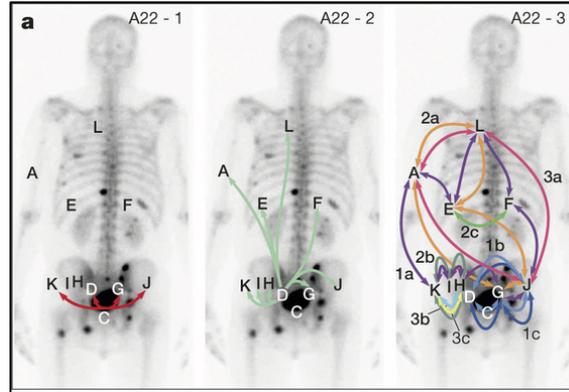
Tumor Evolution is Key to Understanding and Treating Cancer

Regional intratumor heterogeneity



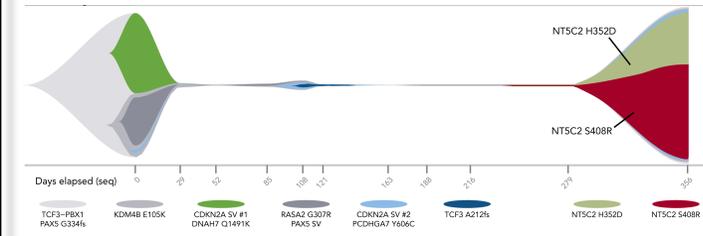
Gerlinger M et al. NEJM (2012).
Renal cell carcinoma

Metastasis

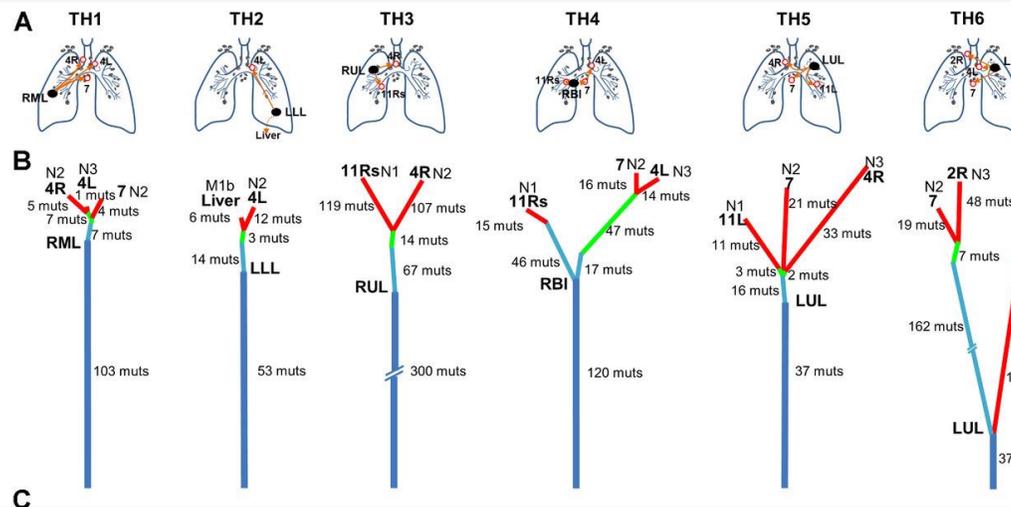


Gundem et al., Nature 2015

Longitudinal sequencing treatment response



Li et al., Blood 2020

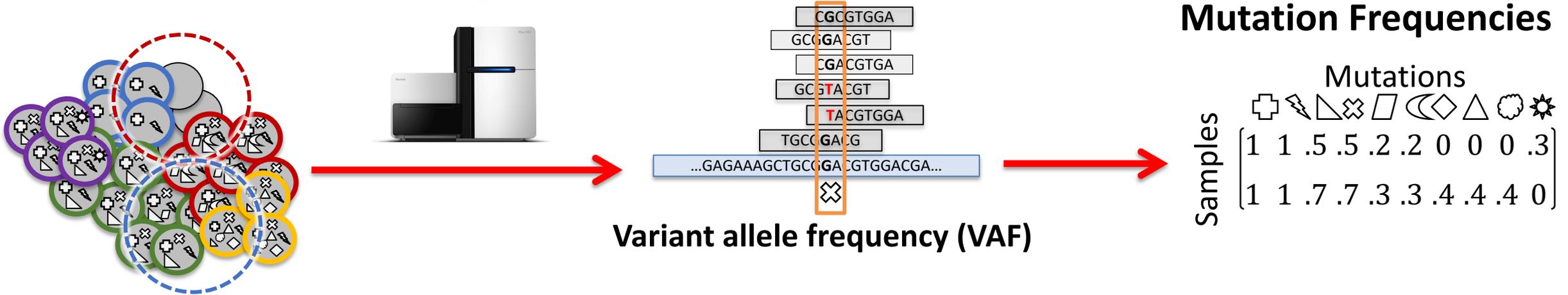


Common patterns of tumor evolution

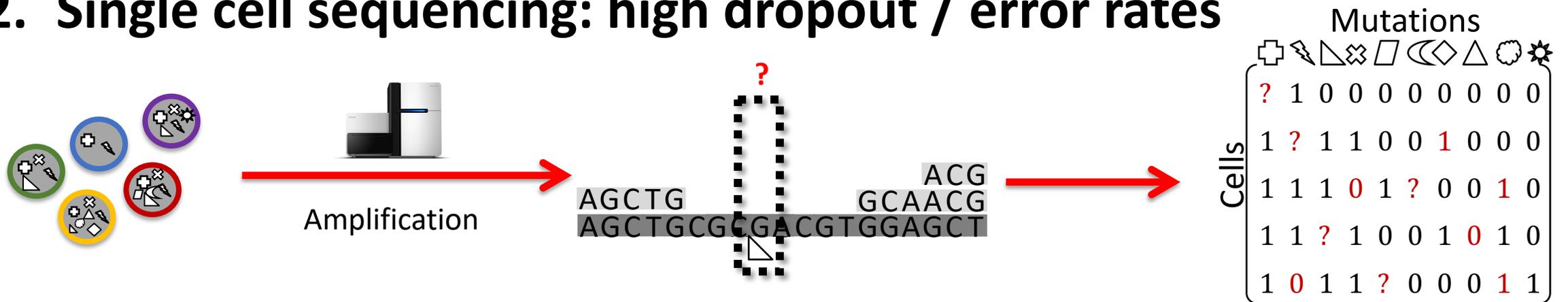
Um SW et al.
Cancer Research (2016)
Lung primary and mets

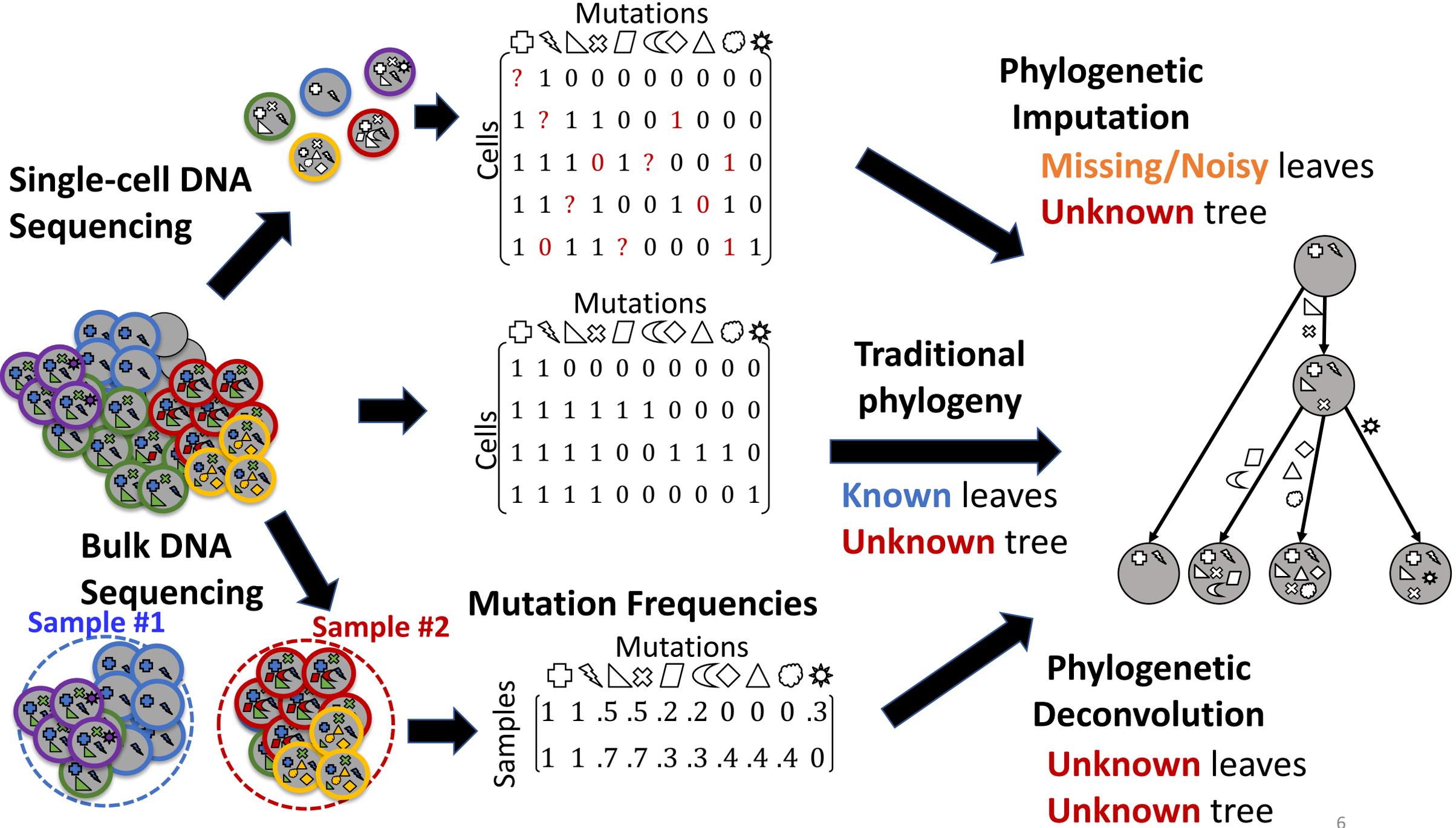
Deriving accurate tumor phylogenies is difficult

1. Bulk sequencing: mixture of mutations



2. Single cell sequencing: high dropout / error rates





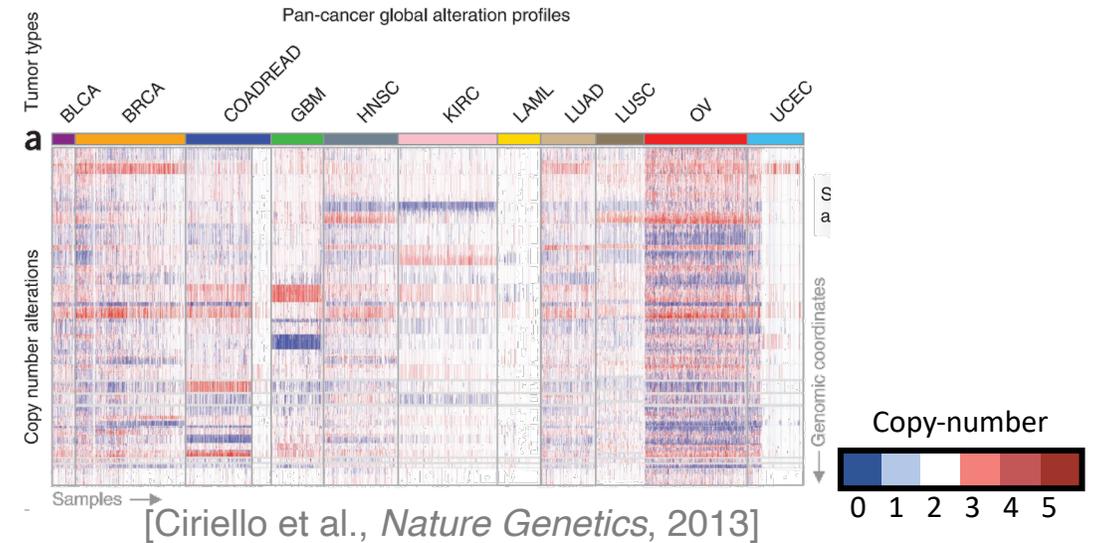
Deriving accurate tumor phylogenies is difficult

3. Aneuploid genomes

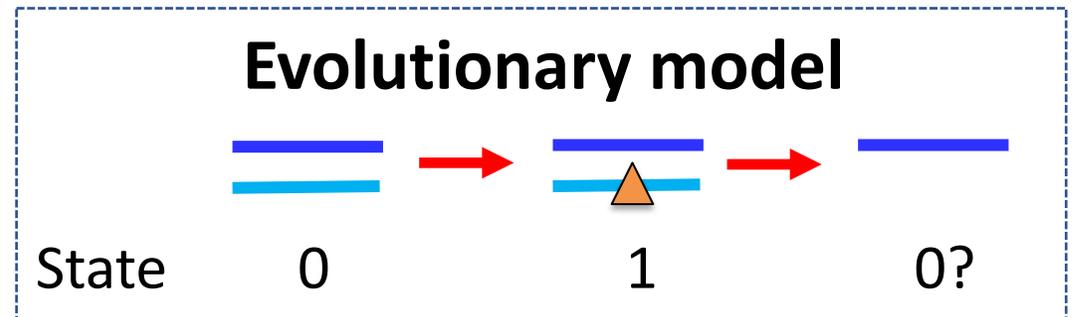
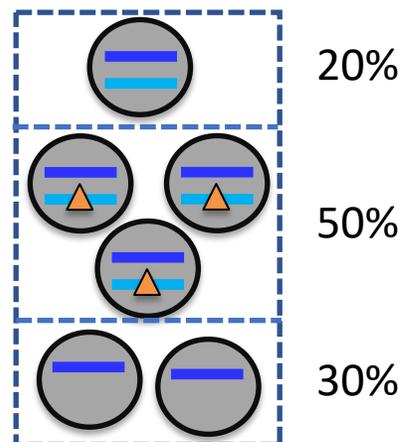
TCGA data

- ~23 focal CNAs (15Mb avg.) per sample
- ~9 arm-level CNAs per sample
- ~37% of tumors with WGDs

[Zack et al., *Nature Genetics*, 2013]



