



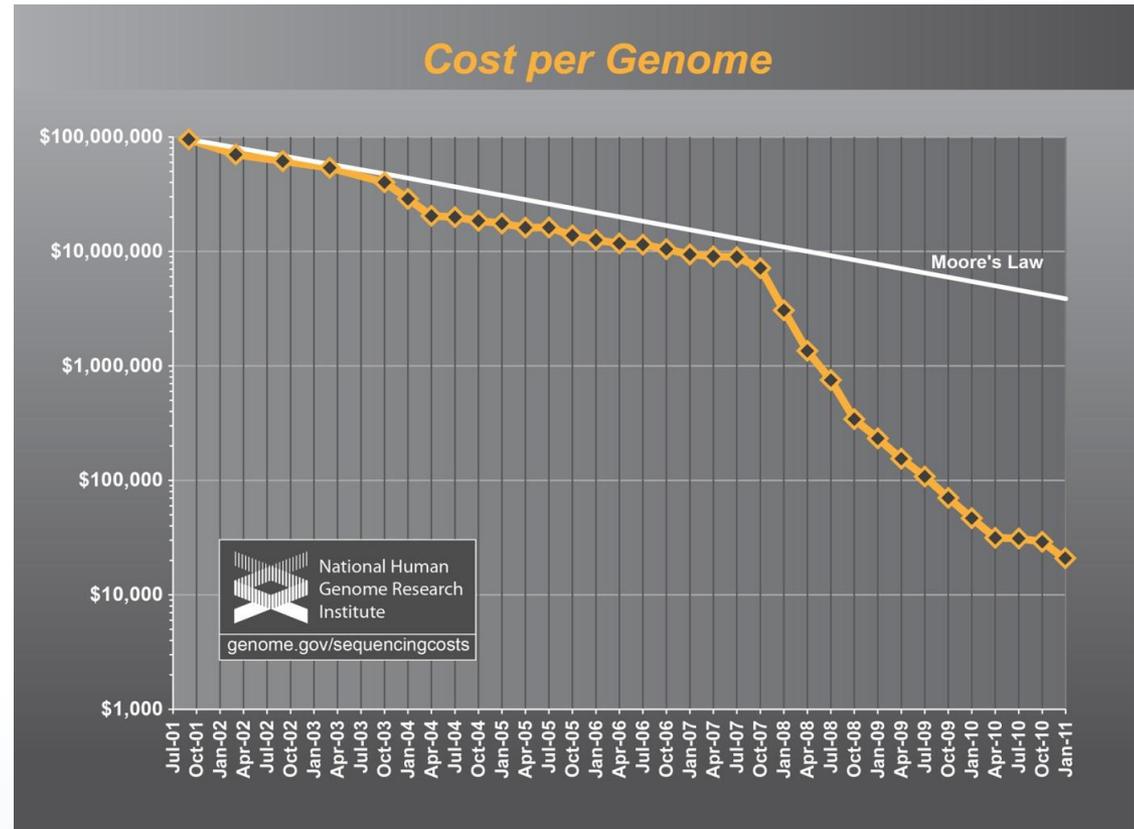
# Cancer and Evolutionary Genomics

**David Haussler**

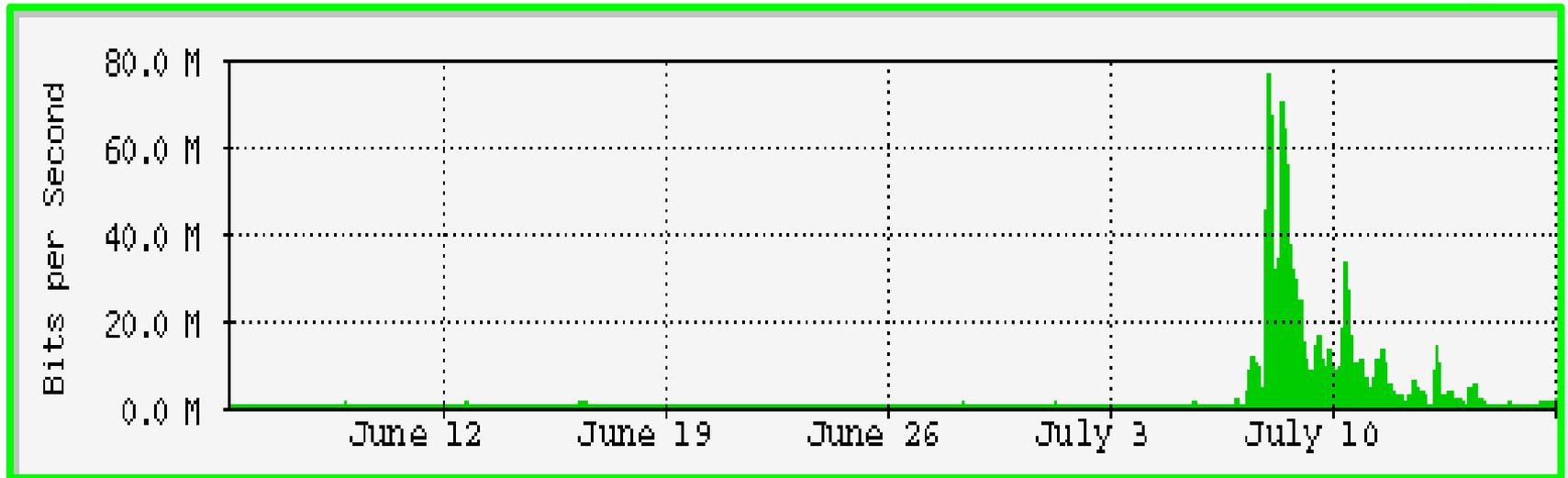
**Center for Biomolecular Science and Engineering,  
UC Santa Cruz**

# DNA sequencing cost reduction

- Researchers can now inexpensively sequence entire genomes.
- The cost is headed toward \$1000 per genome, dramatically outpacing the Moore's Law rate for the decreasing cost of computer processing capacity.



# On July 7, 2000, UCSC posted first human genome on the web



## Outgoing UCSC internet traffic for year 2000

That genome cost \$300M.

Analysis was done on small cluster of Dell desktops.



Small rack of 100 Dell desktops used to assemble first public draft of human genome in 2000



# Time to ramp up

Google Data



# UCSC Cancer Genomics Hub (under construction)

- 5 petabytes of disk storage
- 10 Gigabit dedicated connectivity between data producers, large-scale analysts and database. Modeled after Large Hadron Collider data analysis network
- Secure facility
- Co-location and cloud-computing services to be available on site for TCGA research groups



Erich Weiler and CGHub team

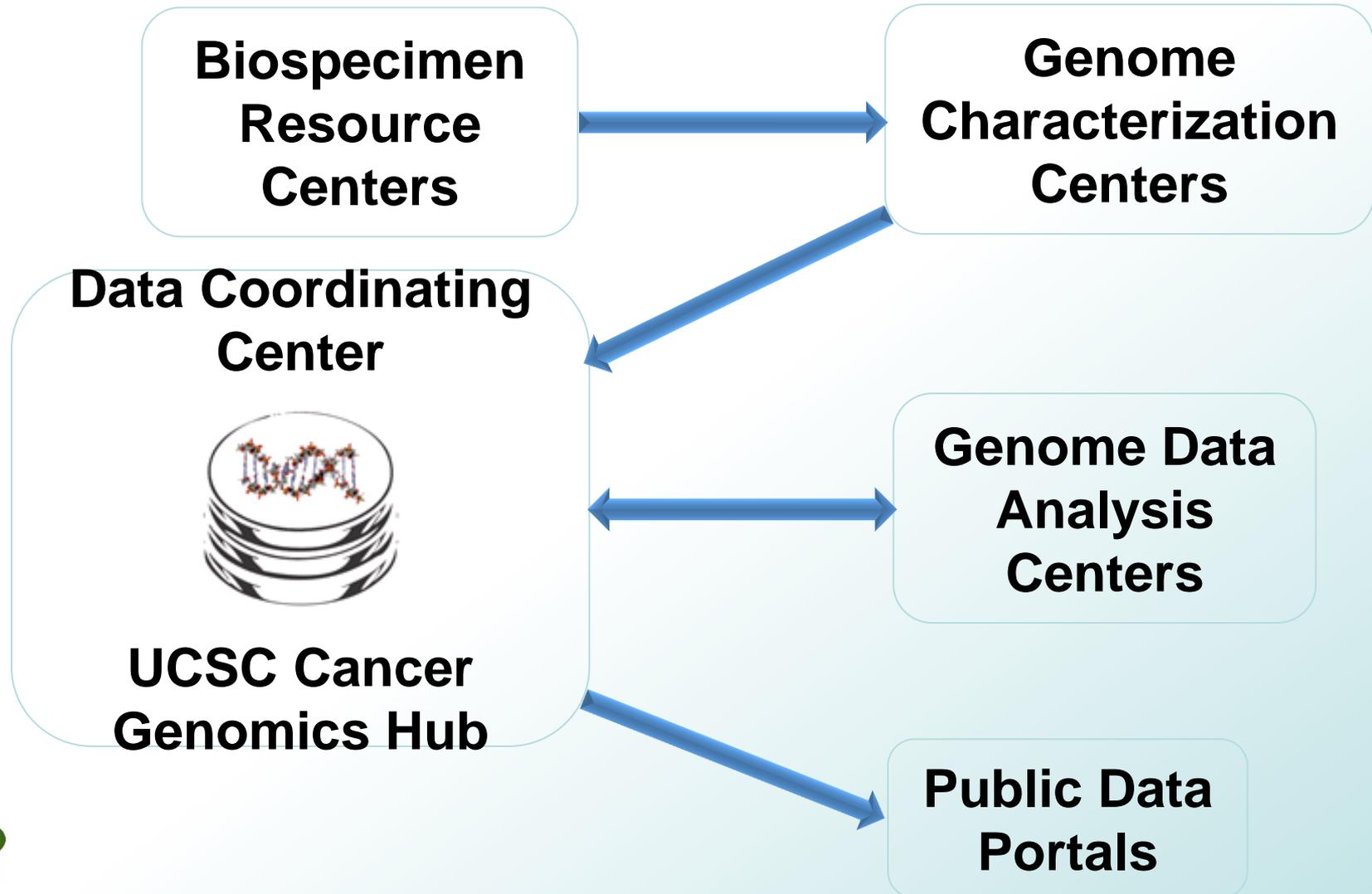


# Cancer genomics will lead the way to personal genomics

- High mortality and cost of care make additional cost of sequencing tumor genomes relatively minor.
- Disease is caused by changes to the genome; highly individual.
- Many genes are targeted by available drugs.
- Standard of care often fails.
- Once standard of care fails, can explore strategies based on genome analysis that have not been completely validated by a traditional clinical trial (e.g., combination therapies).
- We may not need a perfectly accurate quantitative model of how most types of cancer cells work to figure out how to selectively kill them (e.g., immunology-based cancer treatments). A full genomic scan may provide a suitable “kill signature.”
- A full-genome scan will provide a means to detect a recurrence very early from a simple blood test.



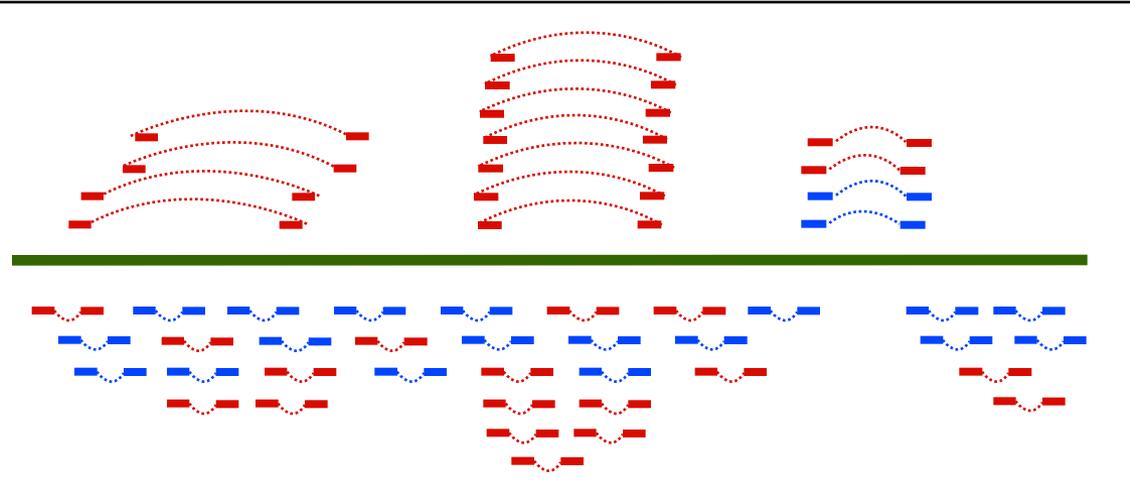
# The Cancer Genome Atlas (TCGA): >20 cancer types, 500 tumors from each



# Sequencing Cancer Genomes (Broad, Wash U., Baylor, plus Vancouver and other smaller centers)

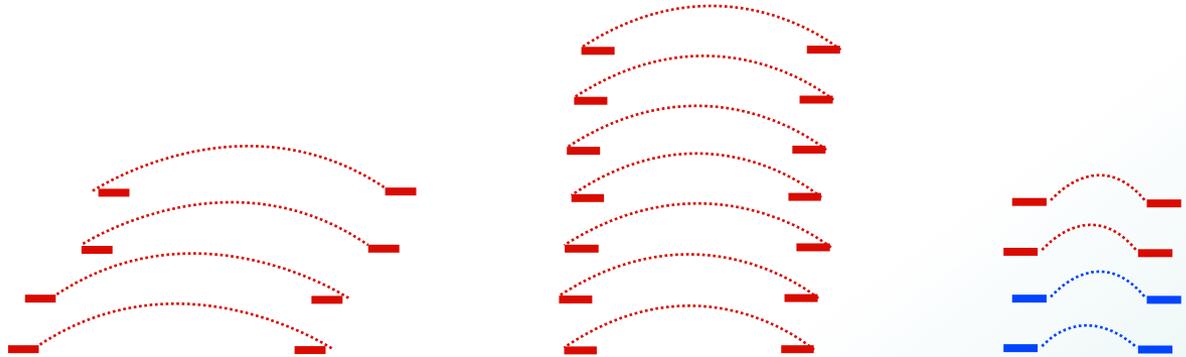


**Reference**



# Mapped reads:

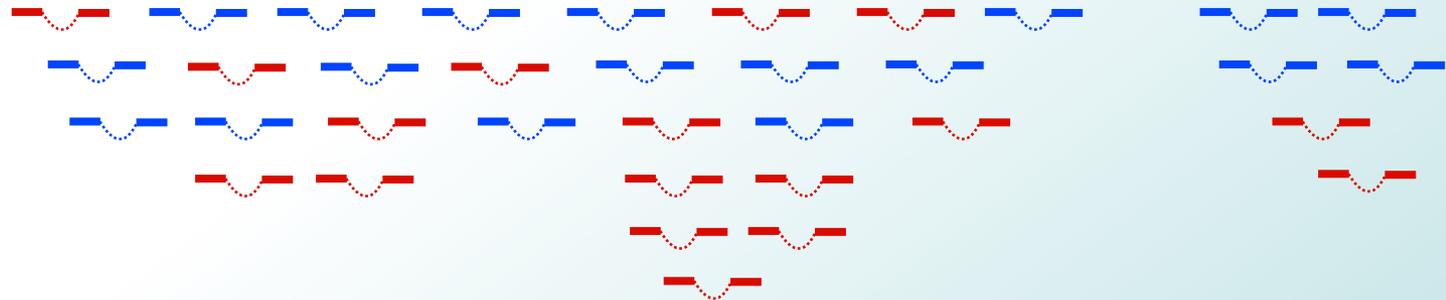
Discordant  
Germline  
Tumor



Reference

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Concordant  
Germline  
Tumor



# Low-level interpretation of mapped reads:

*Inversion*

*Tandem Duplication*

*Germline Deletion*

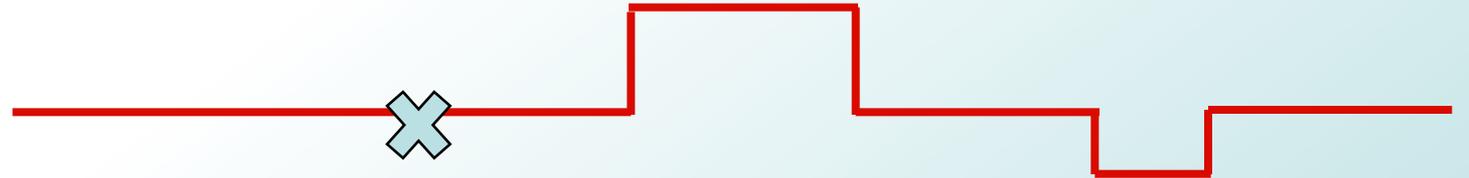
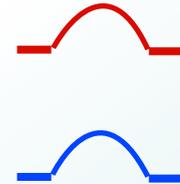
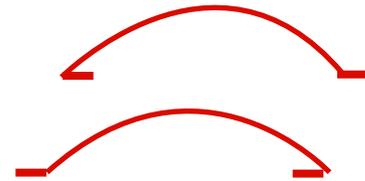
Tumor Breaks

Germline Breaks

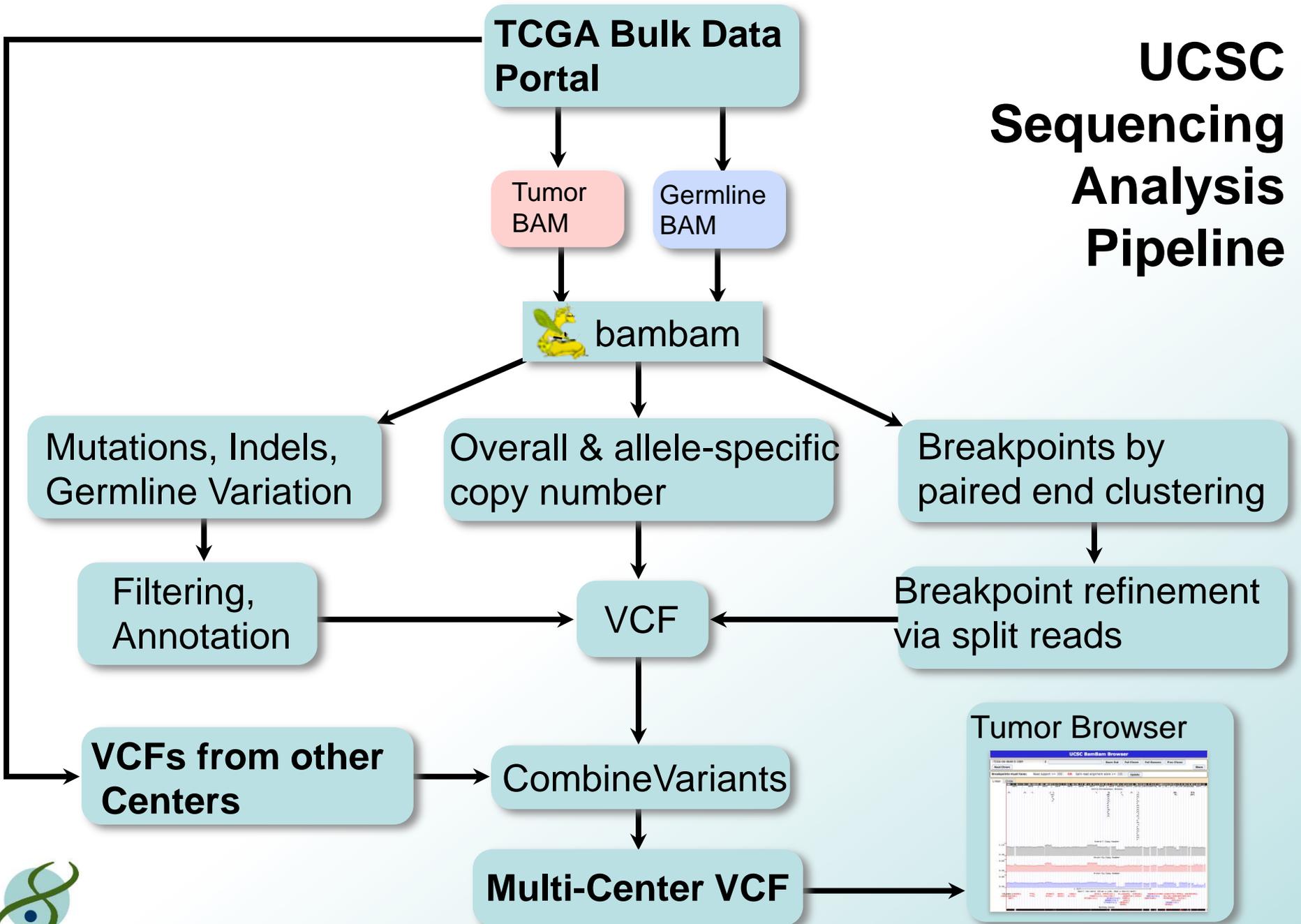
Reference

Germline Copy Number

Tumor Copy Number



# UCSC Sequencing Analysis Pipeline



# Tumor TCGA-06-0188

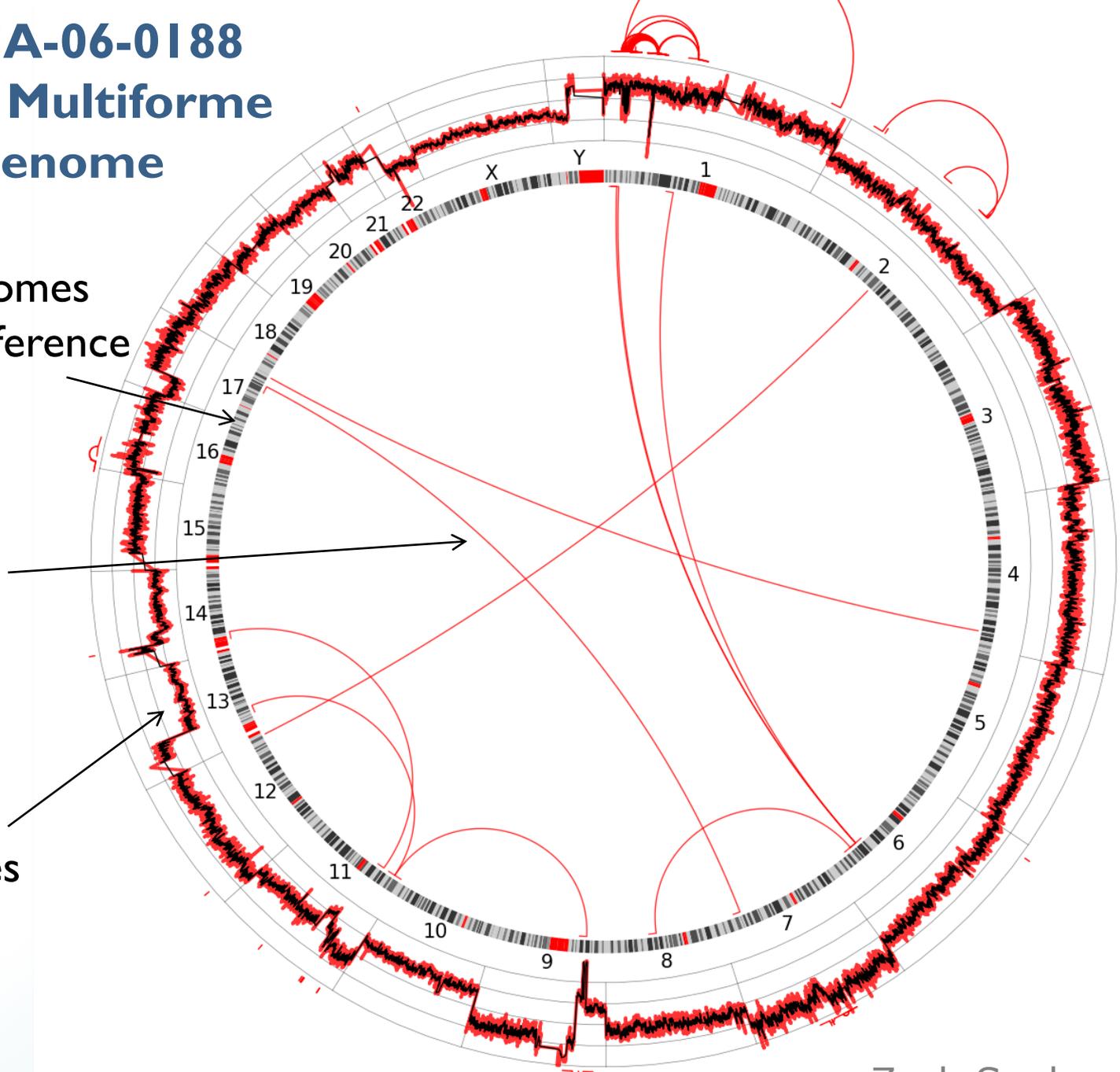
## Glioblastoma Multiforme

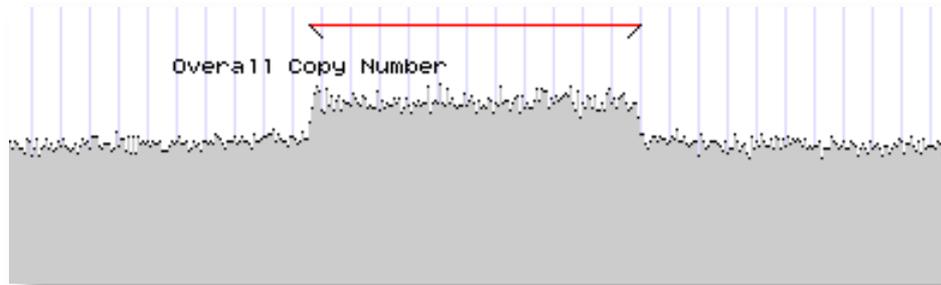
### Whole Genome

Human chromosomes  
1-22, X and Y (reference  
genome)