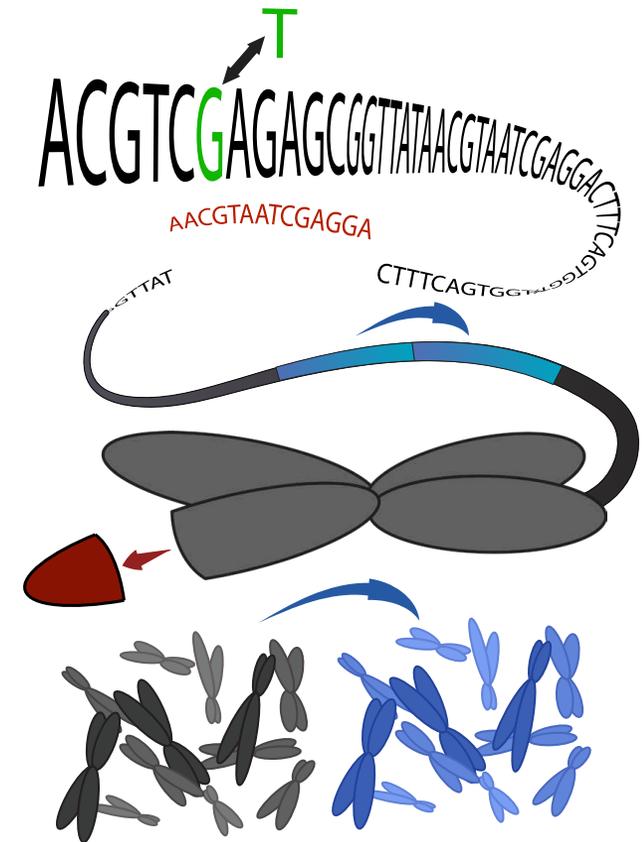
Copy number states and proportions



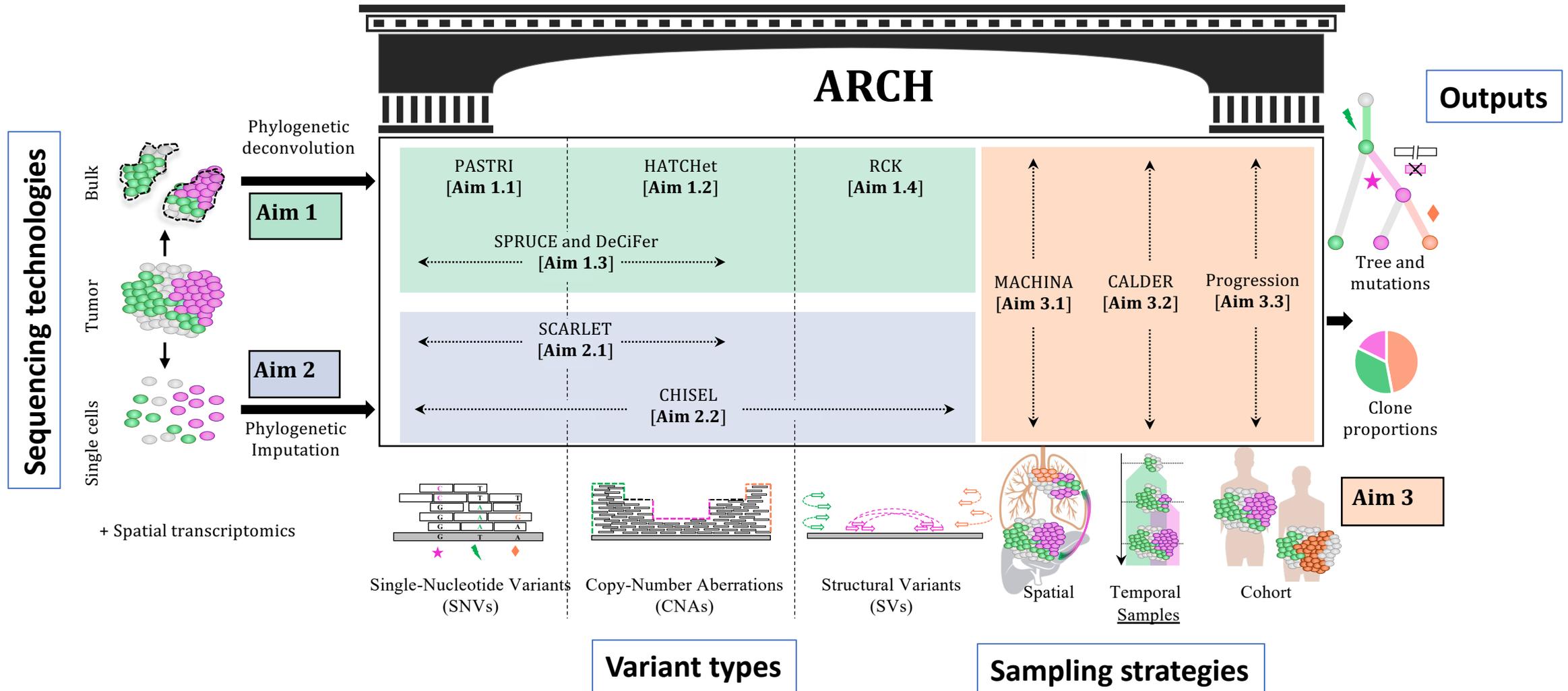
Motivation and Goal

- **Unique challenges of cancer sequencing data** (bulk vs. single-cell sequencing, copy number aberrations, etc.) are often not adequately modeled in standard phylogenetics software.
- Numerous **specialized** algorithms and tools have been developed recently to address **specific challenges** in tumor heterogeneity/evolution but tools are scattered and not always accessible

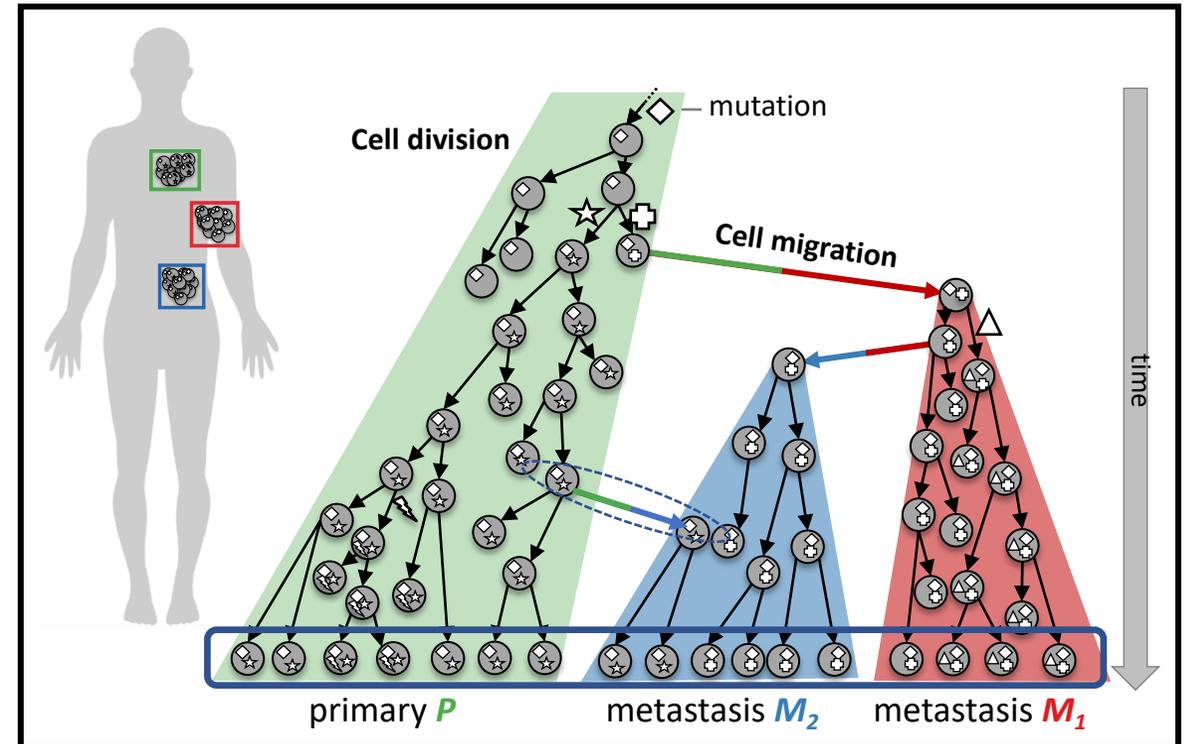
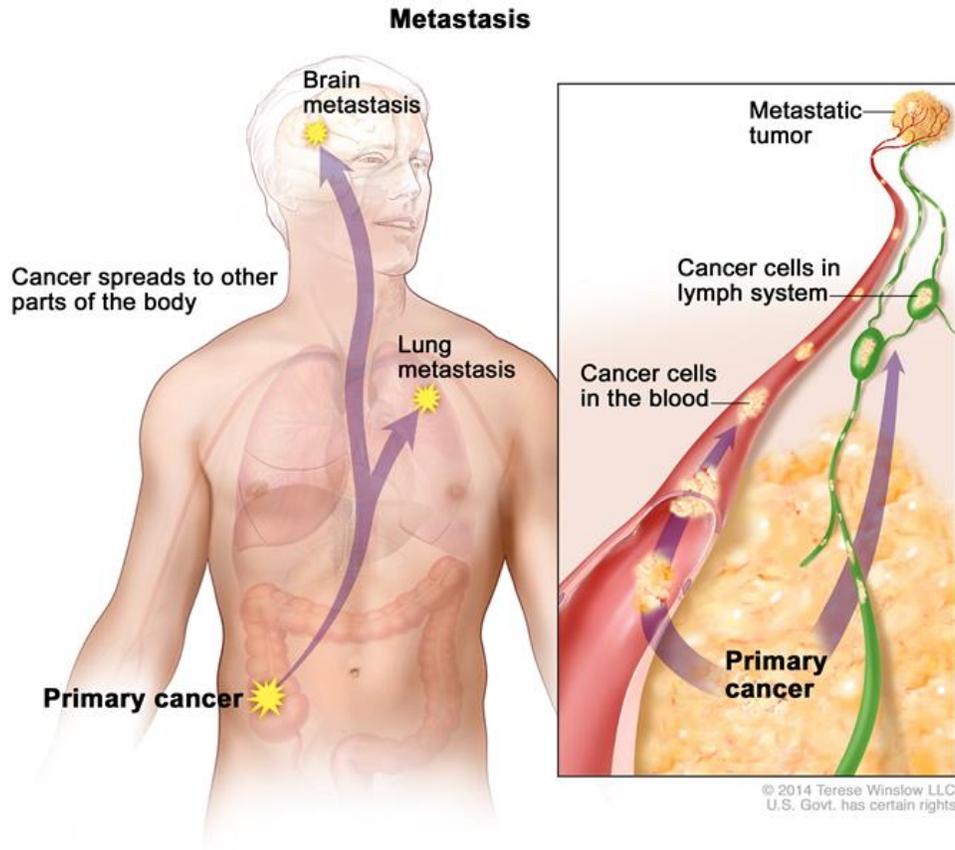
Goal: Develop a **comprehensive, robust and user-friendly software package** for tumor heterogeneity and cancer evolution studies that integrates analyses across diverse sequencing technologies, sampling strategies, genomic scales, etc.



ARCH: A robust toolkit for tumor heterogeneity and evolution



How do cancer cells metastasize to seed tumors at distant locations?

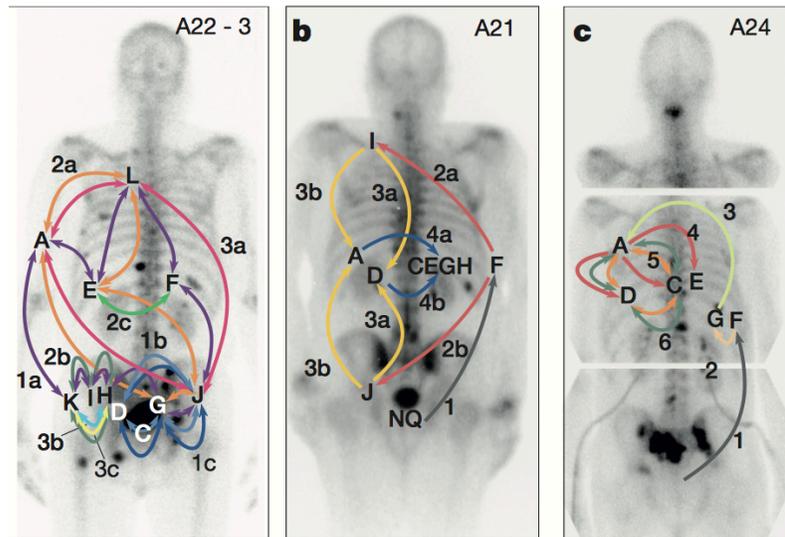


Traditional view: Each metastasis results from a single migration event (**monoclonal**)
Recent studies: Multiple cellular migrations between anatomic sites (**polyclonal**)

Polyclonal/Multiclonal/Re- Seeding of Metastases?

Prostate Cancer

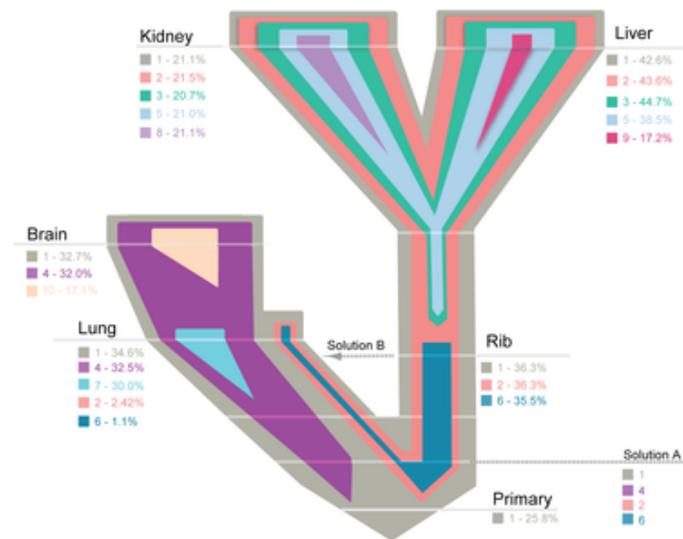
[Gundem et al. (2015) *Nature*]



“..in all five patients with **poly-clonal seeding**, subclones...were found to have **re-seeded** multiple sites.”

Breast Cancer

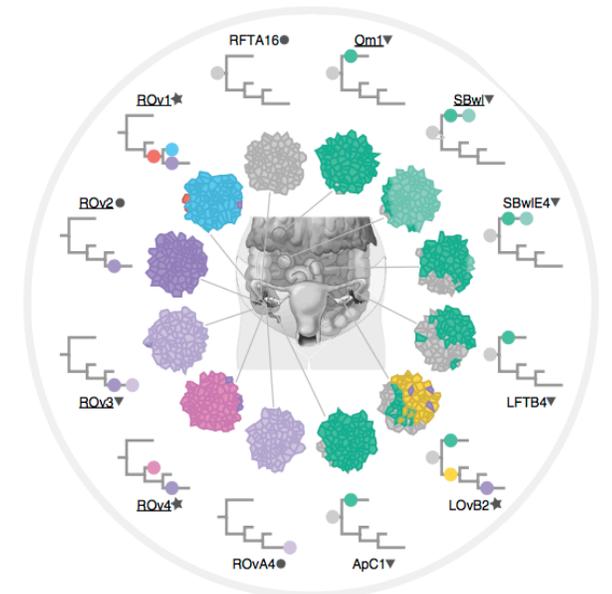
[Hoadley KA, et al. (2016) *PLOS Medicine*]



“**multiclonal seeding** from the primary tumor to the metastases can occur...”

Ovarian Cancer

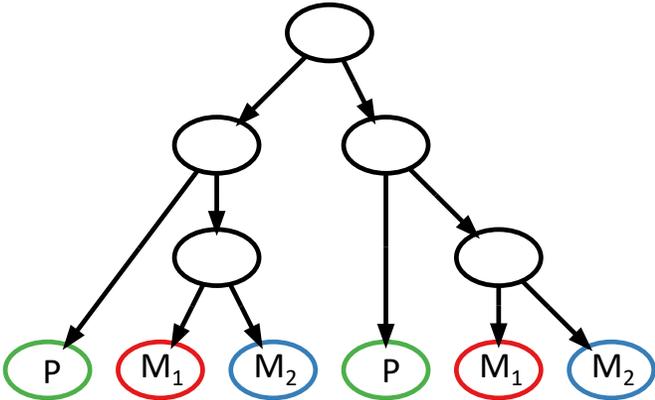
[McPherson et al. (2016) *Nature Genetics*]



“multiple samples composed of divergent lineages is concordant with **polyclonal reseeding** or **polyclonal migration**...”

Migration Patterns in Metastasis

Cell/clone tree T

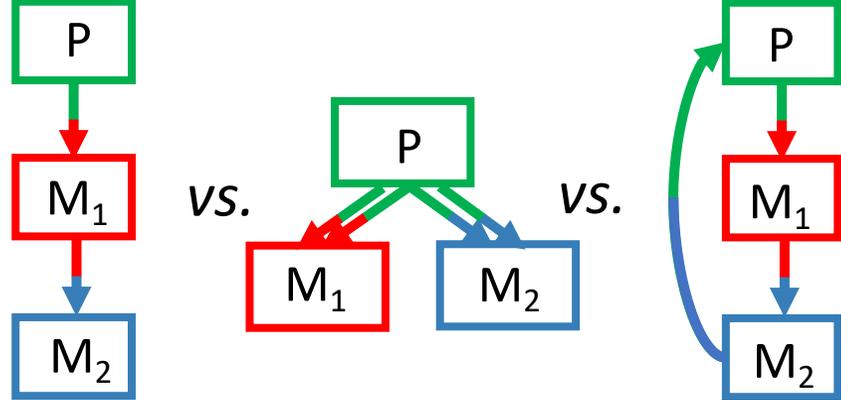


MACHINA



Anatomical locations of ancestral cells is **unknown**

Migration graph S



Monoclonal **Polyclonal** **Reseeding**

- 1. Cell/clone tree T does **not** uniquely determine migration pattern S .
- 2. Uncertainty in tree T for bulk sequencing \rightarrow **substantial** uncertainty in migration pattern S .