Rearrangements  
In the tumor

Number of copies  
In the tumor





chr2 : 29,064,107

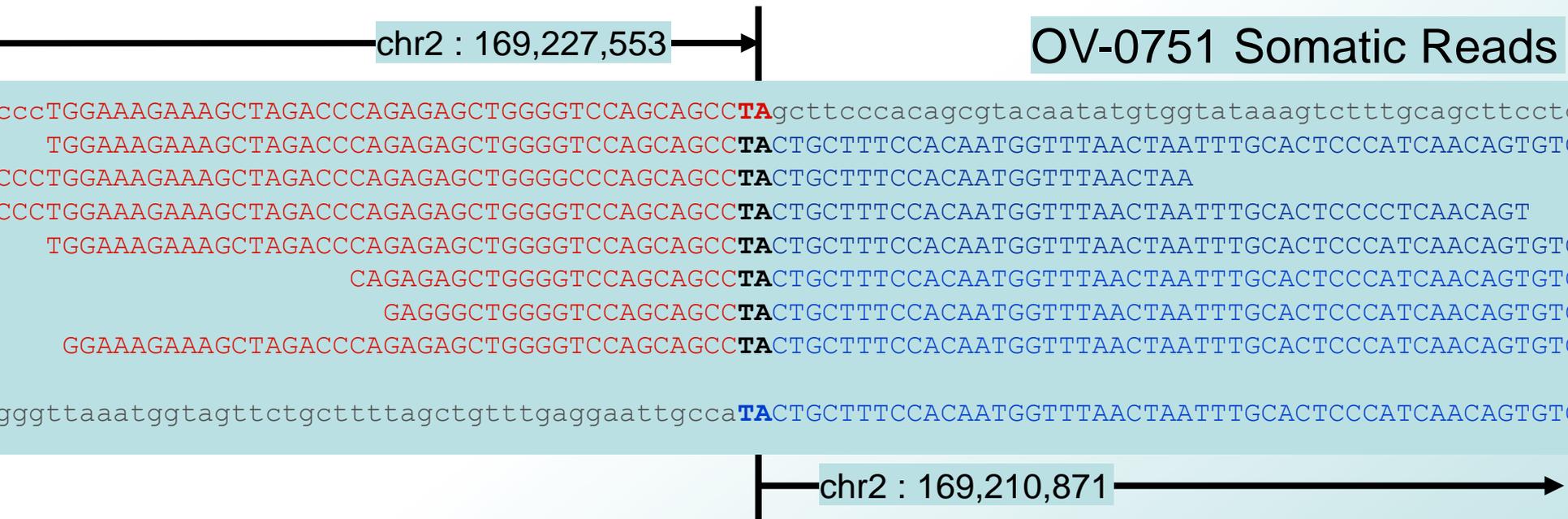
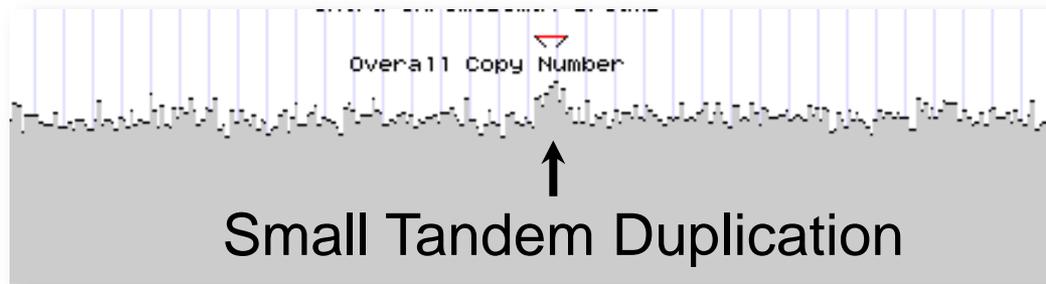
OV-0751 Somatic Reads

ATTGCTGGCTGGCTGCACCCTATATTGTCTGAGAACAGAGTGGCTACAggaggtattaaccccacctgatctcacgatgggagaggagacgcca  
 ATTGCTGGCTGGCTGCACCCTATATTGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGCCATCAGAGGGCATCTCC  
 ATTGCTGGCTGGCTGCACCCTATATTGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGCCATCAGAGGGCATCTCCTCCATCTCCCATCG  
 ATTGCTGGCTGGCTGCACCCTATATTGTCTGAGAACAGAGTGGCTACACAGAAAAGGAGGC  
                   TATATTGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGCCATCAGAGGGCATCTCCTCCATCTCCCATCG  
 ATTGCTGGCTGGCTGCACCCTATATTGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGGCCACAGAGGTCA  
           CTGGCTGGCTGCACCCTATATTGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGCCATCAGAGGGCCTCTCCTCCATCTCCCATCG  
 ATTGCTGGCTGGCTGCACCCTATATTGTCTGAGAACAGAGTGGCTACACAGAAAAGGAGGCC  
 ATTGCTGGCTGGCTGCACCCTATATTGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGCCATCCGAGGGCATCTCCTCCATCTCCCAC  
           GGCTGGCTGCACCCTATAATGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGCCATCAGAGGGCATCTCCTCCATCTCCCATCG  
                   CTAGATTGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGCCCTCAGAGGGCATCACCTCCACTTCCCATCG  
 ATTGCTGGCTGGCTGCACCCTATATTGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGCCATCAGAGGGCATCTCCTCCATCCCCATCC  
           TGCACCCTATATTGTCTGAGAACAGAGTGGCTACACAGAAAATGGAGGCCACAAAGGGCCACTTCCCCACCTCCCCTCC  
  
 cactttctacagacgatgtcaccttcacctCACAGAAAATGGAGGCCATCAGAGGGCATCTCCTccatctcccatcg

chr2 : 28,500,054

Tandem Duplication Size = 564,053 bp



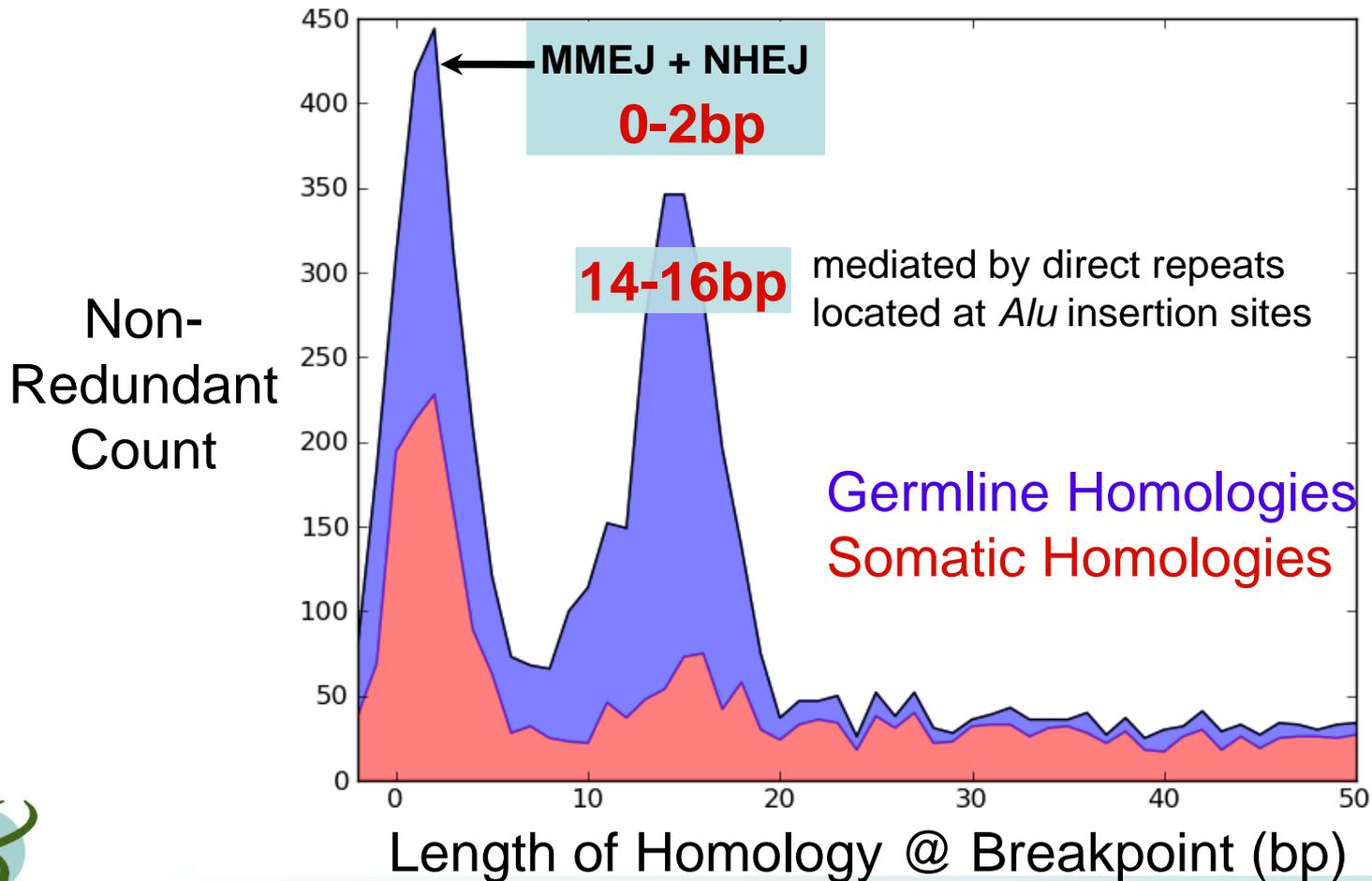


Tandem Duplication Size = 16,682 bp



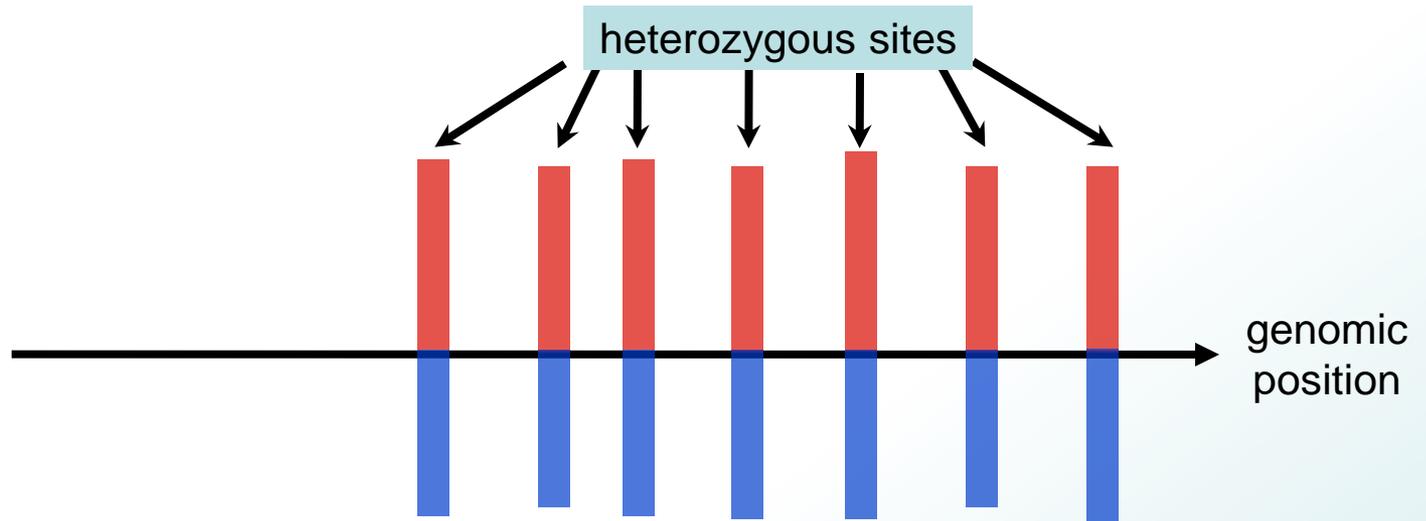
# Somatic Breakpoints are enriched for Non-Homologous End Joining (NHEJ)

## Sequence Homologies at Breakpoints

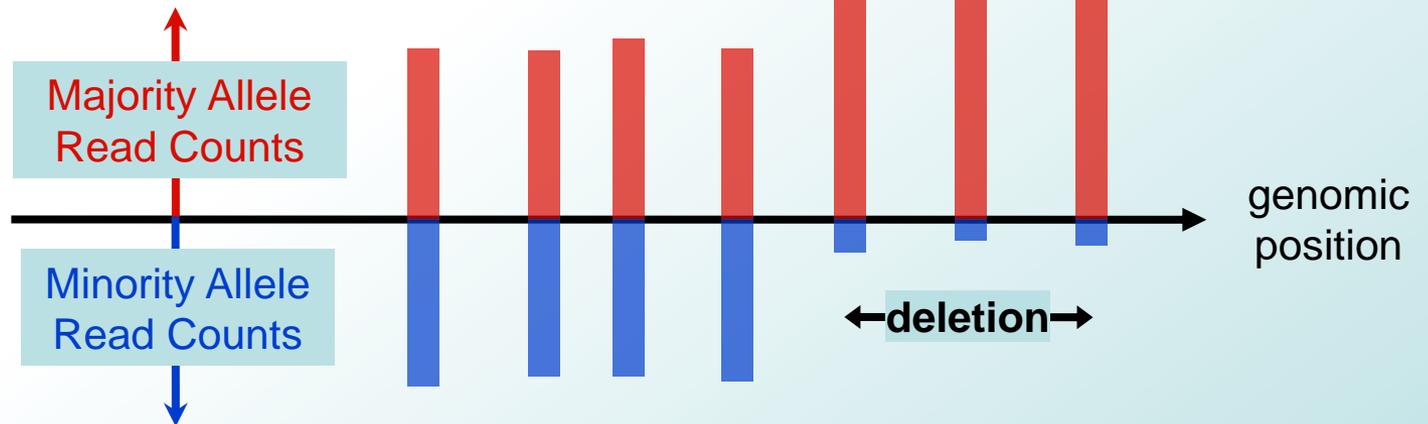


# Allele-Specific Copy Number

**Matched  
Normal**



**Tumor**



# Tumor TCGA-06-0188

## Glioblastoma Multiforme

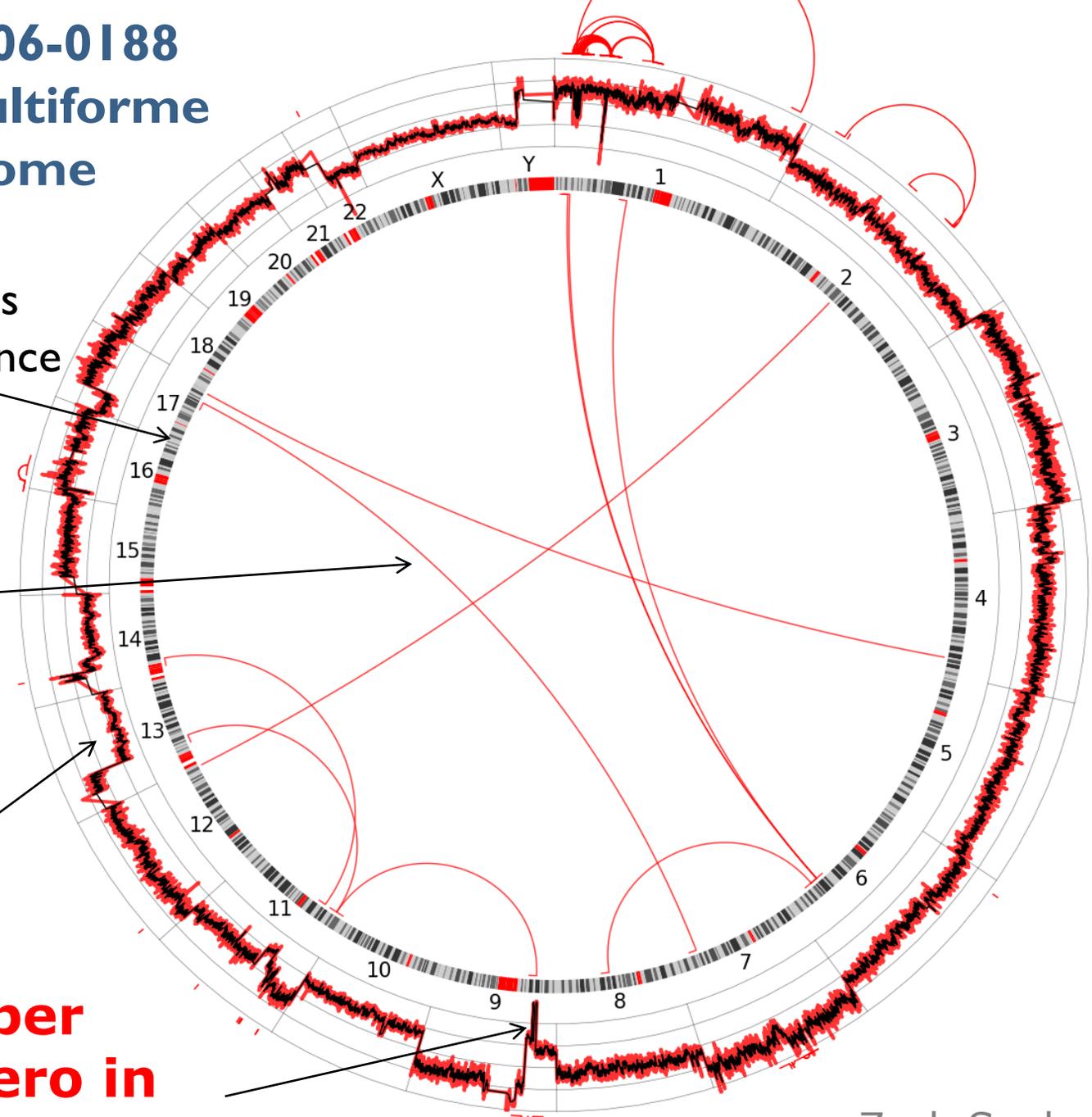
### Whole Genome

Human chromosomes  
1-22, X and Y (reference  
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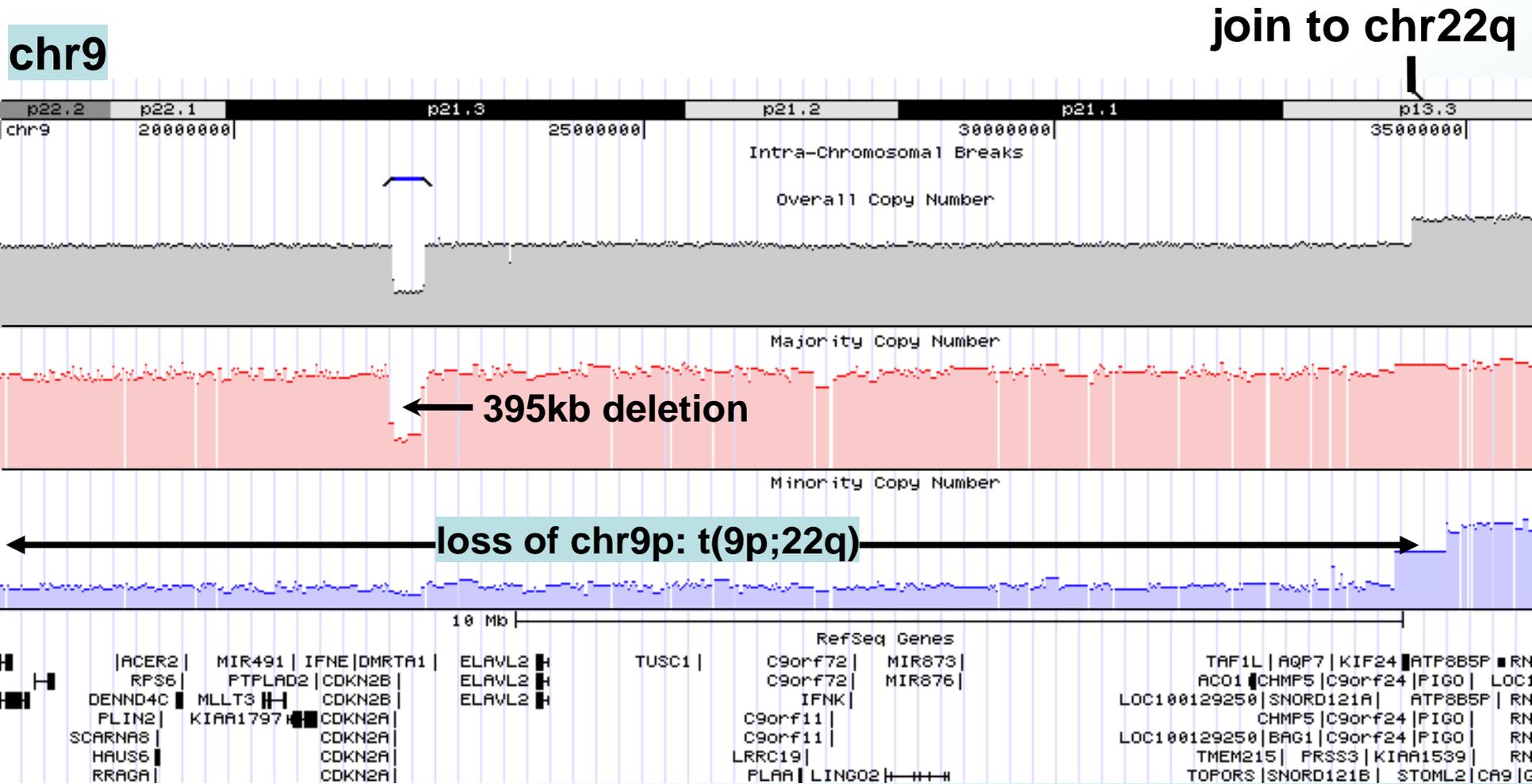
Rearrangements  
In the tumor