Mohammed El-Kebir

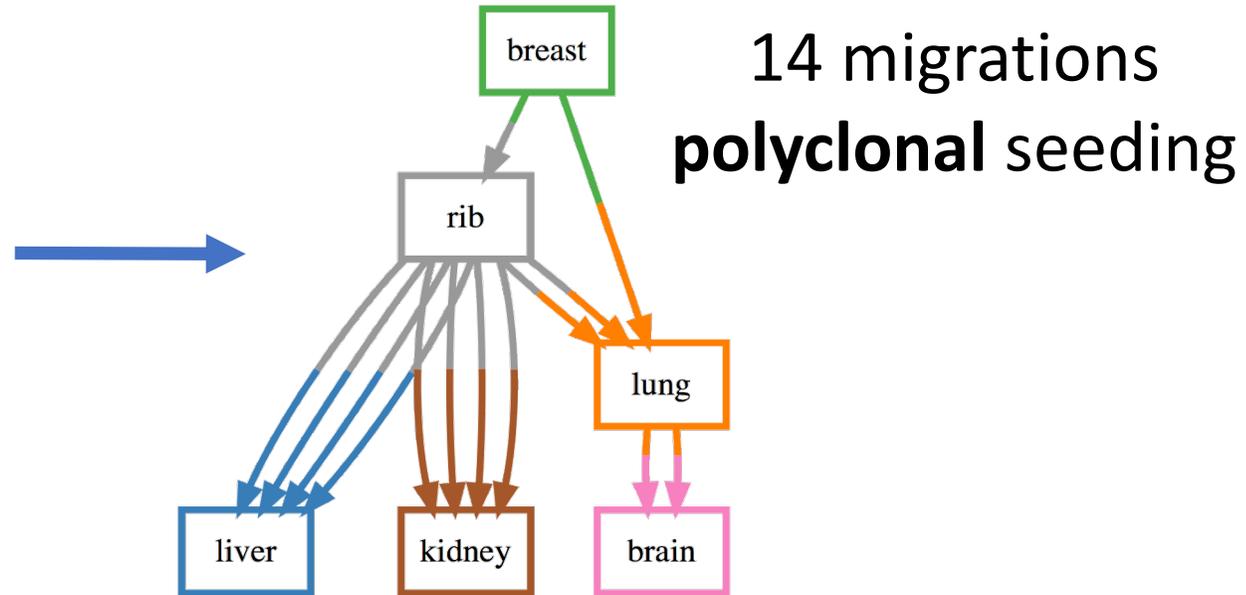
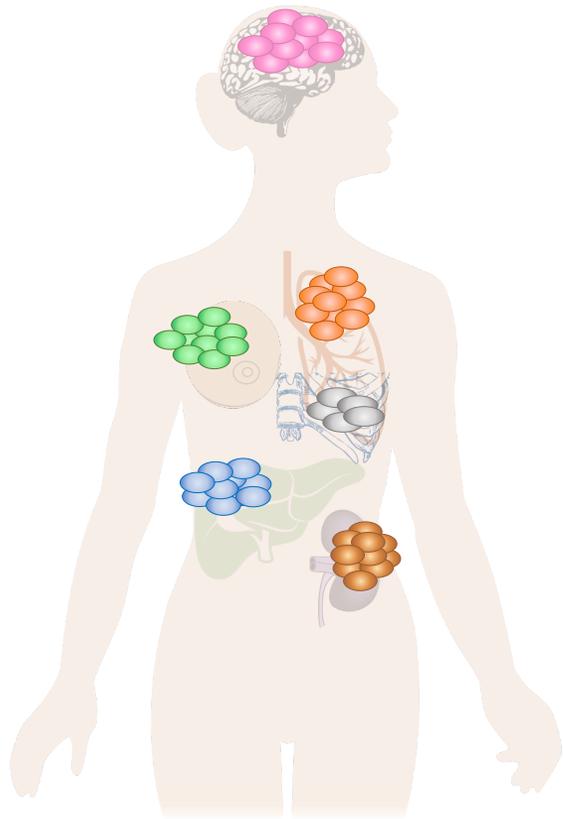


Gryte Satas

[El-Kebir et al. *Nature Genetics* 2018]

Inferring Migration Patterns in Metastasis

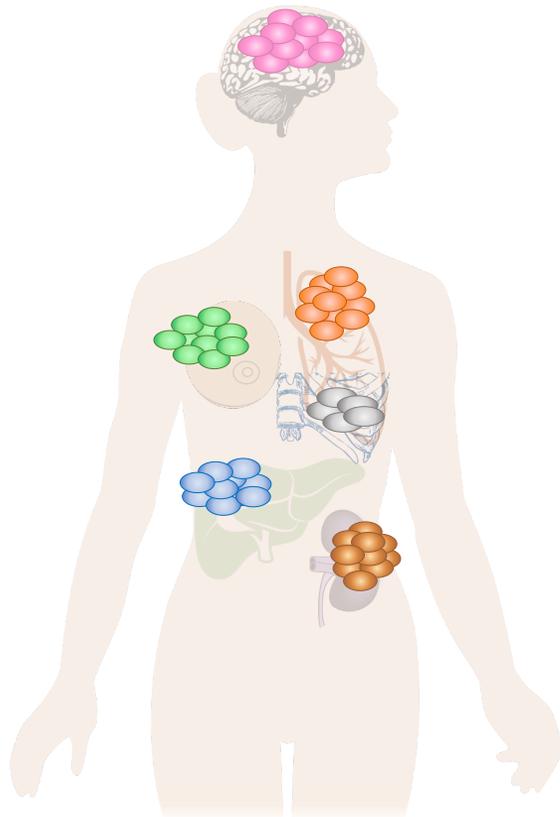
Metastatic Breast Cancer



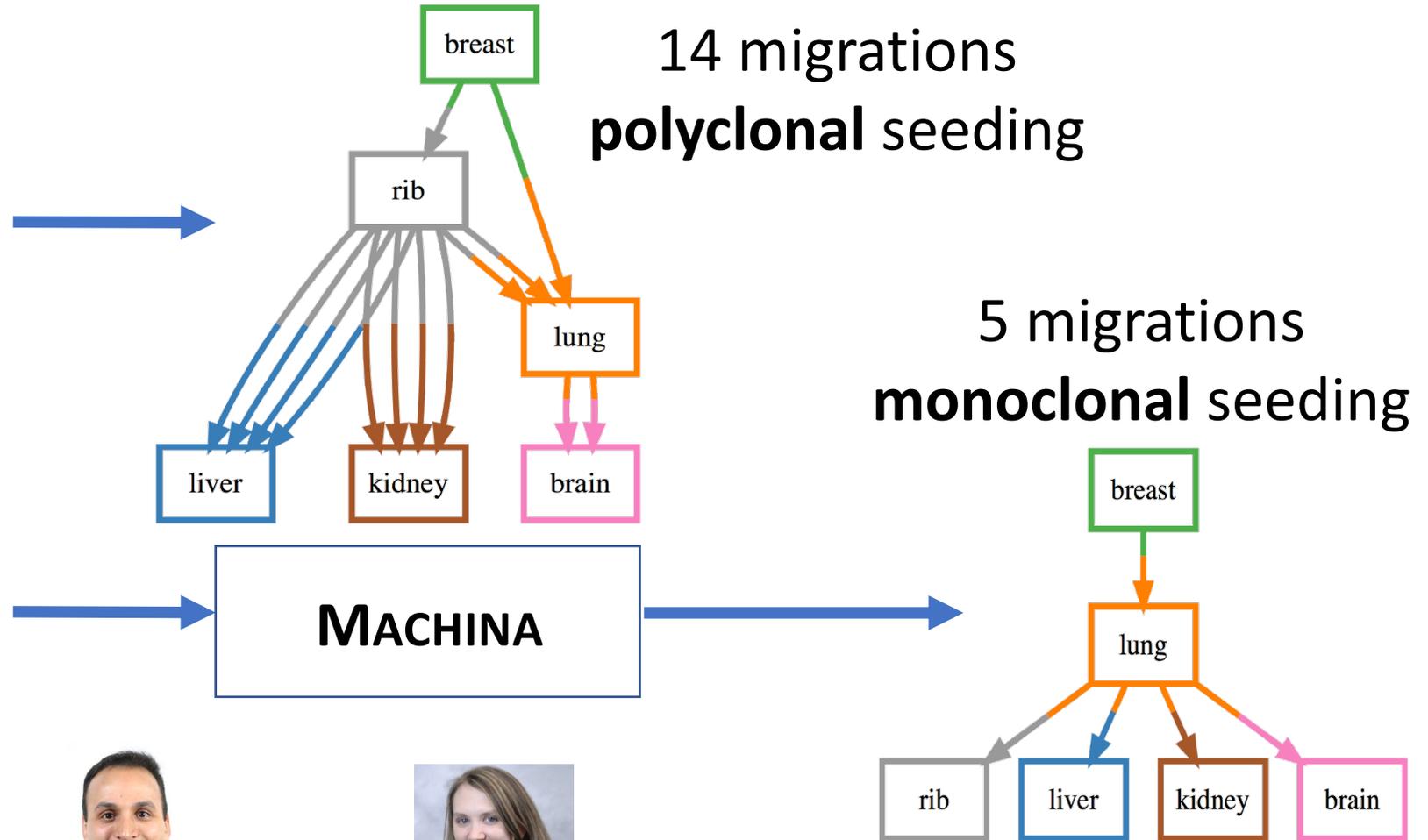
Hoadley KA,, et al.
PLOS Medicine (2016)

Parsimonious Migration Patterns in Metastasis

Metastatic Breast Cancer



Hoadley KA,, et al.
PLOS Medicine (2016)



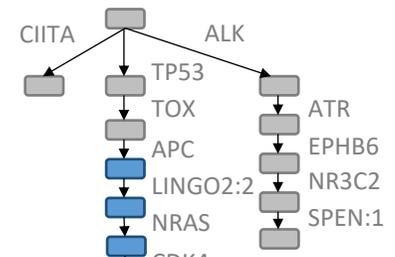
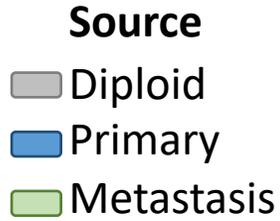
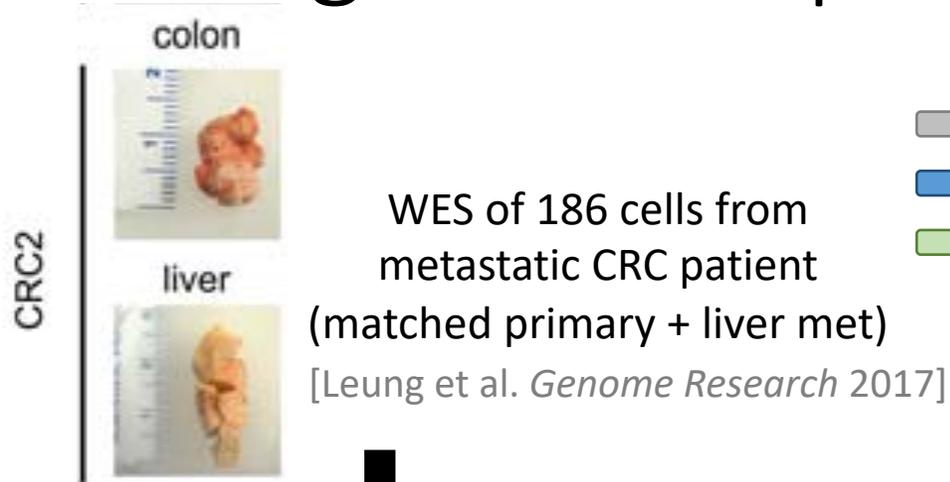
Mohammed El-Kebir



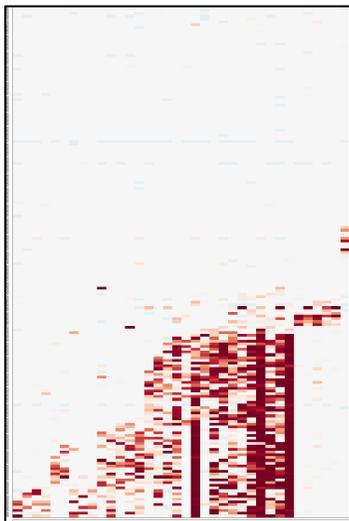
Gryte Satas

[El-Kebir, et al. *Nature Genetics* 2018]

Single-cell sequencing to the rescue?



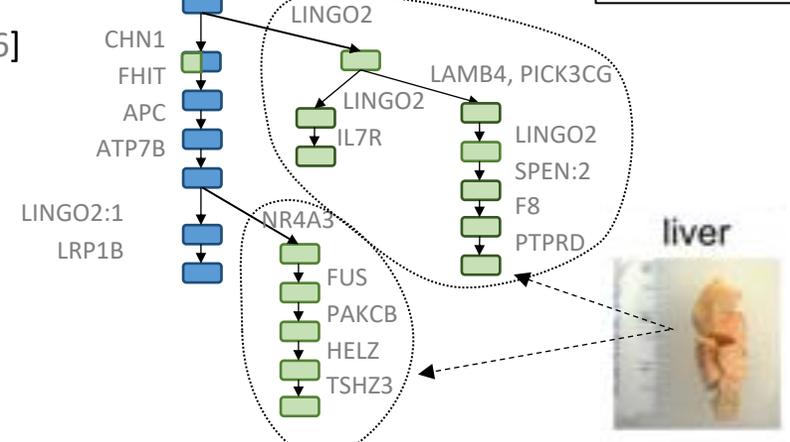
Single nucleotide mutations



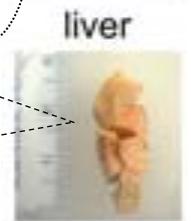
SCITE

[Jahn et al., *Genome Biology* 2016]

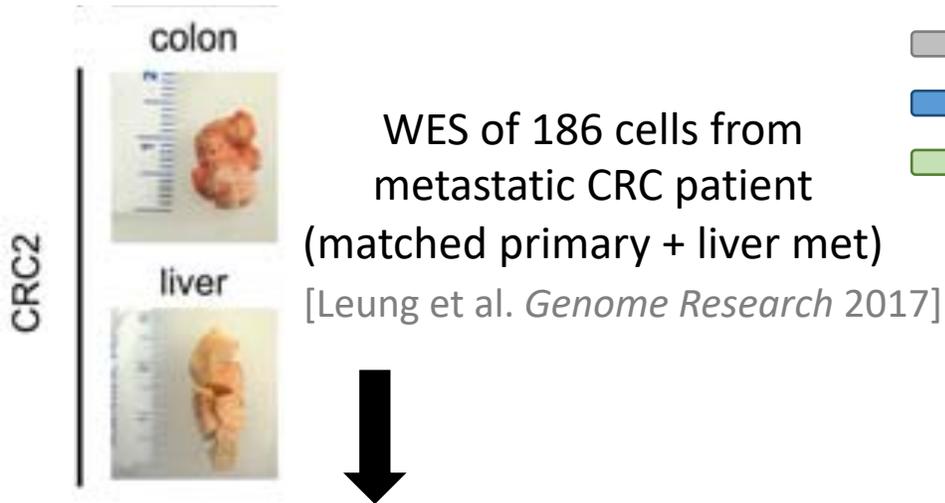
Infinite sites assumption:
Mutation occurs at most once



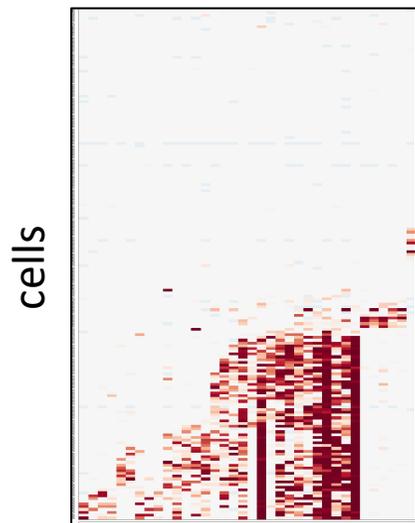
Two independent cellular migrations from primary tumor to metastasis!
(Polyclonal seeding)



Copy number data inconsistent with SNV-based phylogeny

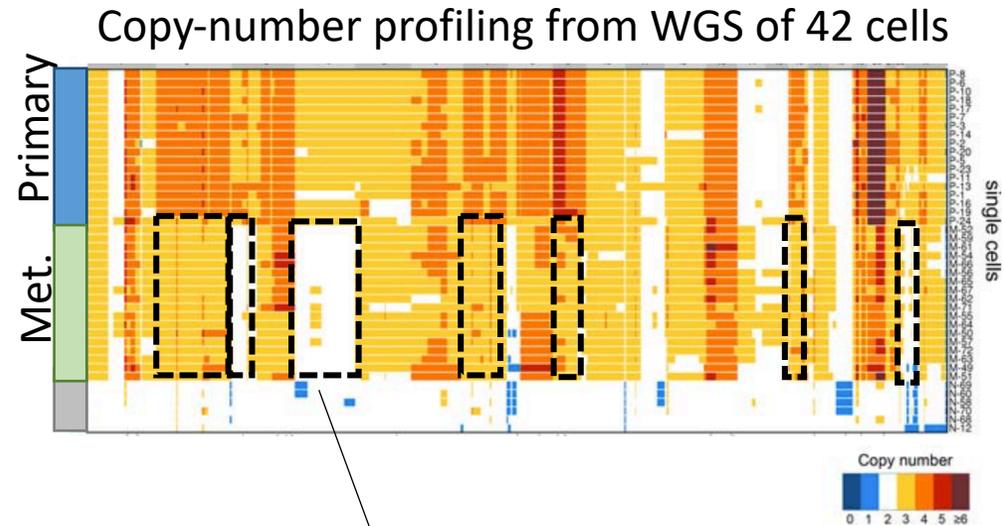
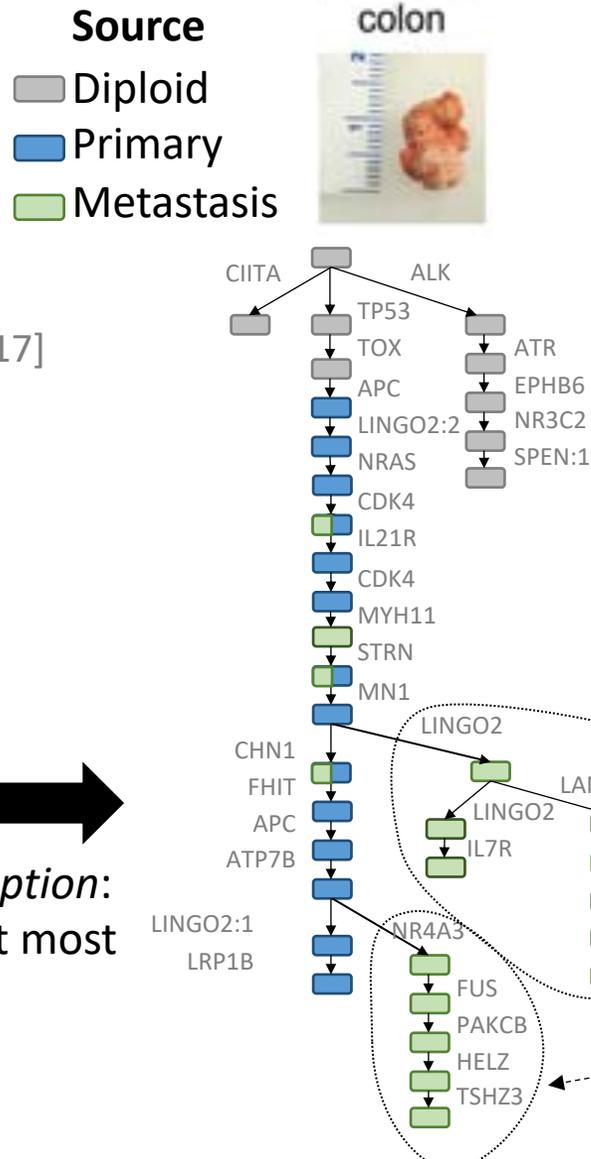


Single nucleotide mutations



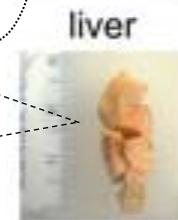
SCITE

Infinite sites assumption:
Mutation occurs at most once



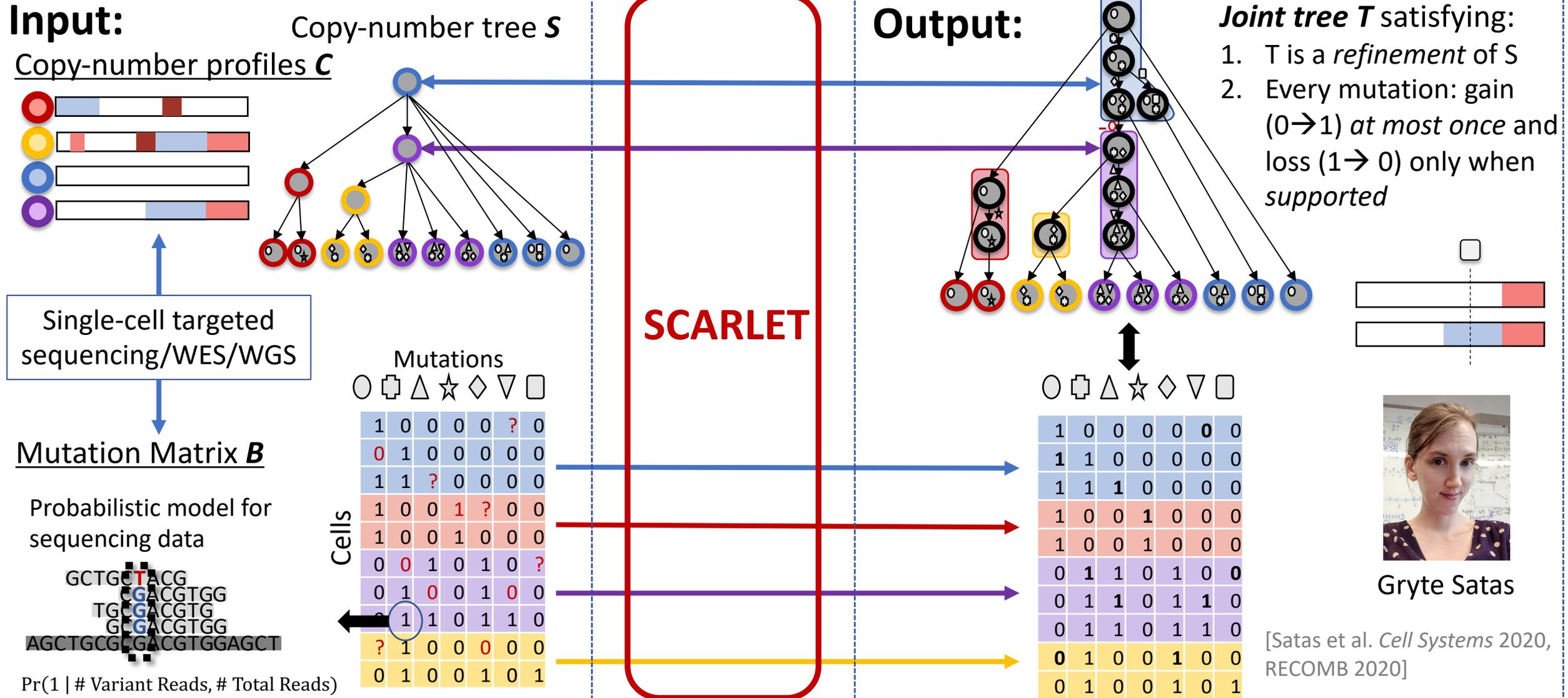
Multiple metastasis-specific CNAs
All occurred twice independently?

Two independent cellular migrations from primary tumor to metastasis!
(Polyclonal seeding)



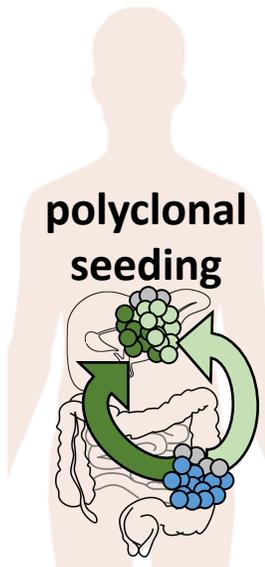
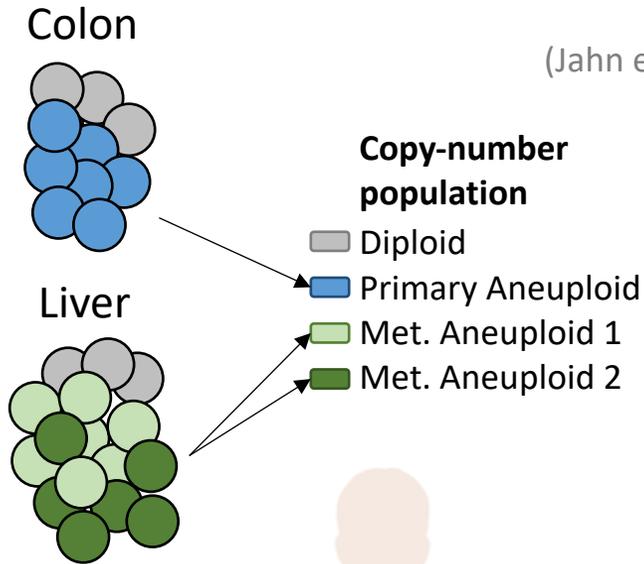
SCARLET: Construct Tumor Evolution across Genomic Scale

(Single-Cell Analysis for Reconstructing Loss-supported Evolution of Tumors)

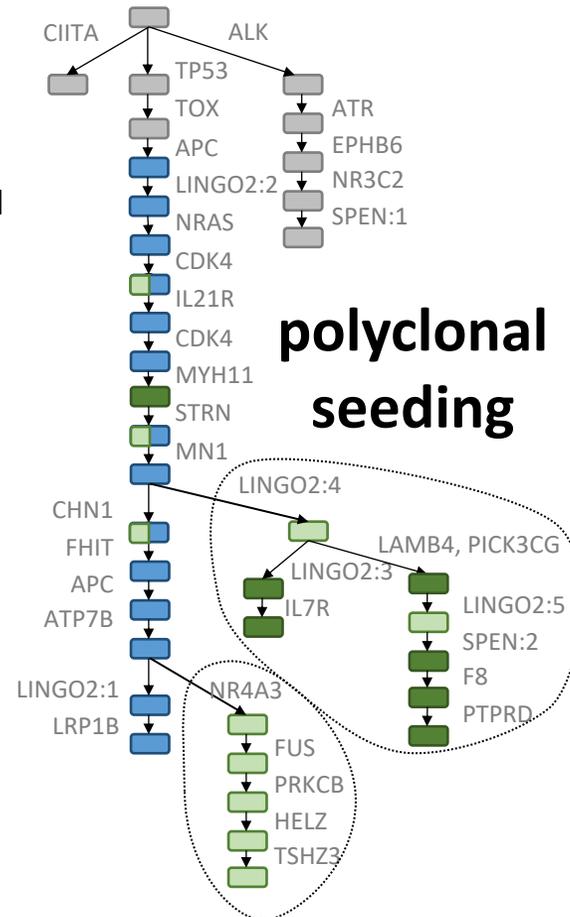


Single-nucleotide mutations → *polyclonal seeding* of liver metastasis

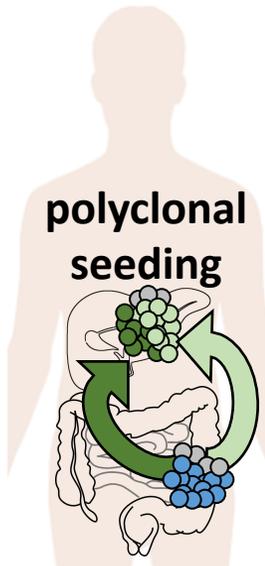
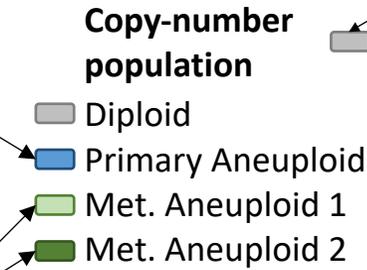
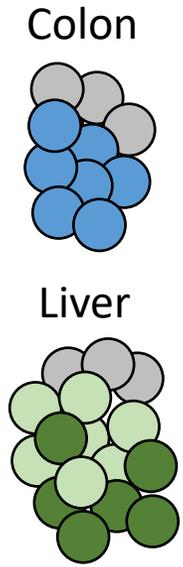
(Leung et al., *Genome Research*, 2017)



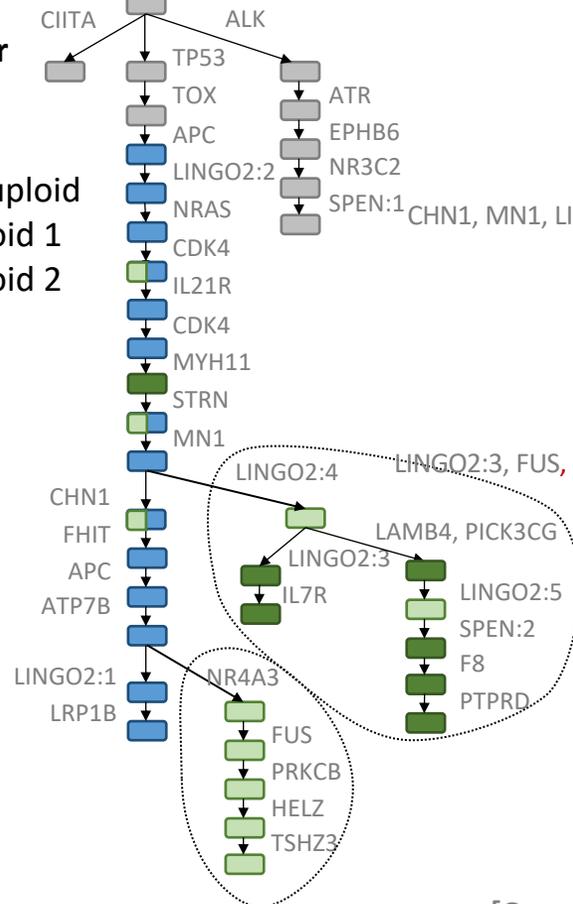
SCITE
(Jahn et al., *Genome Biology* 2016)



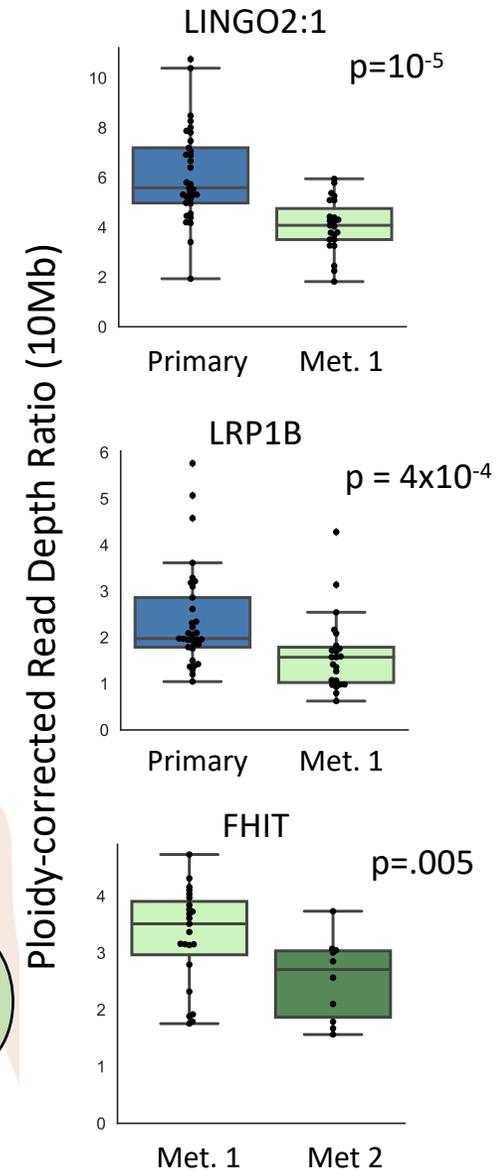
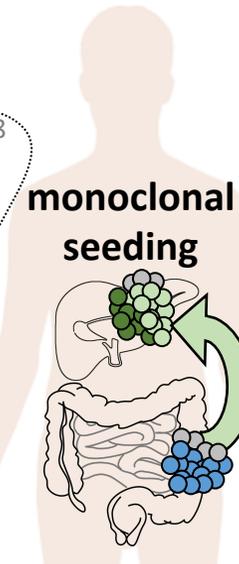
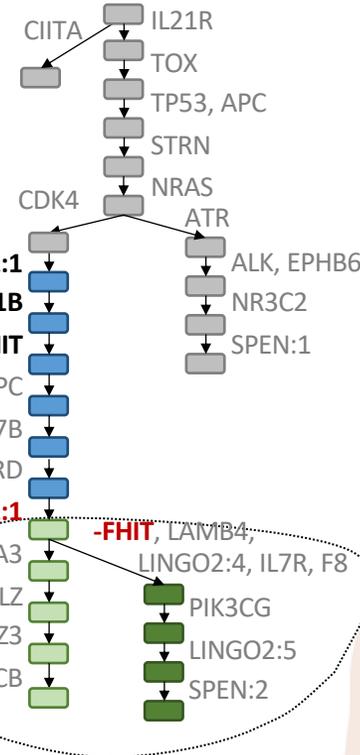
SCARLET: single-nucleotide + copy number mutations → *monoclonal seeding* of metastasis