Number of copies  
In the tumor

**Copy number  
drops to zero in  
one place**



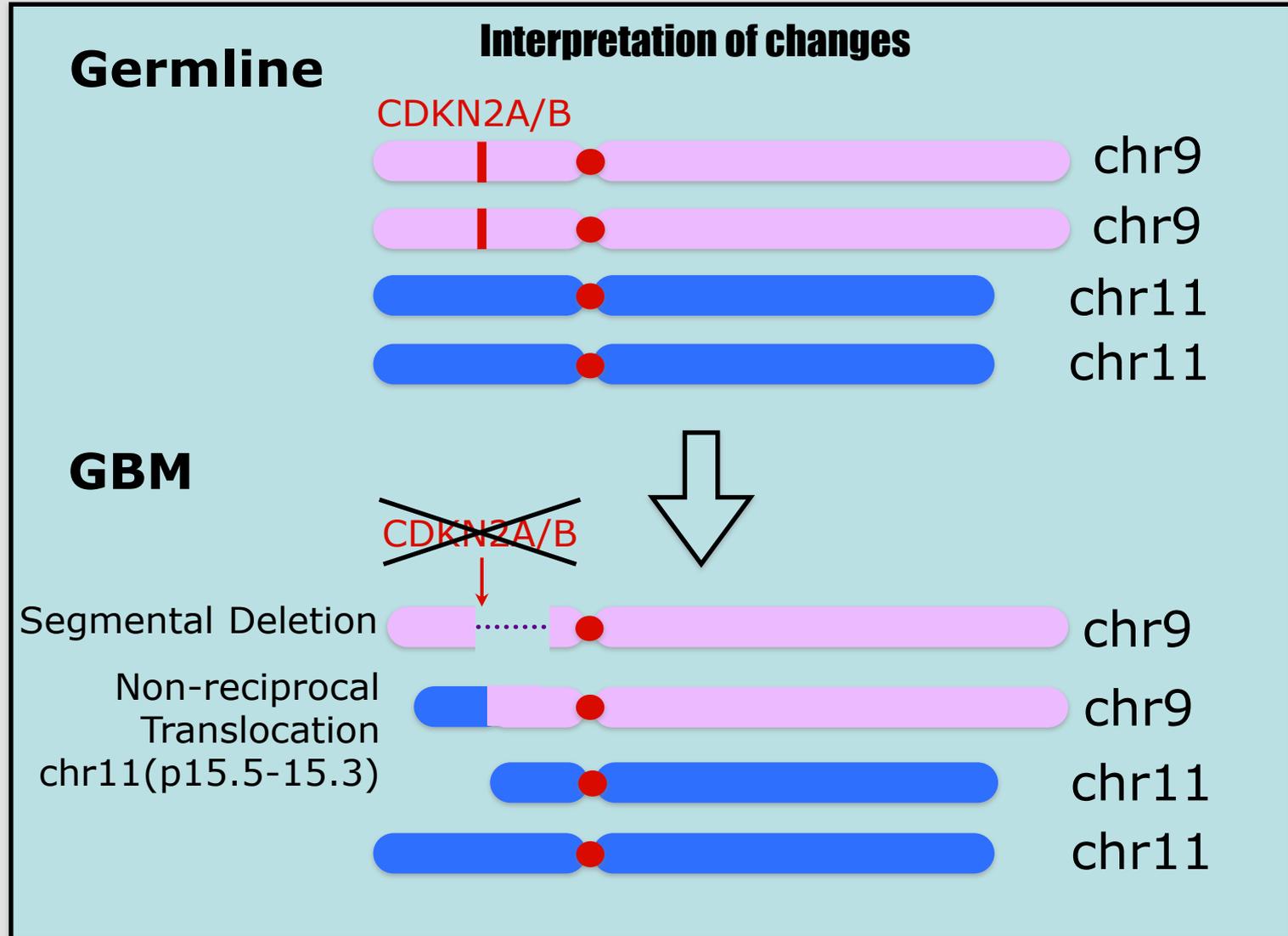
# Glioblastoma: TCGA-06-0145



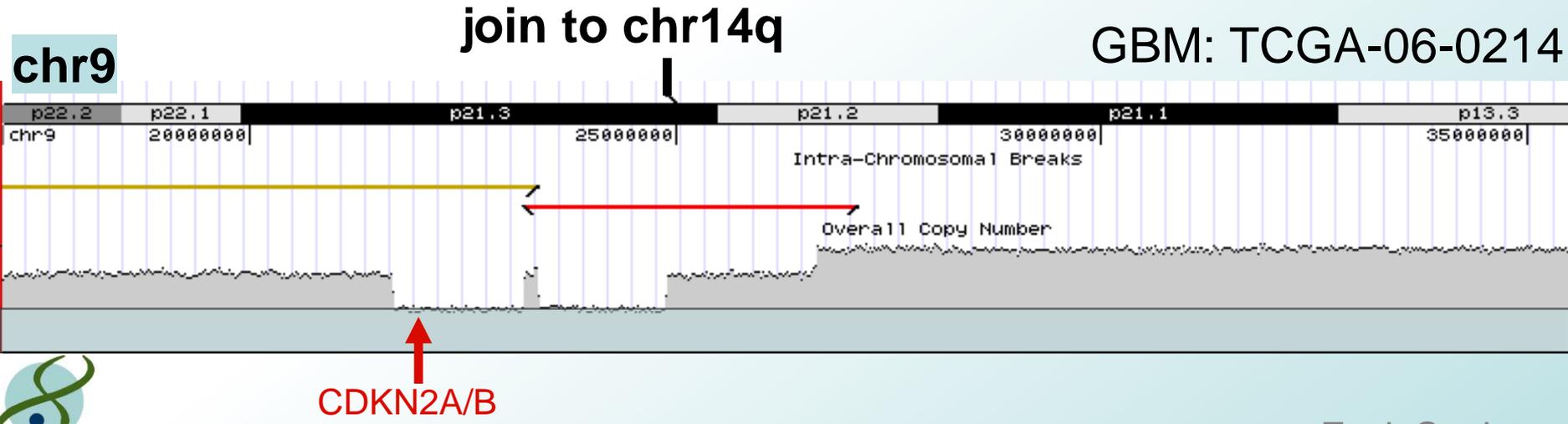
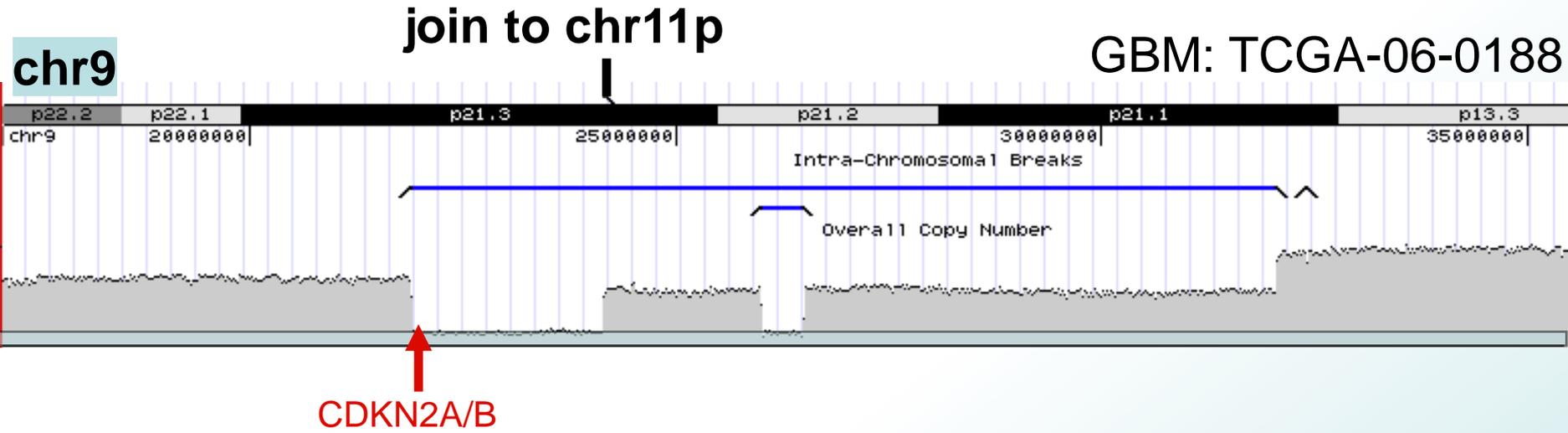
**Homozygous loss of CDKN2A/B**

via inter- and intra-chromosomal rearrangements.

# Glioblastoma: TCGA-06-0145



# Similar double-loss motif in other GBMs

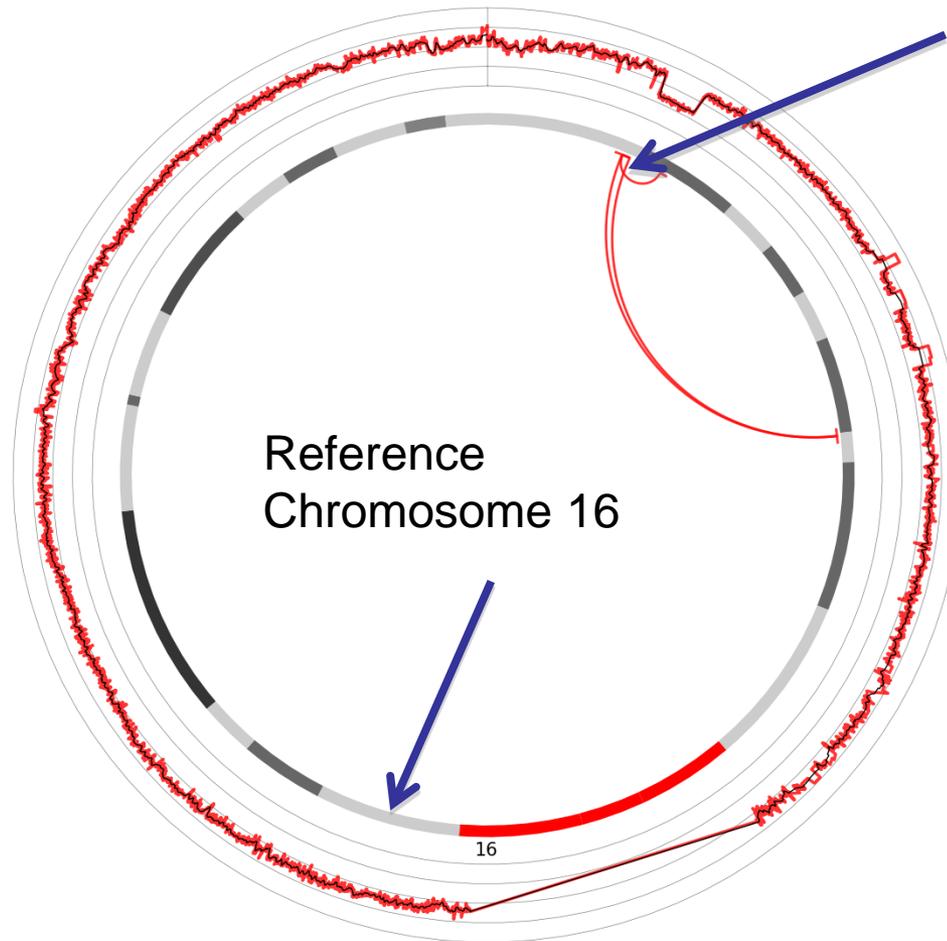


# Similar events lead to double loss of CDKN2A/B in GBM

	One Copy Deleted by	Other Copy Deleted by
<b>5</b> GBMs	Focal Loss	Arm-Level loss of chr9p (via inter-chrom translocation)
<b>3</b> GBMs	Focal Loss	Arm-Level loss of chr9p (mechanism unknown)
<b>2</b> GBMs	Focal Loss	Complete loss of chr9
<b>1</b> GBM	Focal Loss	Complex event
<b>5</b> GBMs	<i>No loss detected</i>	<i>No loss detected</i>



# Simple Example of Tumor Genome reconstruction from this Glioblastoma Tumor

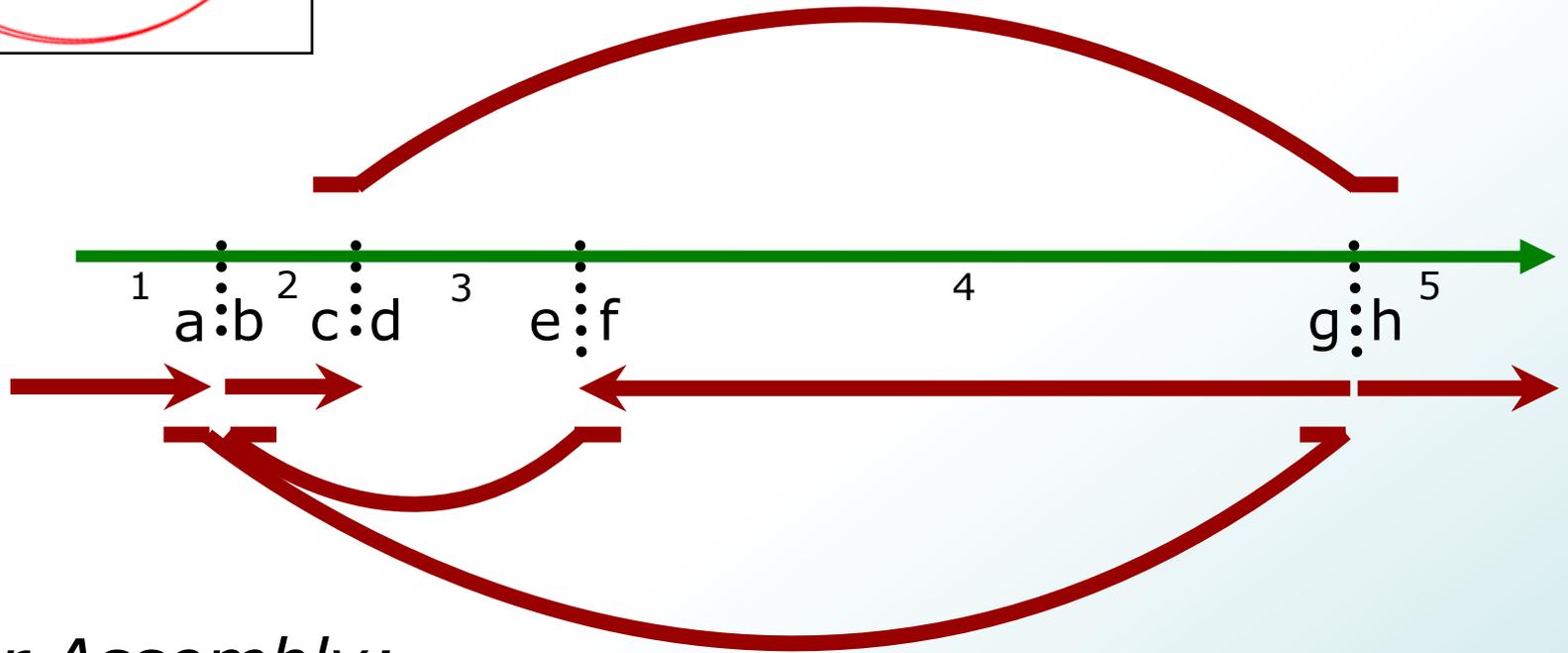
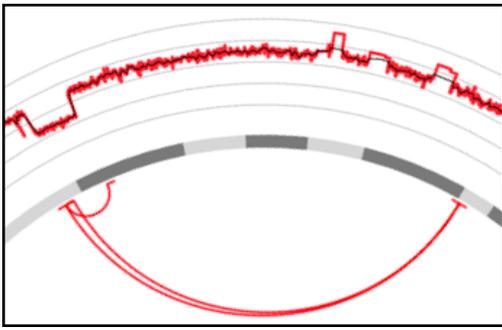