SCITE (Jahn et al., *Genome Biology* 2016)



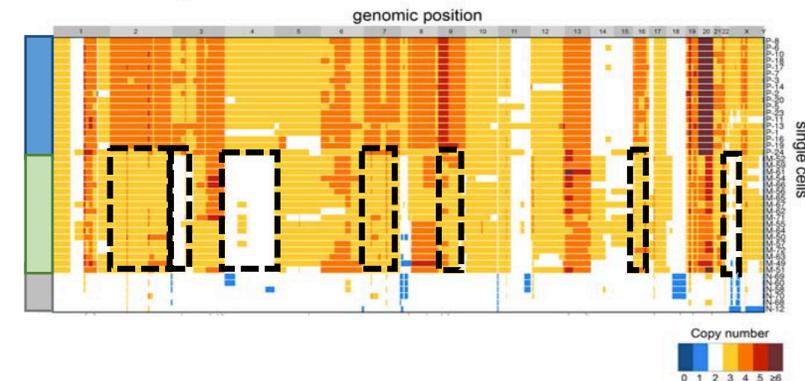
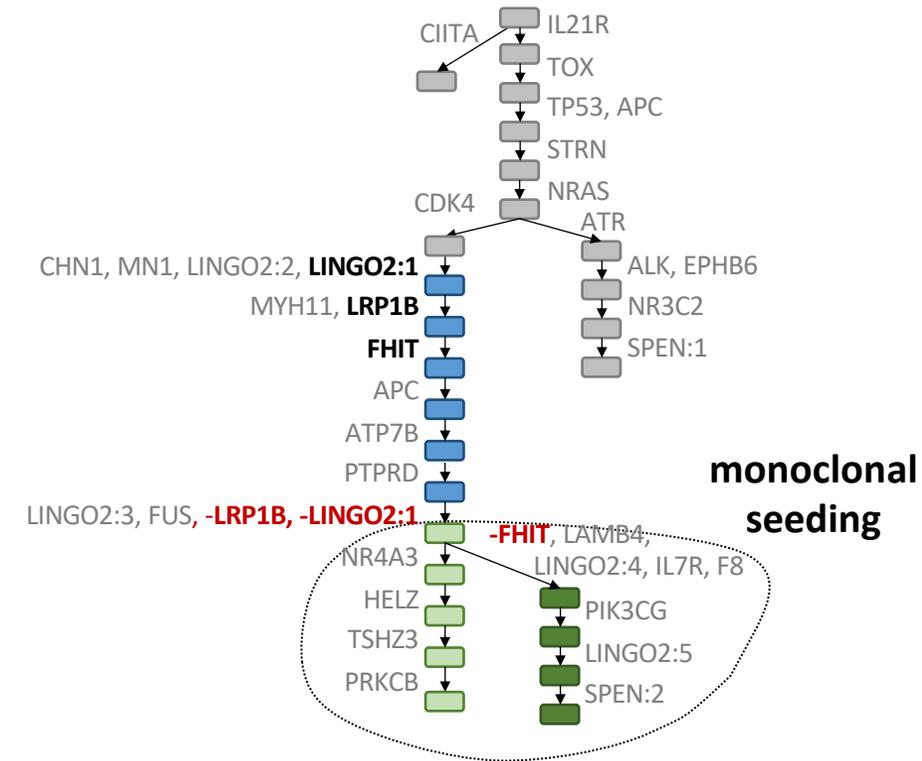
SCARLET



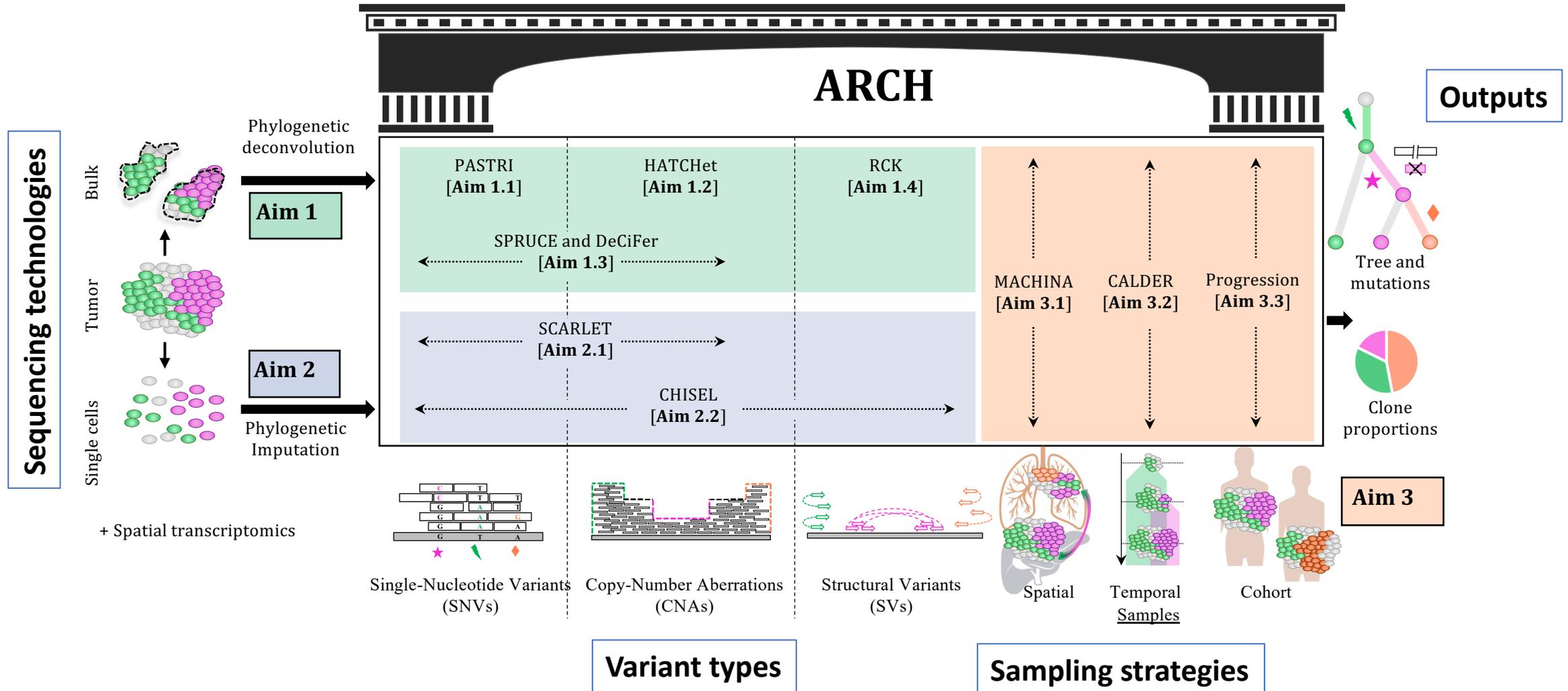
Summary

Inference of metastatic seeding patterns (monoclonal vs. polyclonal vs. reseeding of metastases) requires:

1. Deriving reliable phylogenies from bulk or single-cell sequencing data, each with unique challenges
2. Analyzing mutations across genomic scale; e.g. interactions between single-nucleotide mutations and copy number aberrations



A robust toolkit for tumor heterogeneity and evolution

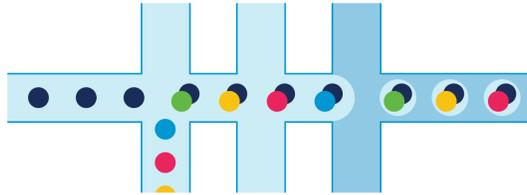
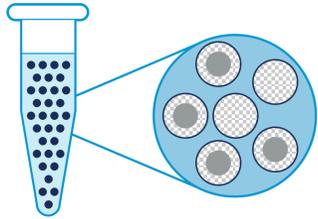


Ultra low-coverage whole-genome single-cell sequencing

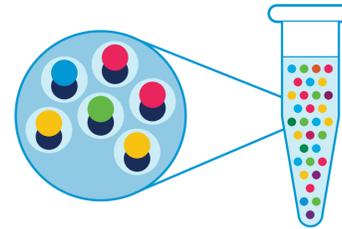
Chromium Single Cell CNV Solution

10x
GENOMICS

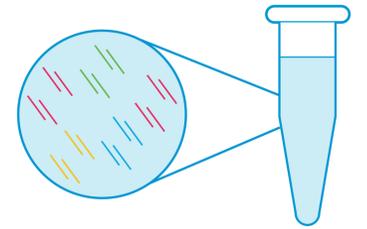
Single cells



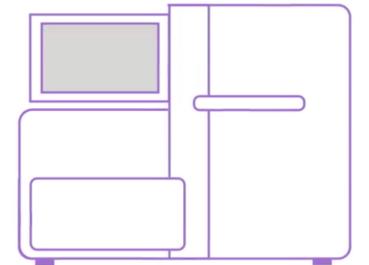
Barcoded cells



Barcoded library



DNA Sequencing



Aligned reads

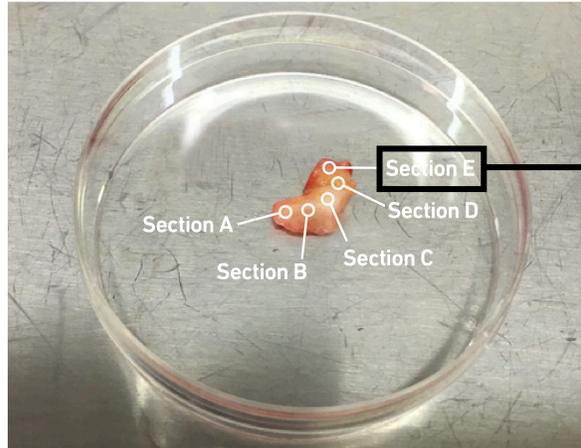


Ultra-low (~.03x)
coverage per
single cell from
~2000 cells

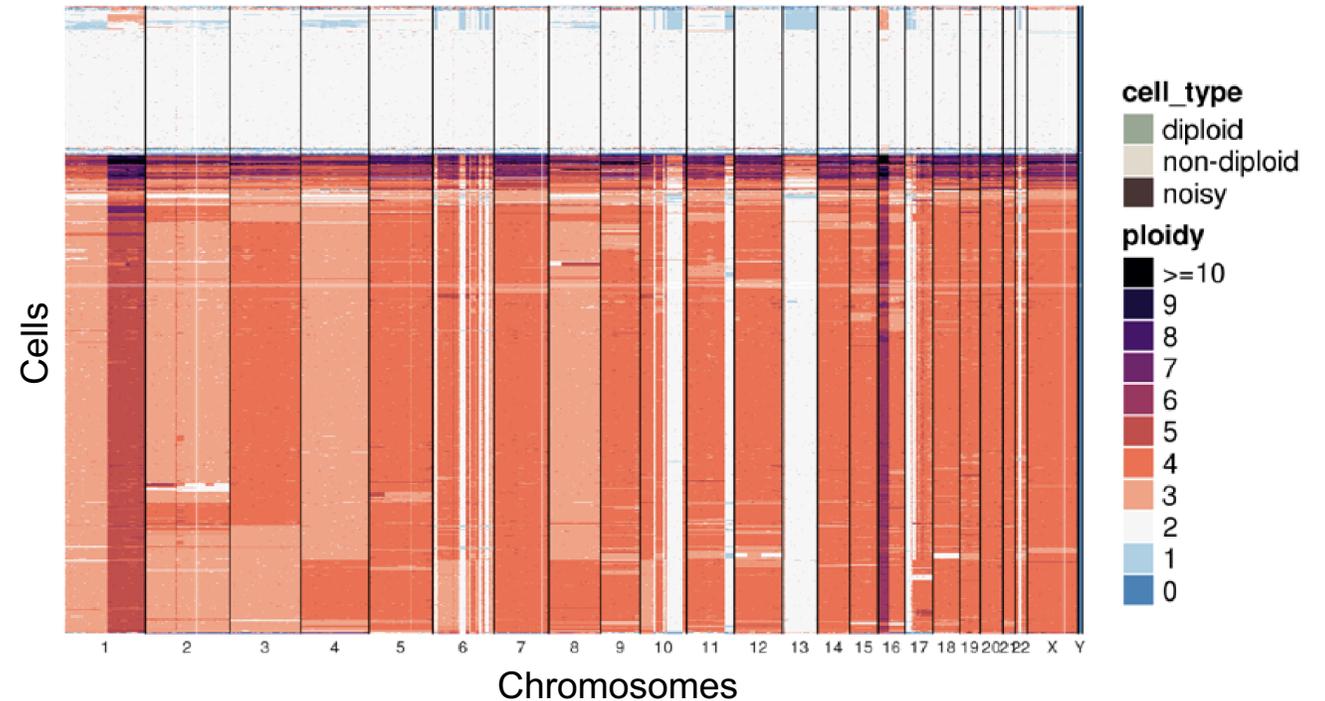


Other technologies: DOP-PCR [Navin et al. Nature 2011] and **DLP/DLP+** [Zahn et al. Nat. Methods 2017]

Single-cell copy-number analysis in breast cancer



[Assessing Tumor Heterogeneity with Single Cell CNV
www.10xgenomics.com/solutions/single-cell-cnv/]



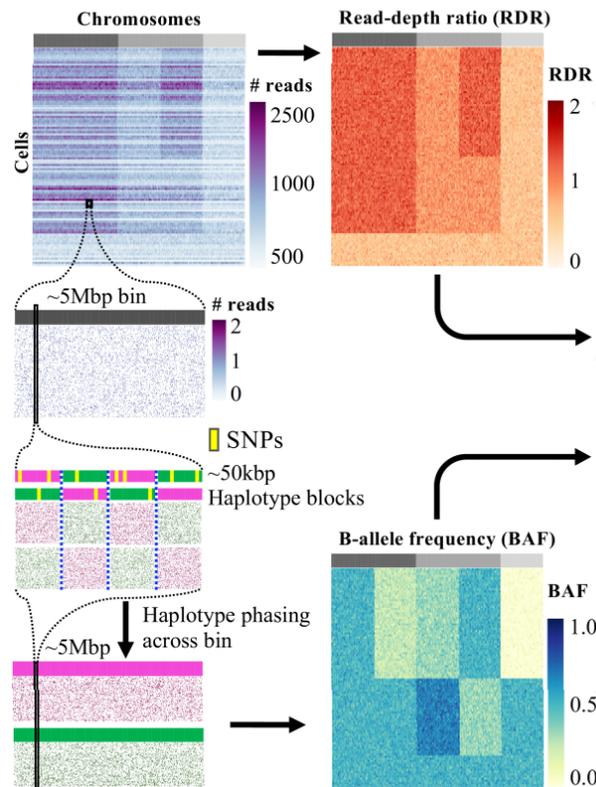
- ~2000 cells from 5 sections of a breast tumor sequenced with 10X CNV Solution
- Cell Ranger DNA inferred **copy numbers** and identified multiple clusters of cells

CHISEL: Copy-number Haplotype Inference in Single-cells using Evolutionary Links

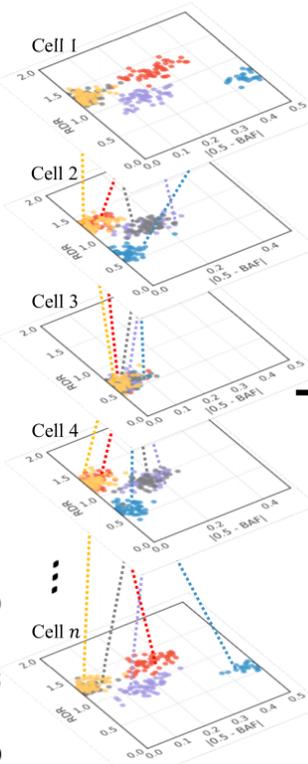


First method to infer **allele-specific copy numbers** from **ultra low-coverage DNA sequencing WGS**

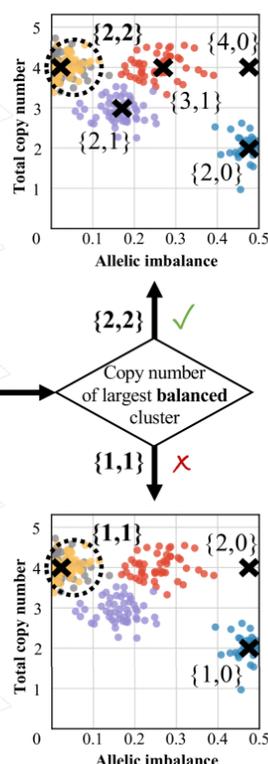
(A) Computation of RDR and BAF



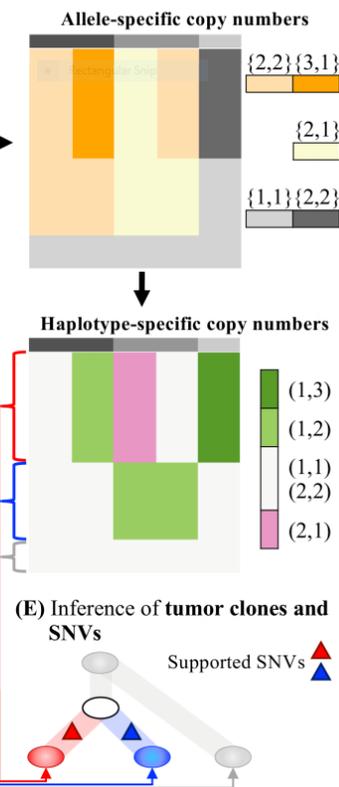
(B) Global clustering of bins along genome and across cells



(C) Inference of allele-specific copy numbers



(D) Inference of haplotype-specific copy numbers



[S. Zaccaria and B. Raphael, *Nature Biotechnology* (2020)]

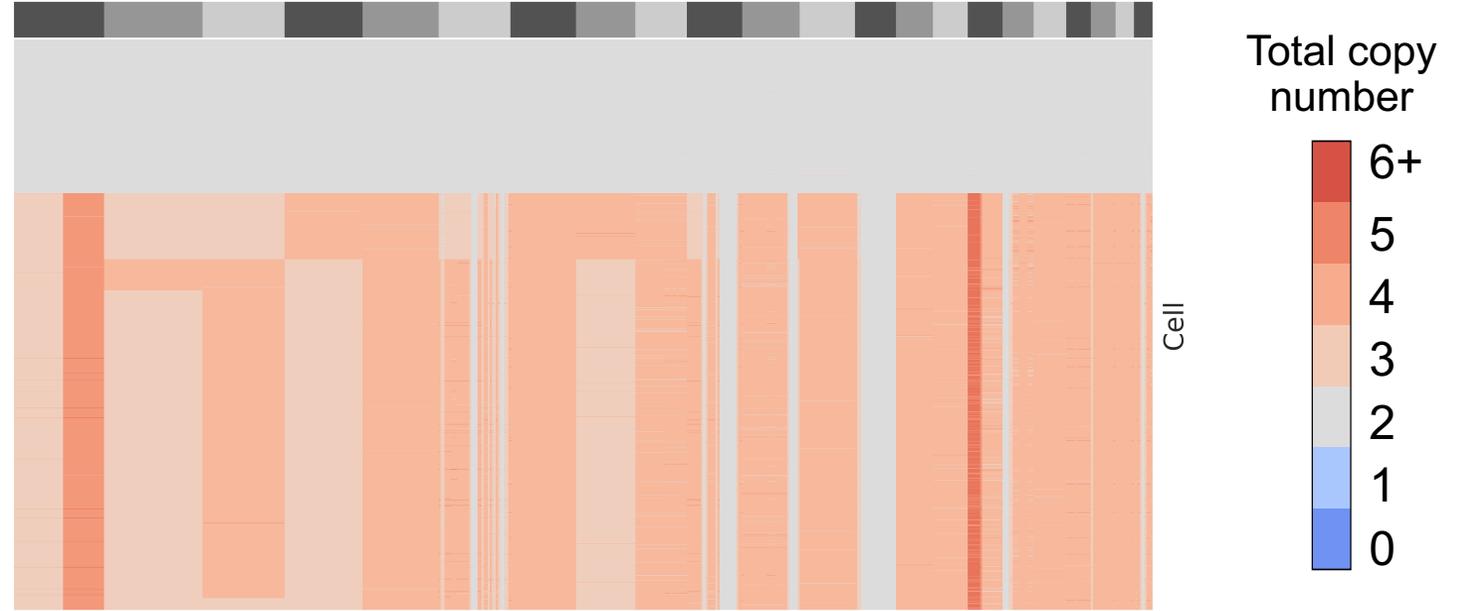


Simone Zaccaria

CHISEL reveals events invisible to total copy number analysis

Total copy number

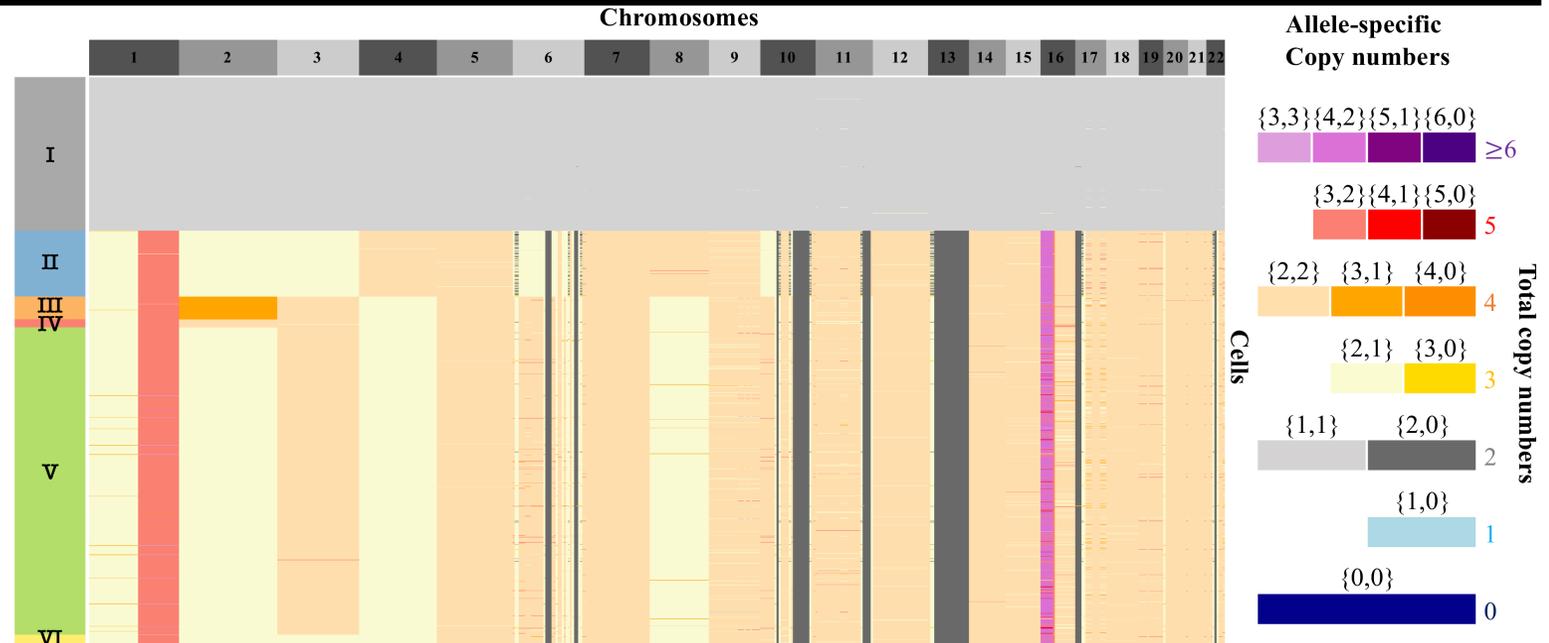
$$c = \hat{c} + \check{c}$$



Tumor section E from breast cancer patient S0:

Allele-specific copy numbers

$$\{\hat{c}, \check{c}\}$$



Copy neutral loss of heterozygosity (CN-LOH)

Tumor section E from breast cancer patient S0:

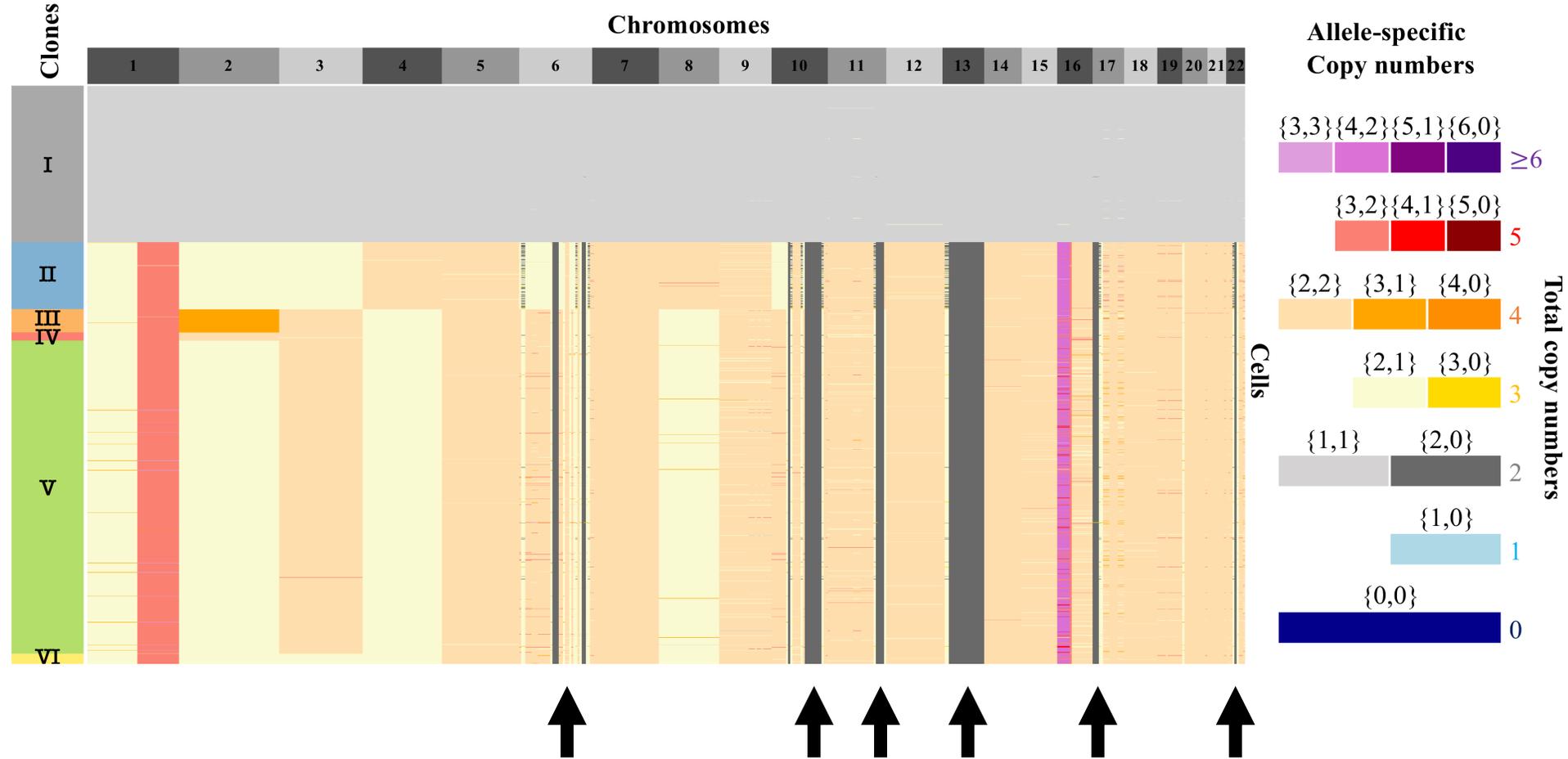
- Allele-specific copy numbers $\{\hat{c}, \check{c}\}$
- Total copy number $c = \hat{c} + \check{c}$

Copy neutral LOH:

$\{2,0\}$

Diploid region:

$\{1,1\}$



CN-LOH supported by BAF in clones

Tumor section E from breast cancer patient S0:

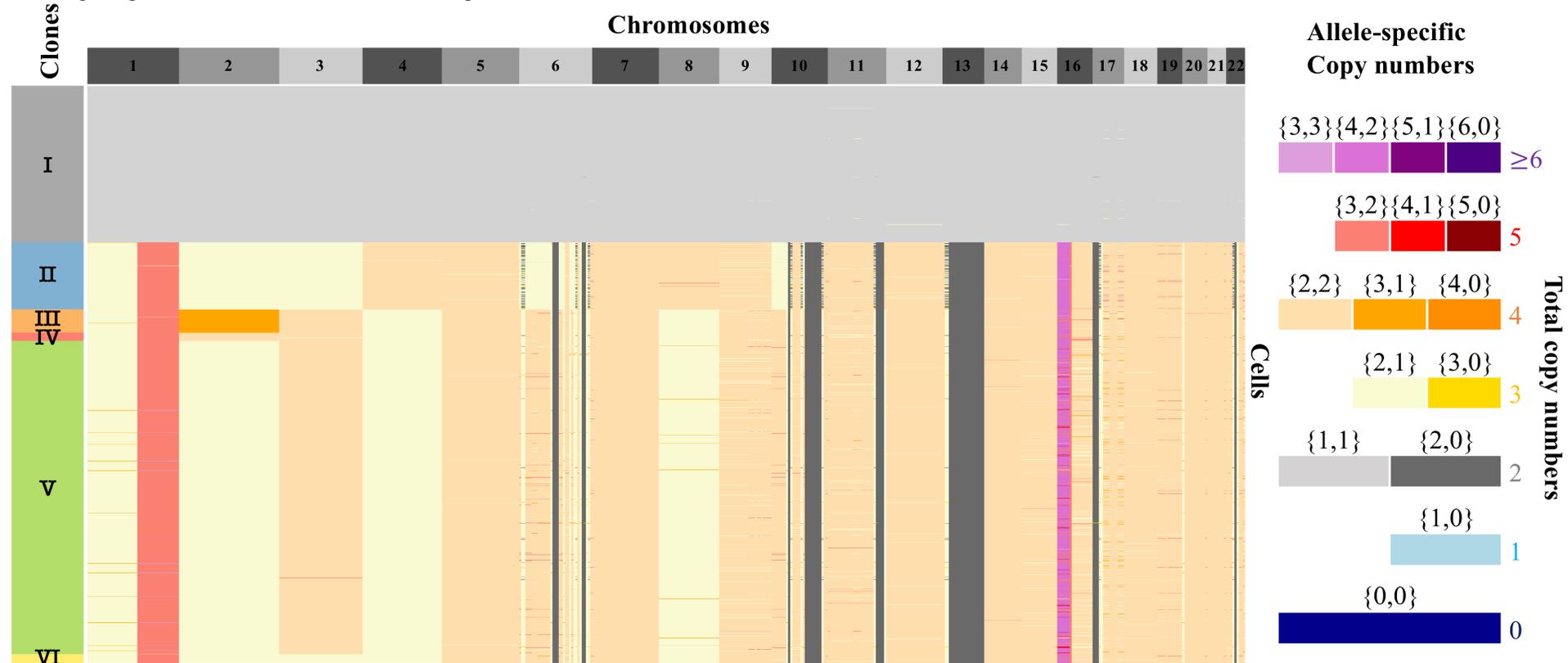
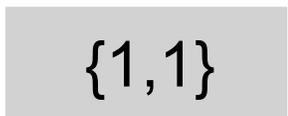
- Allele-specific copy numbers $\{\hat{c}, \check{c}\}$