This region contains the gene A2BP1

The A2BP1 gene is a Tissue-specific alt-splicing regulator, important in **brain**, heart, muscle



# We walk the adjacencies to determine order of segments in the tumor



*Tumor Assembly:*

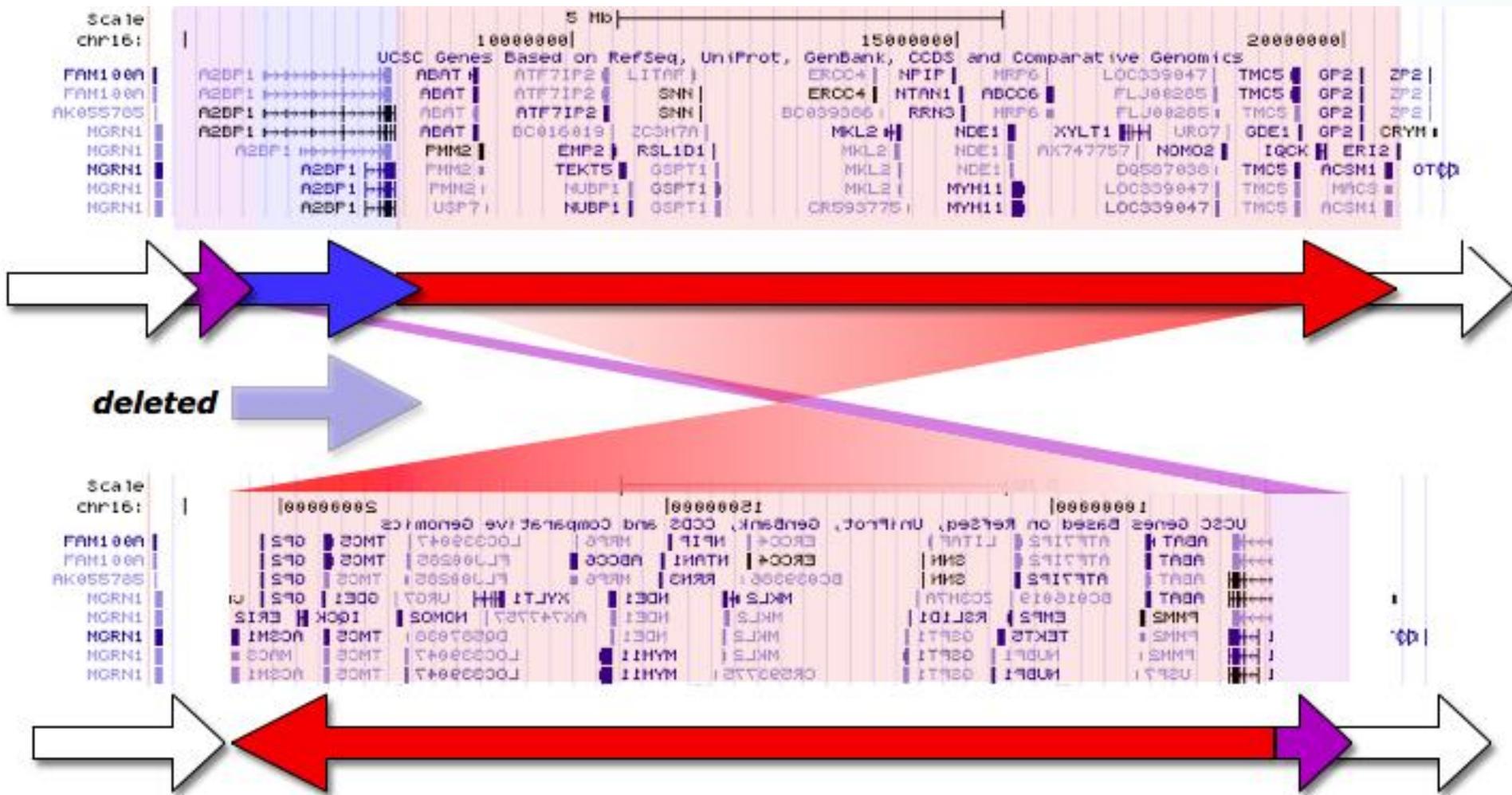


*Tumor Copy Number:*



# Tumor Browser View of TCGA GBM

Region in Germline Genome, all on same parental haplotype

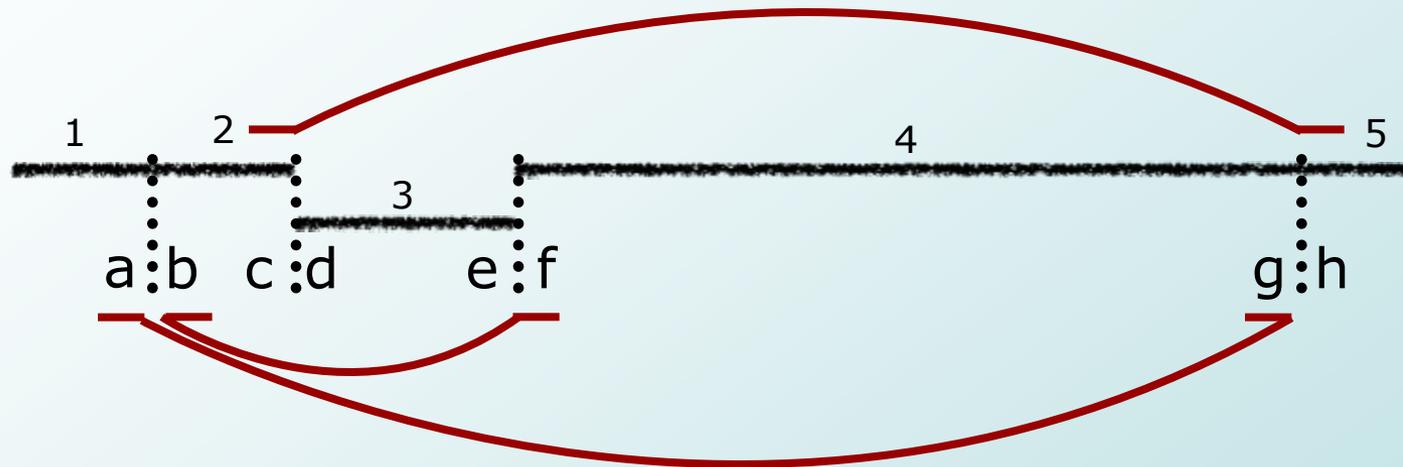
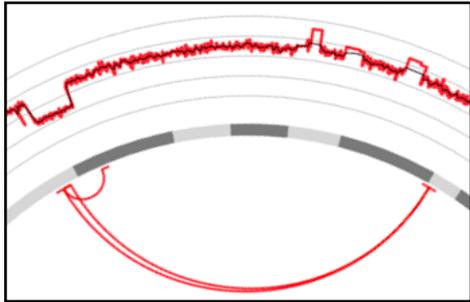


Tumor Genome Micro-Assembly

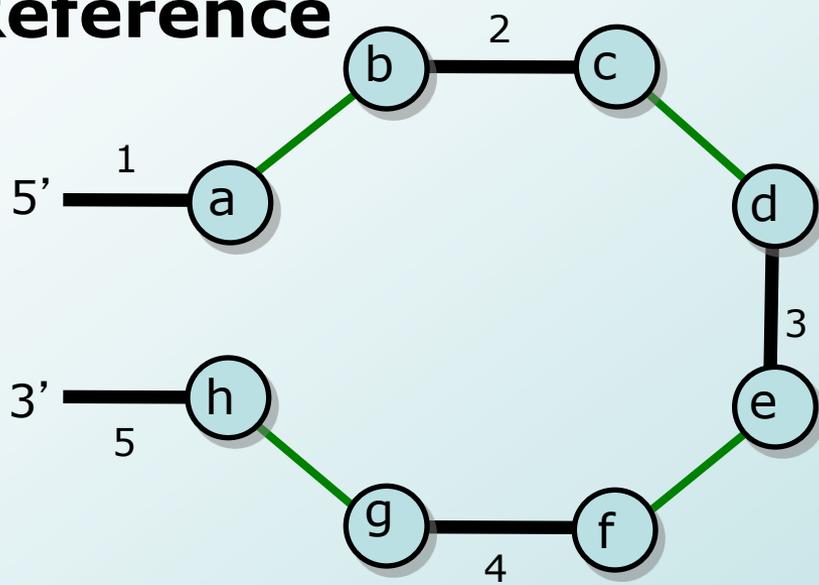
J. Zachary Sanborn



# A Breakpoint graph shows how adjacencies of segment ends change

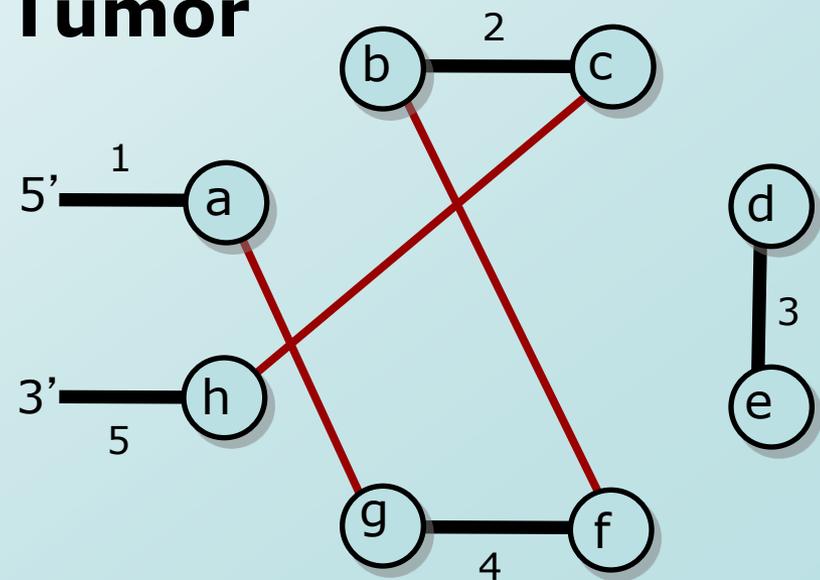


## Reference



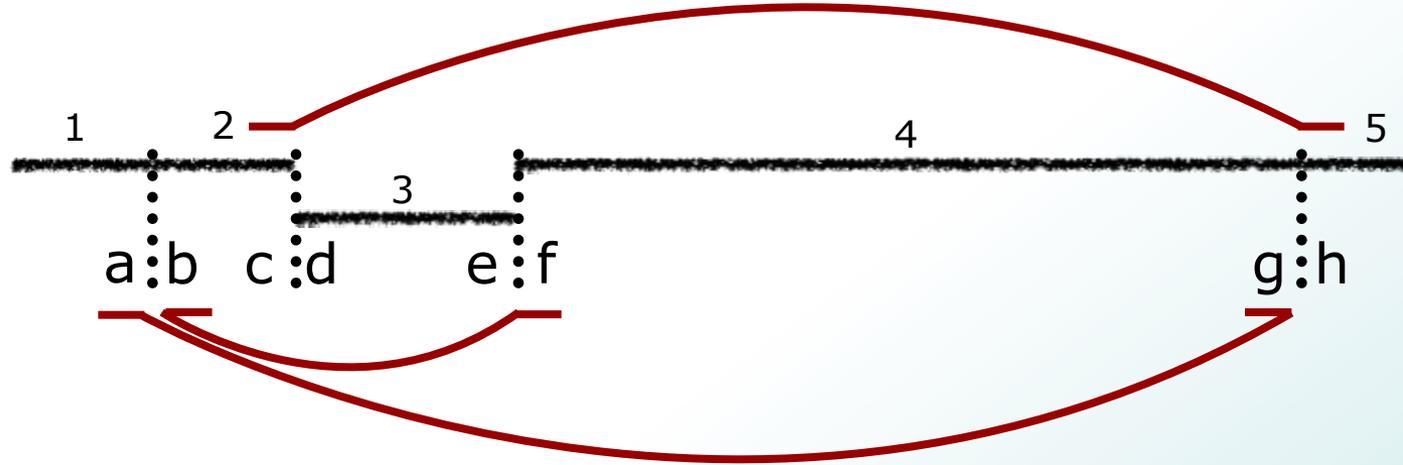
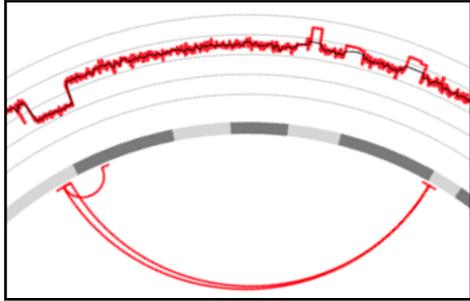
**Genome** = 1 2 3 4 5