- Total copy number $c = \hat{c} + \check{c}$

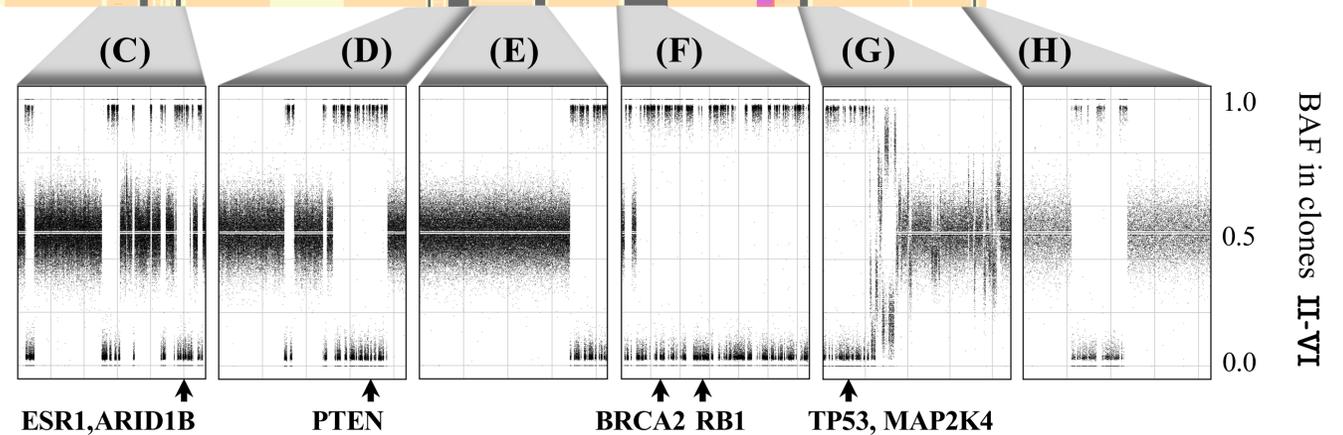
Copy neutral LOH:



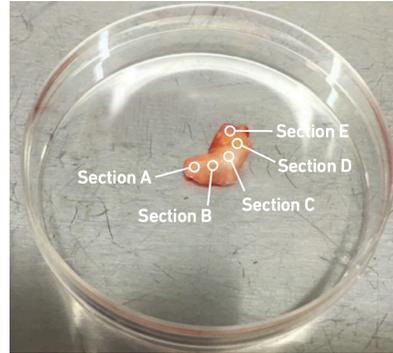
Diploid region:



Known breast-cancer genes



Tumor evolution across all cells in five tumor sections



10,202 cells

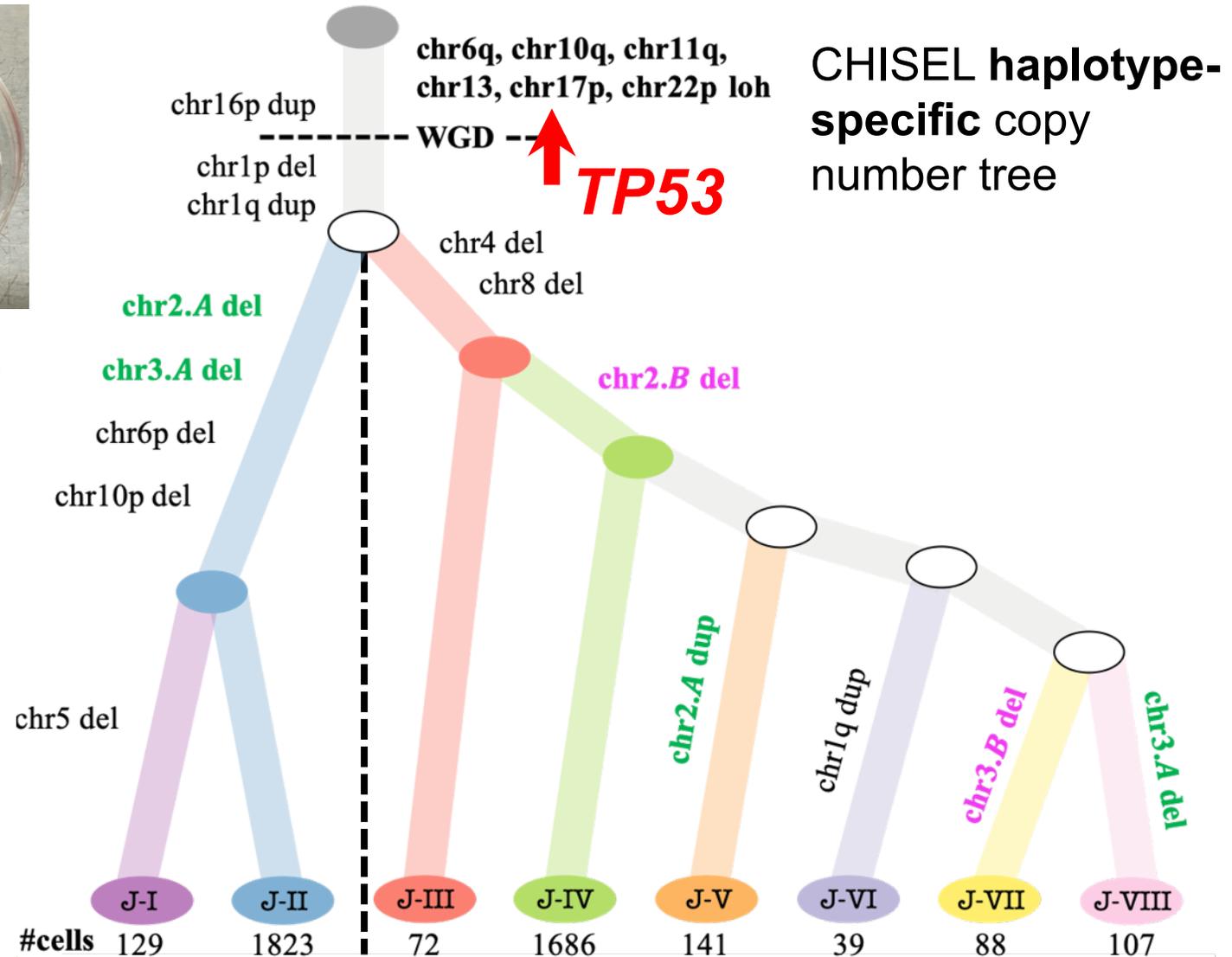
Findings:

1. LOH affects *TP53* before WGD
 → Evidence for *TP53* inactivation preceding WGD

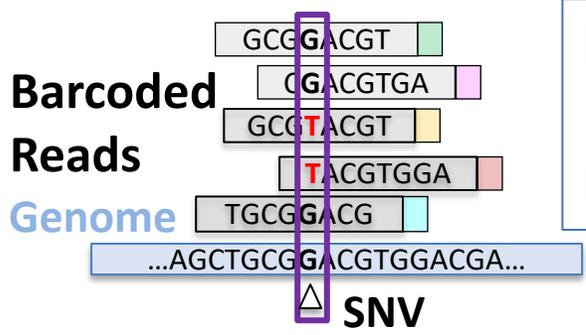
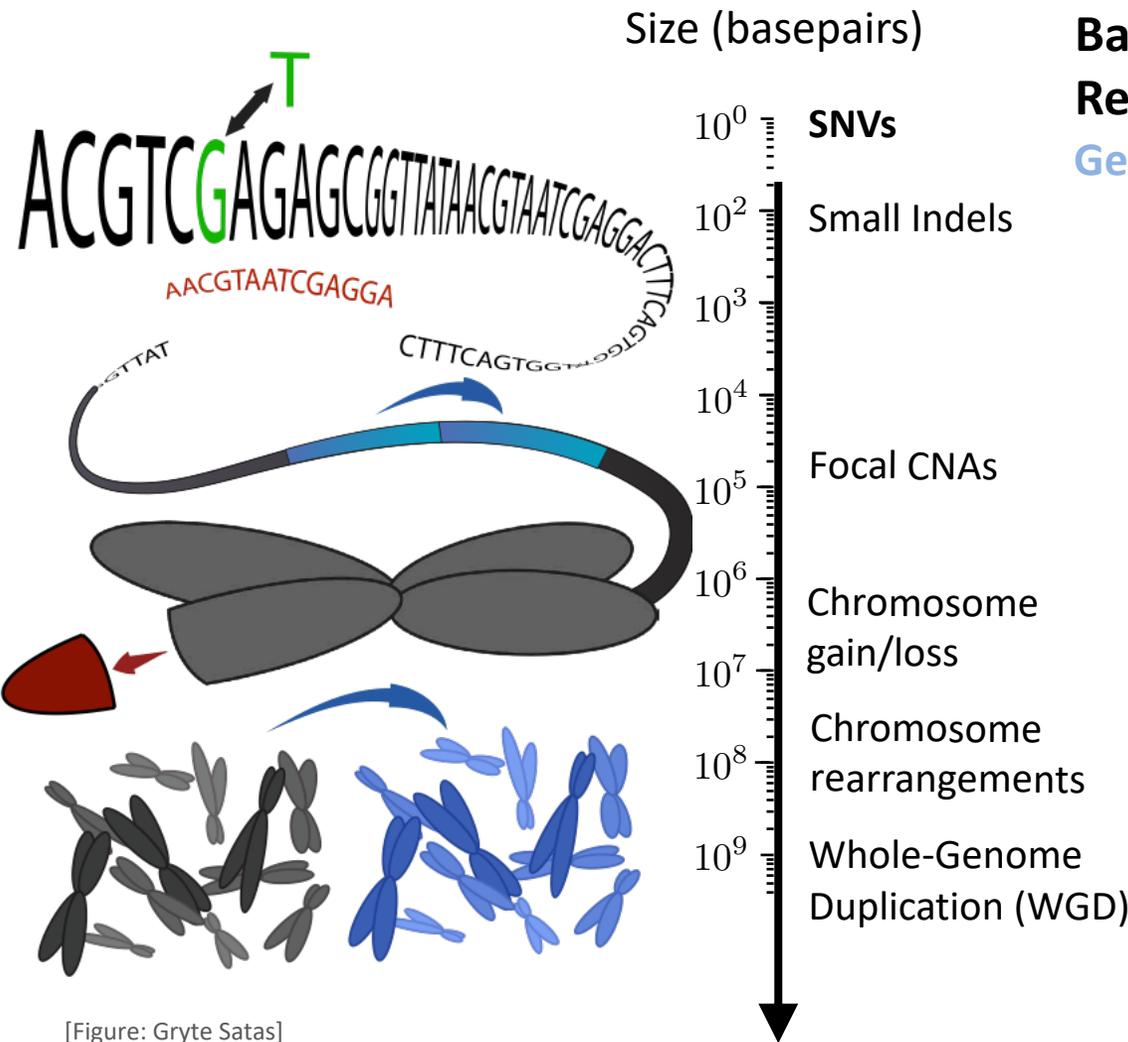
[Bielski et al., *Nature Genetics*, 2018]

2. Mirrored-subclonal CNAs separate two branches and affect breast cancer tumor suppressor genes
 → **Convergent evolution**

[Jamal-Hanjani et al., *NEJM*, 2017]

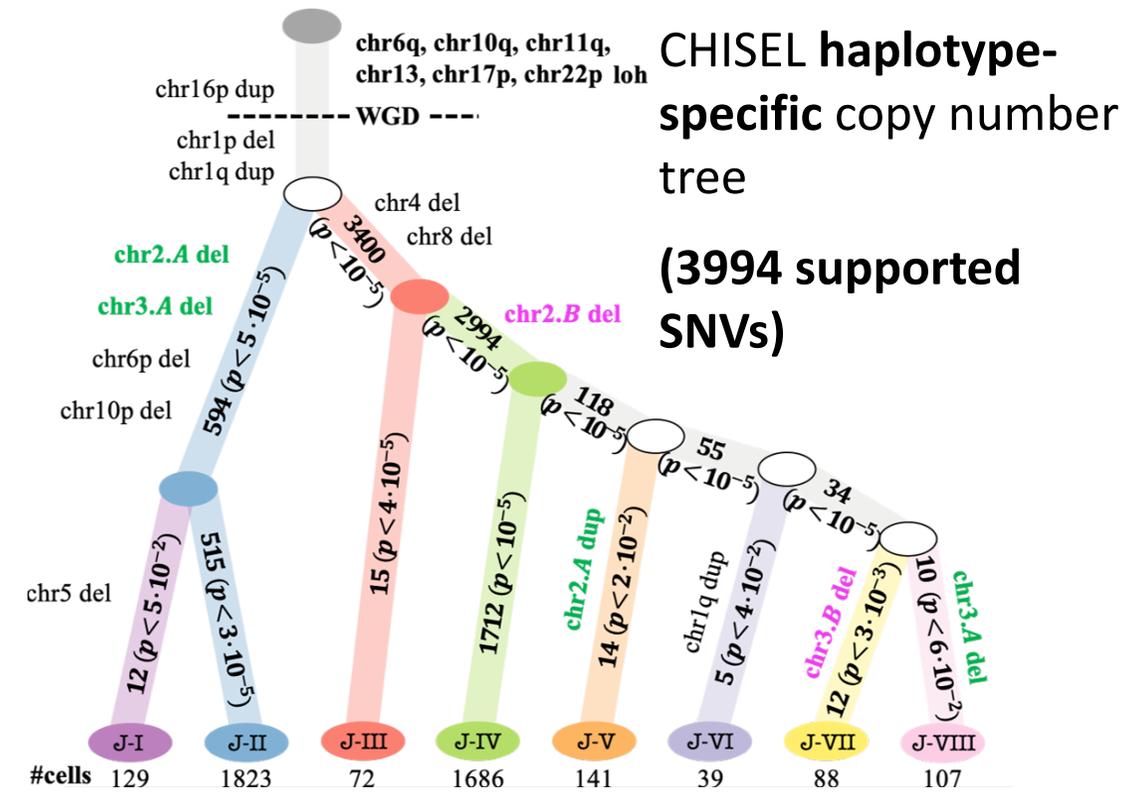


Orthogonal validation using somatic SNVs



Identify from pseudo-bulk sample

Most cells have 0 covering reads!



SBMClone: Infer tumor clones from SNVs in ultra-low coverage single-cell data



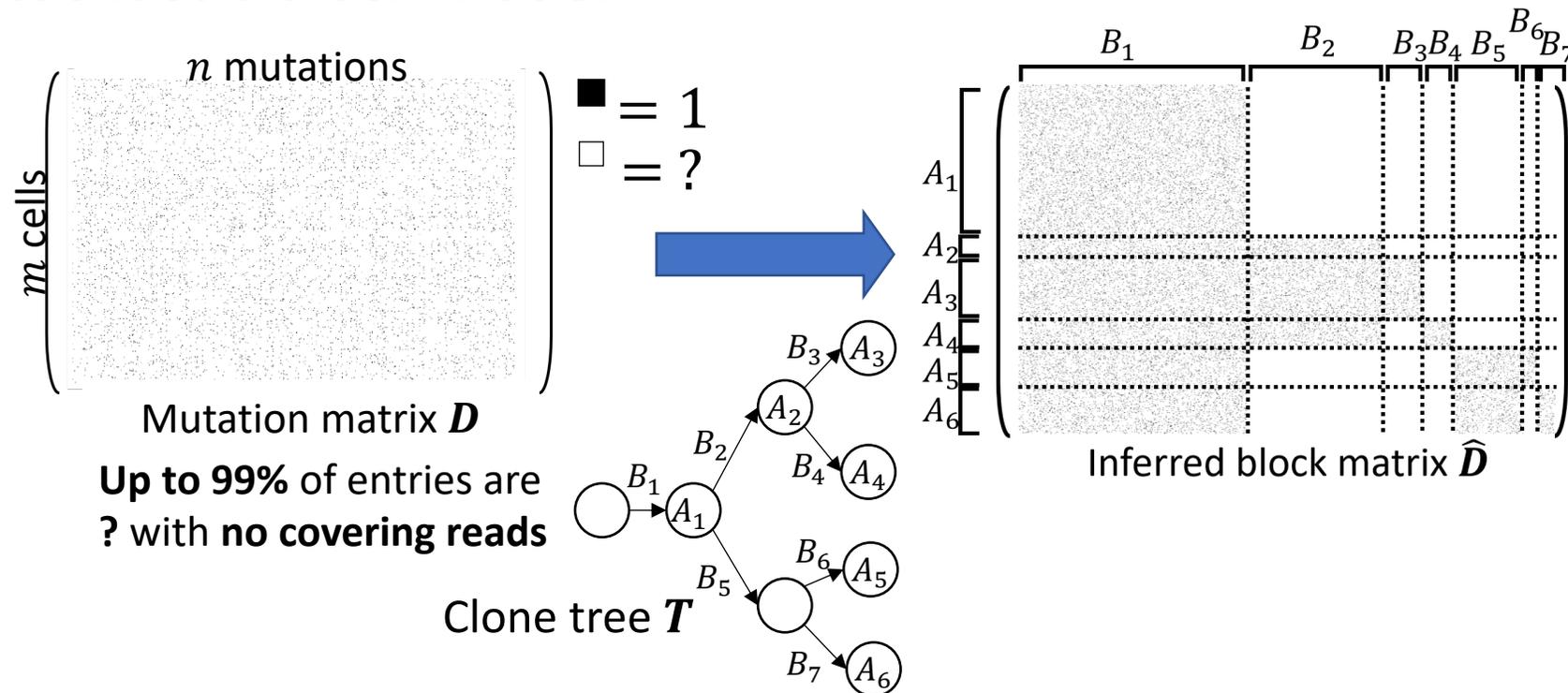
Matt Myers



Simone Zaccaria

Key idea: Clonal structure creates **blocks** in mutation matrix.

Inference: *stochastic block model*

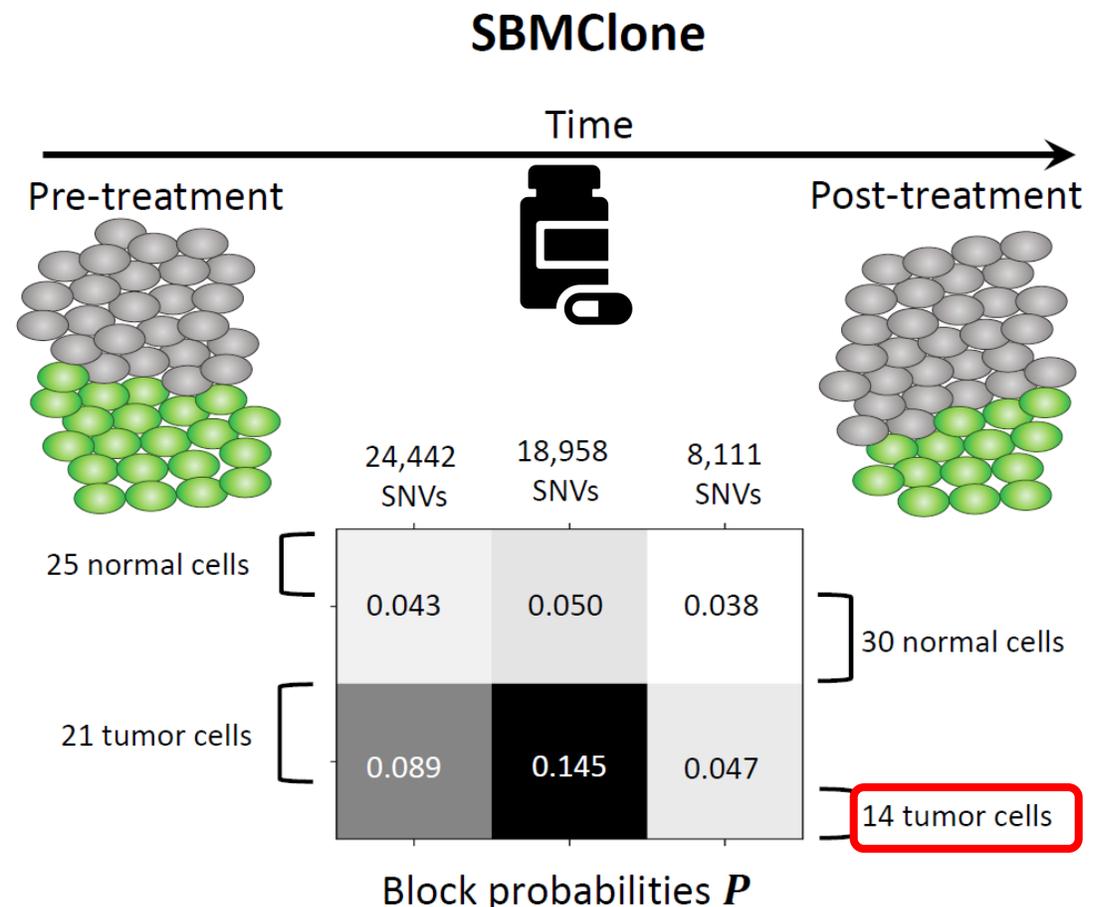
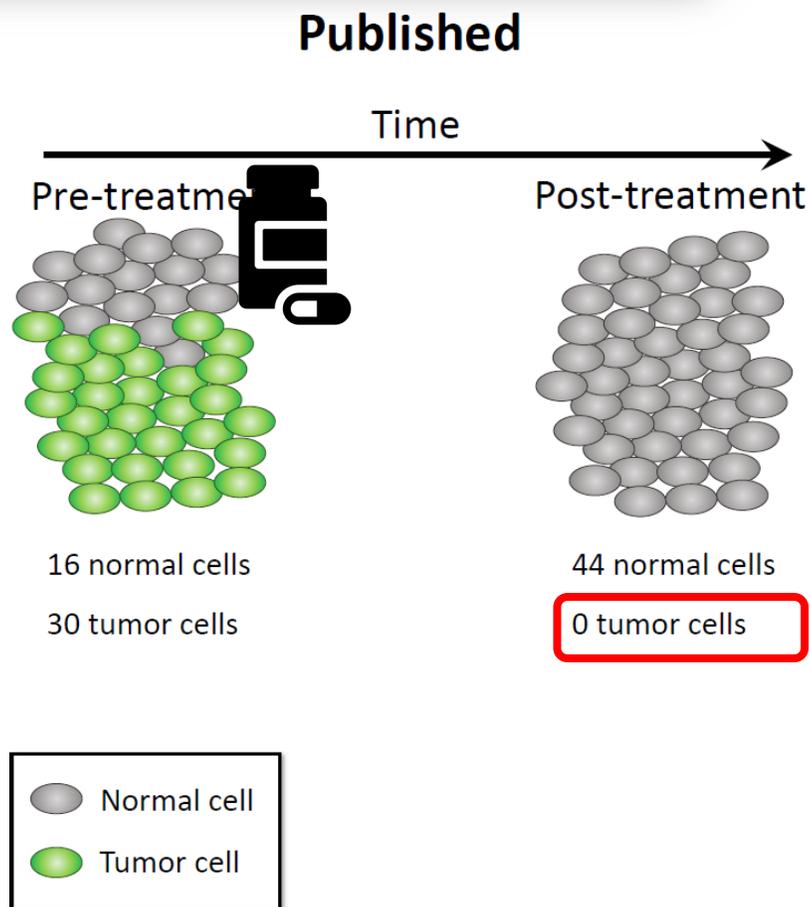


SBMClone identifies tumor cells in both pre- and post-treatment samples → *clonal persistence*

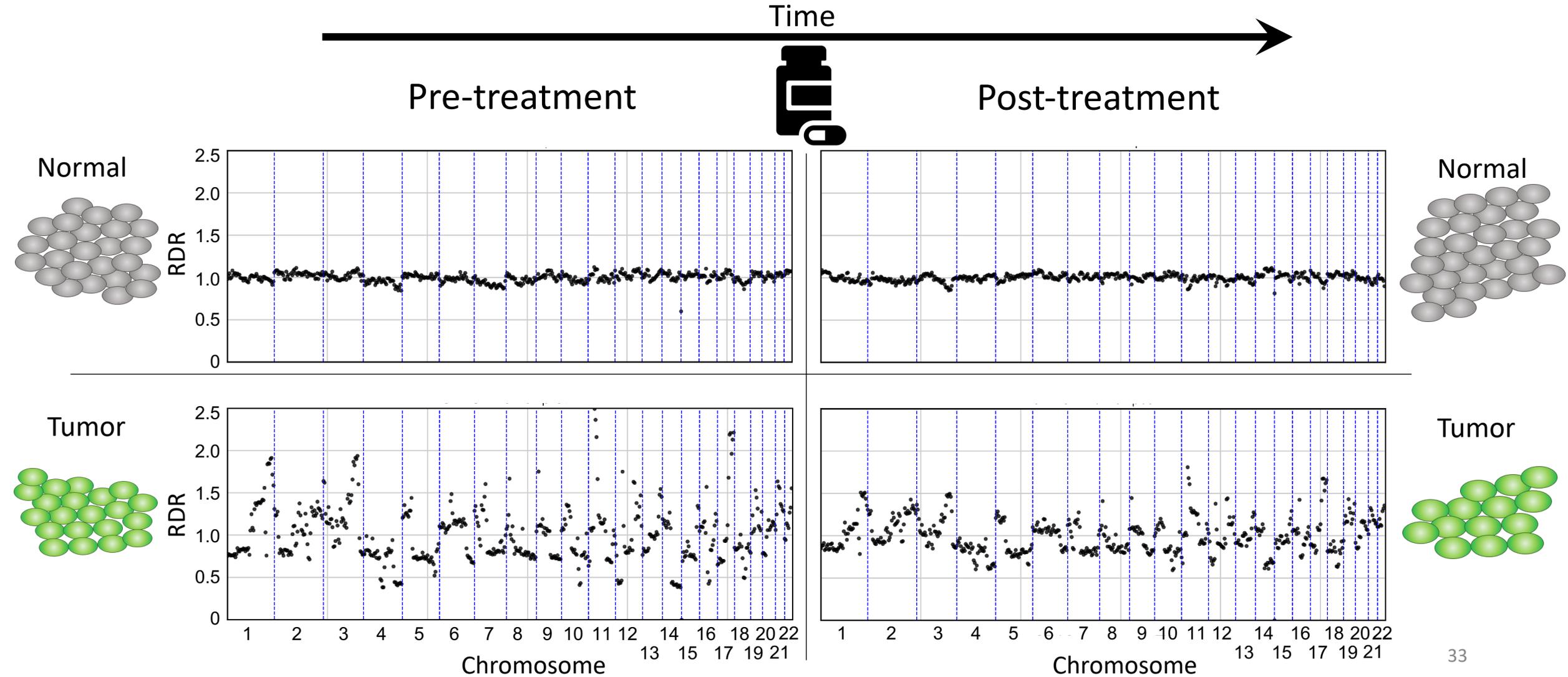
Chemoresistance Evolution in Triple-Negative Breast Cancer Delineated by Single-Cell Sequencing

Charissa Kim,^{1,2,6} Ruli Gao,^{1,6} Emi Sei,¹ Rachel Brandt,¹ Johan Hartman,³ Thomas Hatschek,³ Nicola Crossetto,⁴ Theodoros Foukakis,^{3,7} and Nicholas E. Navin^{1,2,5,7,*}

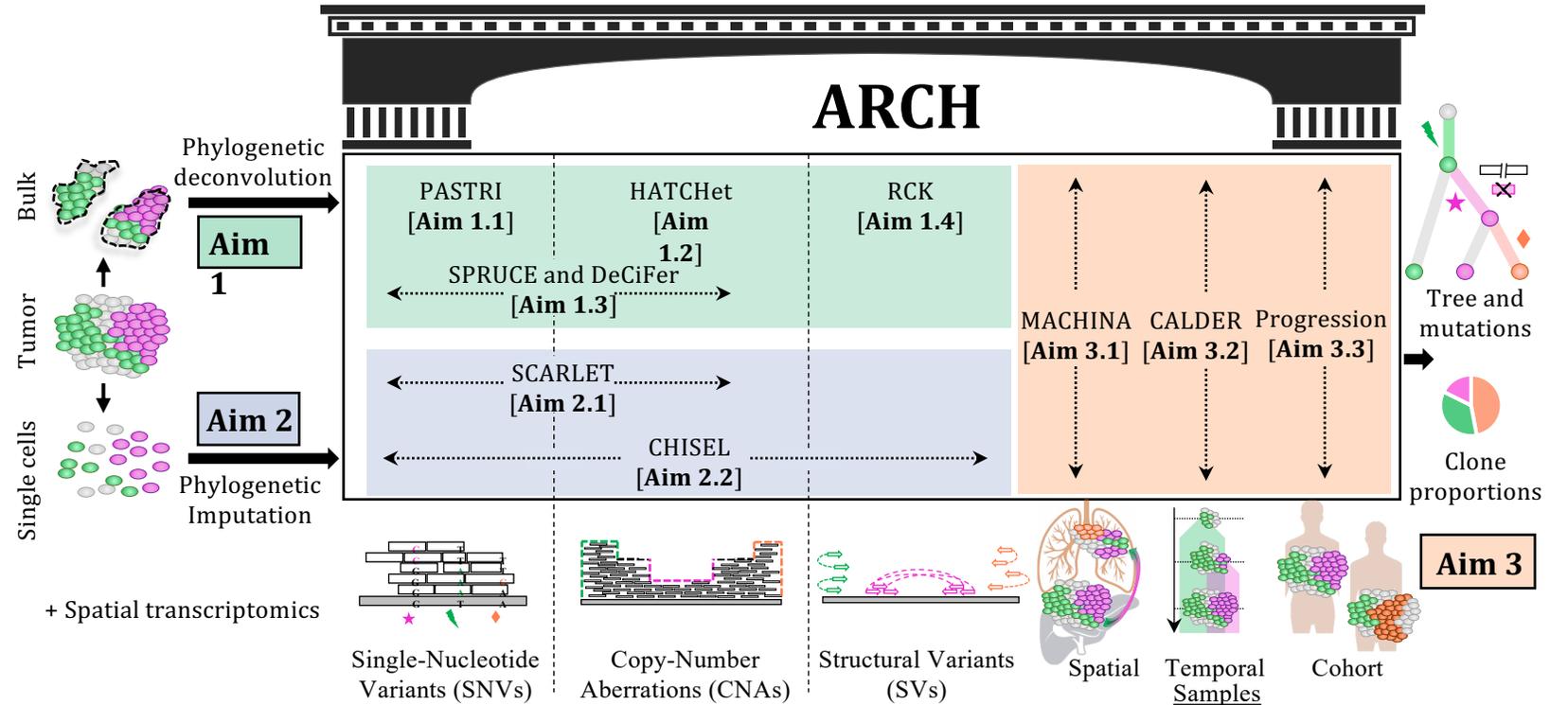
90 cells collected pre- and post-treatment
DOP-PCR sequencing: ≈**0.26X** coverage per cell



Copy-number signal supports tumor cells identified by SBMClone



Goals and Tentative Timeline



	Year 1	Year 2	Year 3	Year 4	Year 5
Software Packaging and Dissemination	Harden existing packages; installation and Docker	R/Bioconductor, Jupyter notebooks, JavaScript viz	Modular software library and API, GenePattern notebooks		Refinements and bug fixes
Software and Algorithm Development	Aim 1.1 Aim 2.1	Aim 1.2 Aim 2.2	Aim 1.3 Aim 3.1	Aim 1.4 Aim 3.2	Aim 3.3
ITCR Collaborative Activities	[Continuous bar spanning all years]				
Milestones	ARCH v0.9		ARCH v1.0		ARCH v2.0 ARCH v2.1

Questions and Feedback

- Contact: braphael@princeton.edu
- Software: <http://github.com/raphael-group>
- ARCH: github.com/raphael-group/arch (Under construction!)