## Tumor

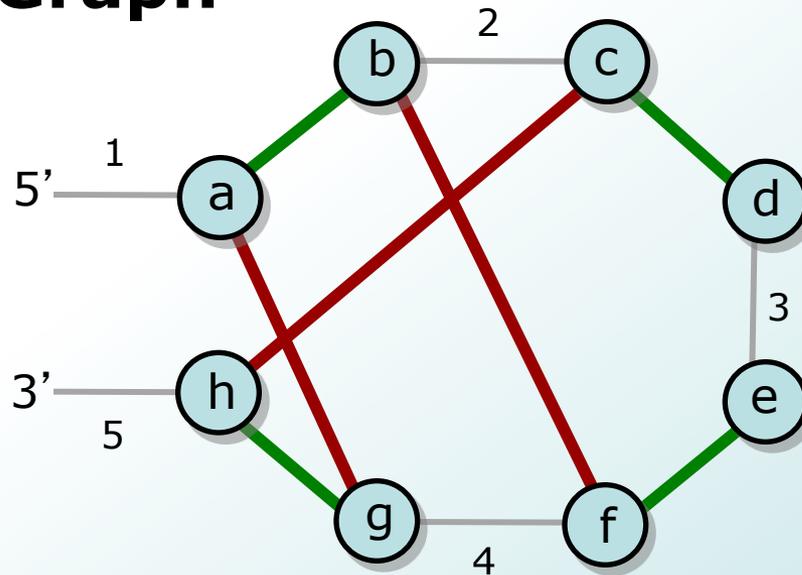


**Genome** = 1 -4 2 5

# A Breakpoint graph shows how adjacencies of segment ends change



## Breakpoint Graph

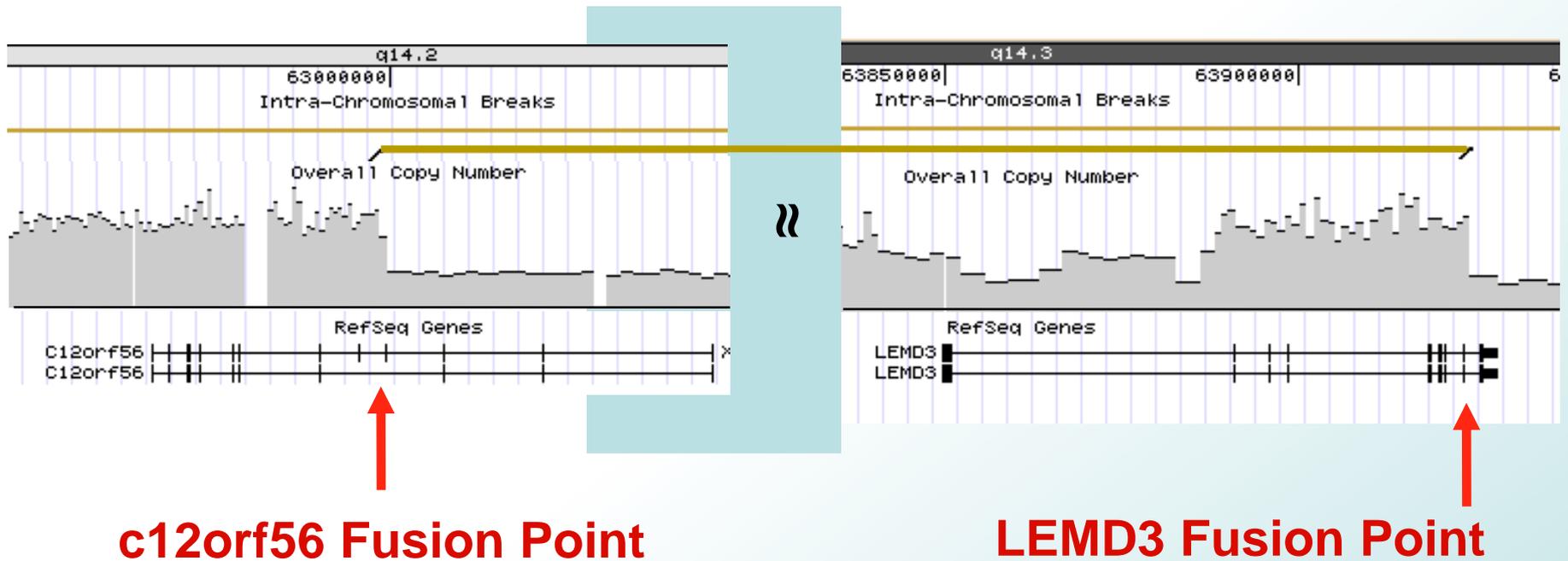


# GBM Gene Fusions

- **Broad's dRanger** identified a set of 7 high confidence rearrangements connecting the introns of two genes, across 17 whole genome TCGA GBM datasets:
  - **3 in-frame**, potentially functional gene fusions:
    - All 3 confirmed by bambam PE clustering, CNV, and bridget split-reads
  - **4 out-of-frame**:
    - 3 confirmed by bambam, CNV, and bridget
    - 1 missed by bambam, but CNV suggests the breakpoint indeed exists



# LEMD3 - c12orf56 Fusion

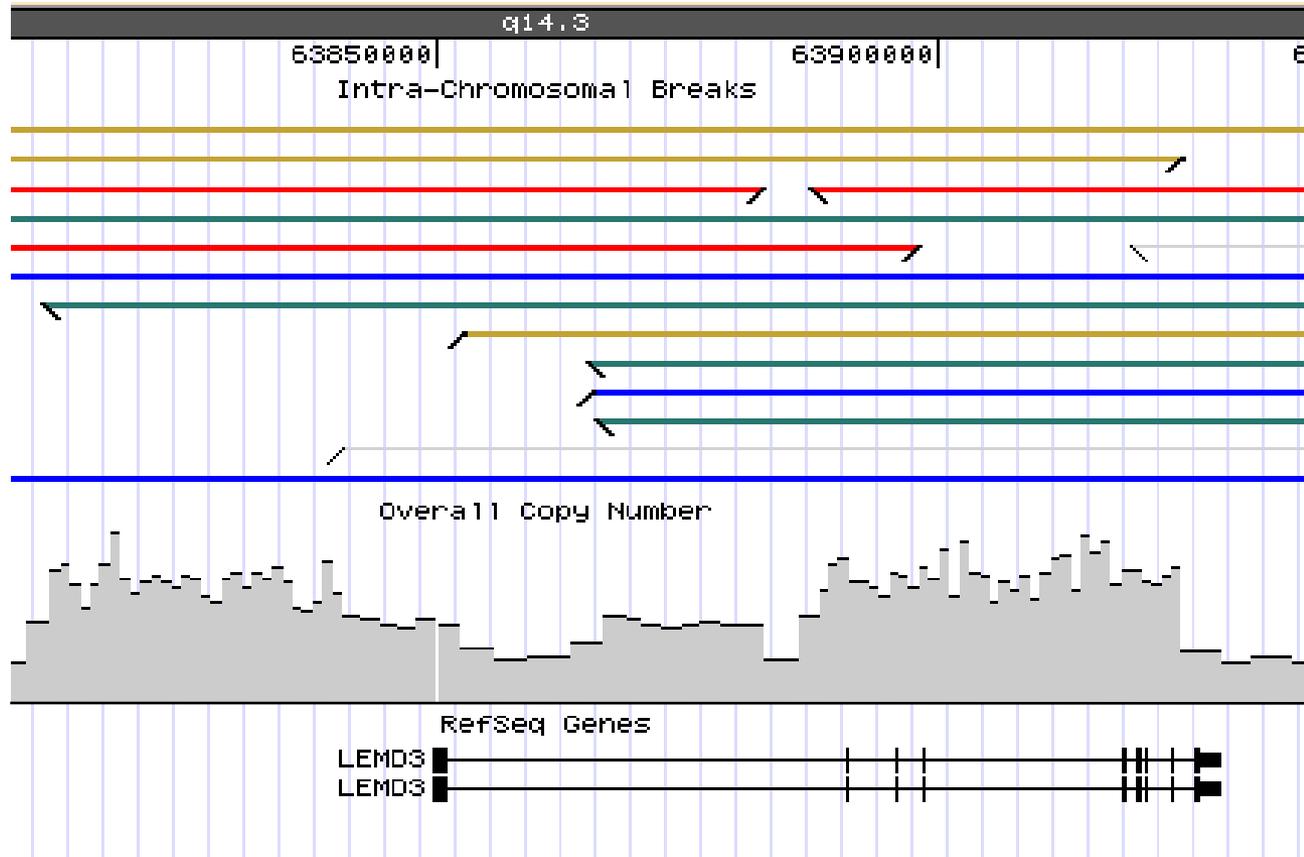


**c12orf56 Fusion Point**

**LEMD3 Fusion Point**



# LEMD3 - c12orf56 Fusion



**LEMD3-c12orf56 Fusion Point**



# LEMD3-c12orf56 - Chromothripsis

TCGA-06-0152-D GBM

chr12:55229102-86277589

Zoom Out

Full Chrom

Full Genome

Prev Chrom

Next Chrom

Share

Breakpoints must have:

Read support  $\geq$  999

OR

Split-read alignment score  $\geq$  100

Update

Linear

Circle

Inter-chromosomal links to **chr7**

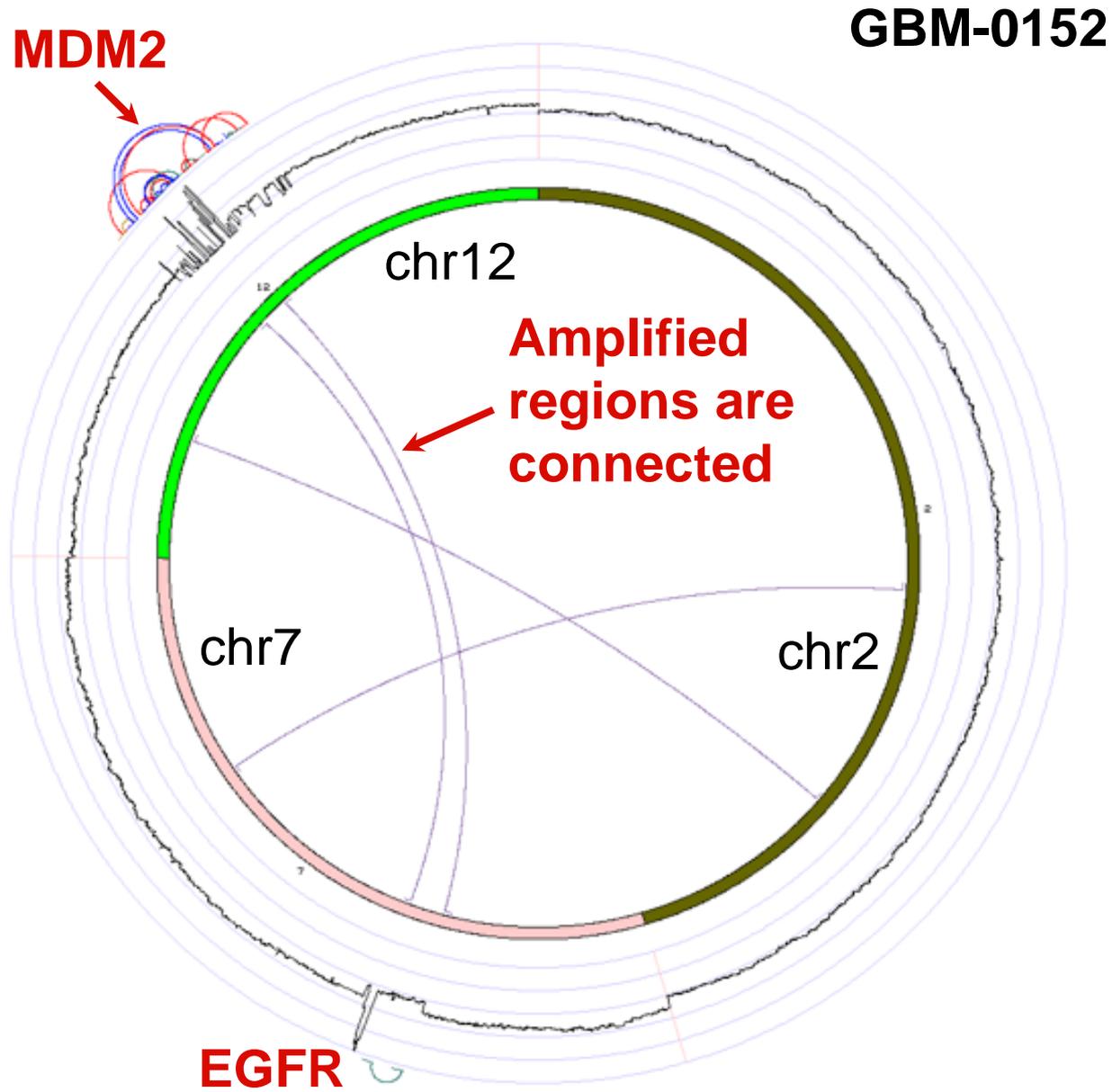


LEMD3-c12orf56 Fusion

MDM2

GBM-0152 chr12

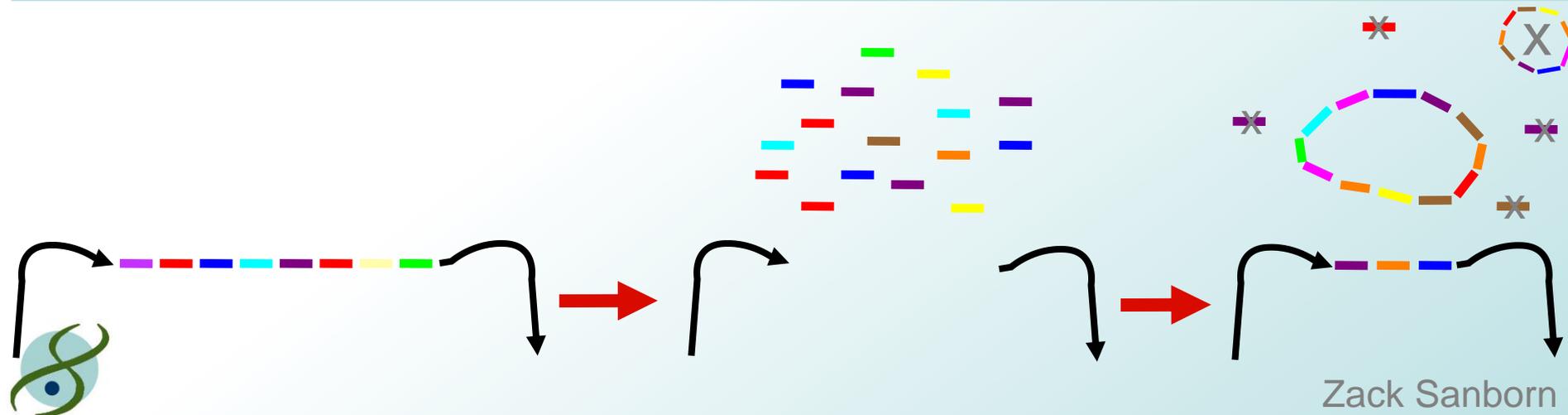




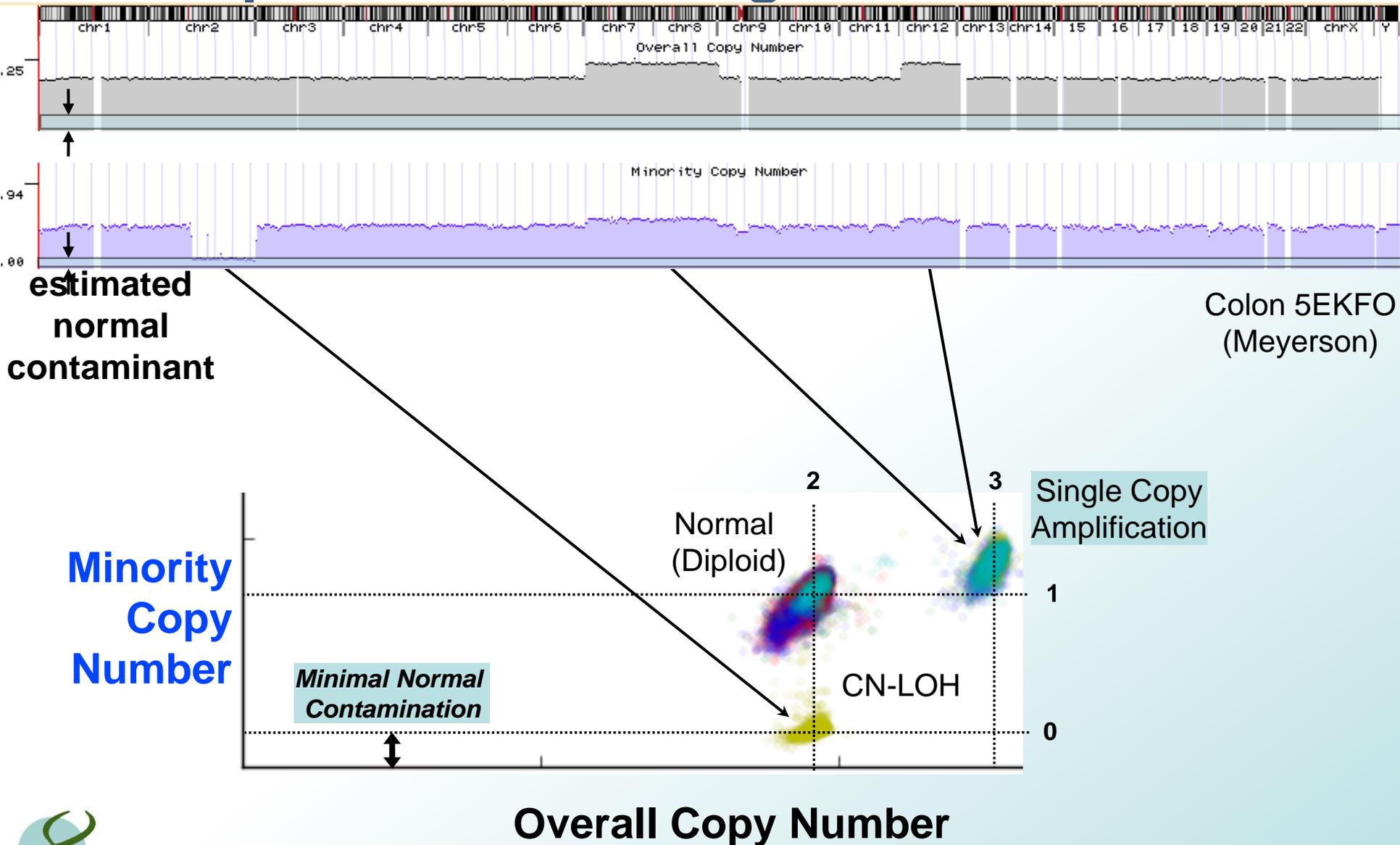
# Massive Genomic Rearrangement Acquired in a Single Catastrophic Event during Cancer Development

Philip J. Stephens,<sup>1</sup> Chris D. Greenman,<sup>1</sup> Beiyuan Fu,<sup>1</sup> Fengtang Yang,<sup>1</sup> Graham R. Bignell,<sup>1</sup> Laura J. Mudie,<sup>1</sup> Erin D. Pleasance,<sup>1</sup> King Wai Lau,<sup>1</sup> David Beare,<sup>1</sup> Lucy A. Stebbings,<sup>1</sup> Stuart McLaren,<sup>1</sup> Meng-Lay Lin,<sup>1</sup> David J. McBride,<sup>1</sup> Ignacio Varela,<sup>1</sup> Serena Nik-Zainal,<sup>1</sup> Catherine Leroy,<sup>1</sup> Mingming Jia,<sup>1</sup> Andrew Menzies,<sup>1</sup> Adam P. Butler,<sup>1</sup> Jon W. Teague,<sup>1</sup> Michael A. Quail,<sup>1</sup> John Burton,<sup>1</sup> Harold Swerdlow,<sup>1</sup> Nigel P. Carter,<sup>1</sup> Laura A. Morsberger,<sup>2</sup> Christine Iacobuzio-Donahue,<sup>2</sup> George A. Follows,<sup>3</sup> Anthony R. Green,<sup>3,4</sup> Adrienne M. Flanagan,<sup>5,6</sup> Michael R. Stratton,<sup>1,7</sup> P. Andrew Futreal,<sup>1</sup> and Peter J. Campbell<sup>1,3,4,\*</sup>

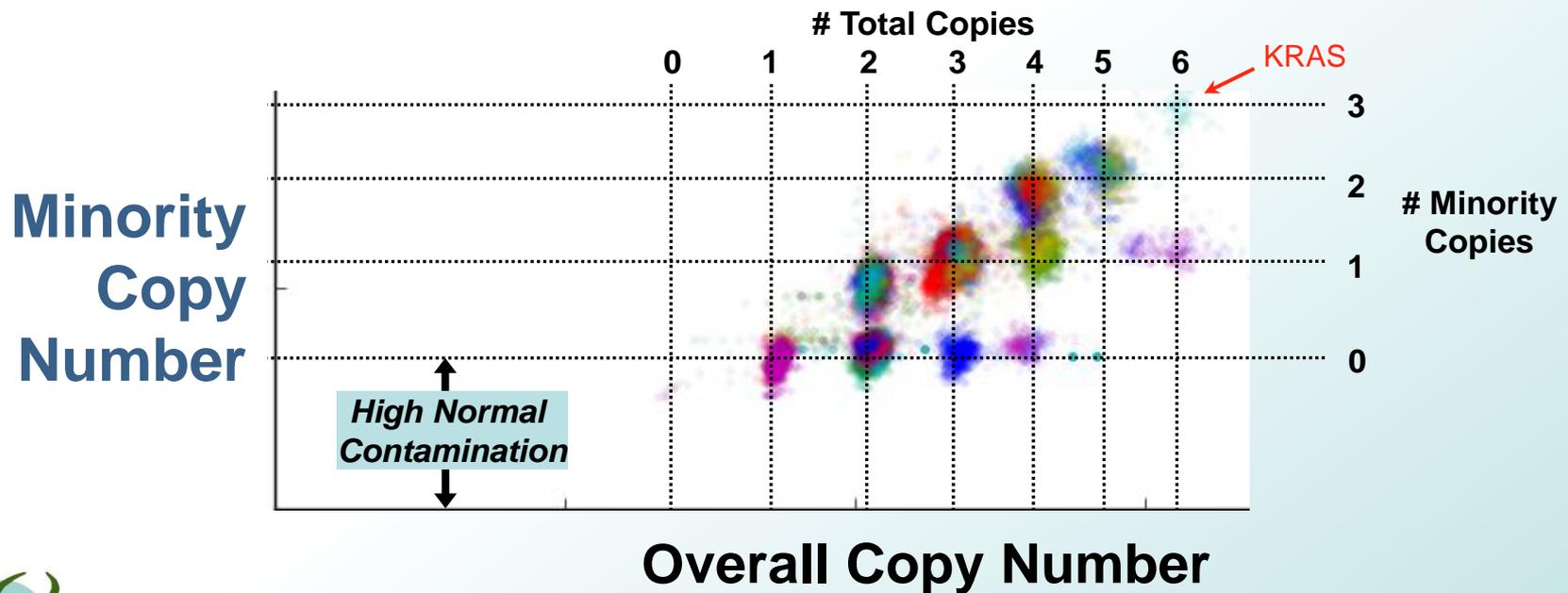
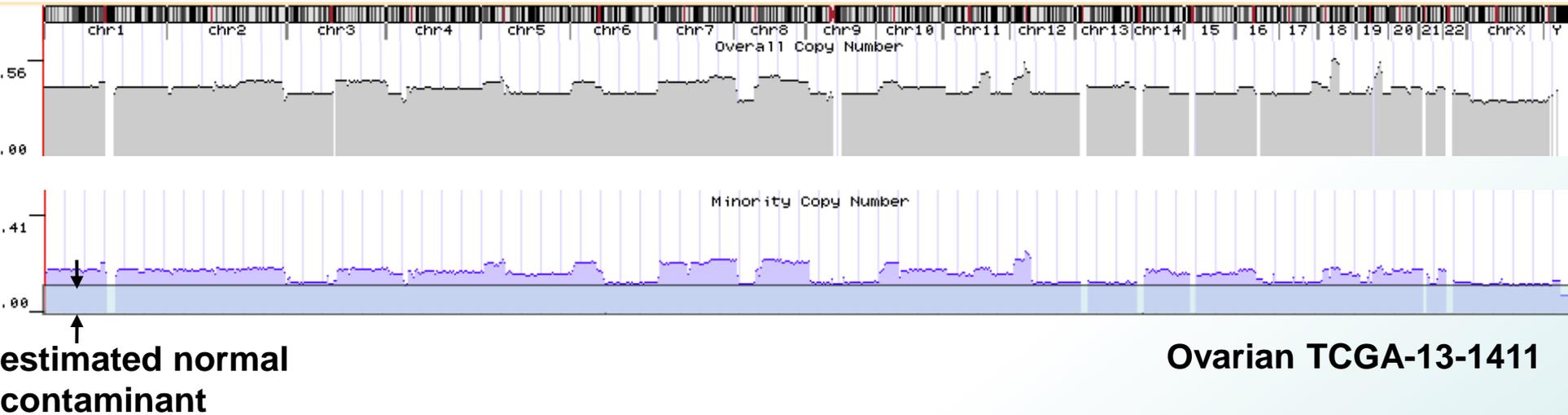
- **Chromothripsis:** DNA shatters into pieces due to some genetic insult when chromosome is in condensed state
- DNA repair mechanisms try to stitch genome back together
- Can generate rearrangements, losses, and double minute chromosomes



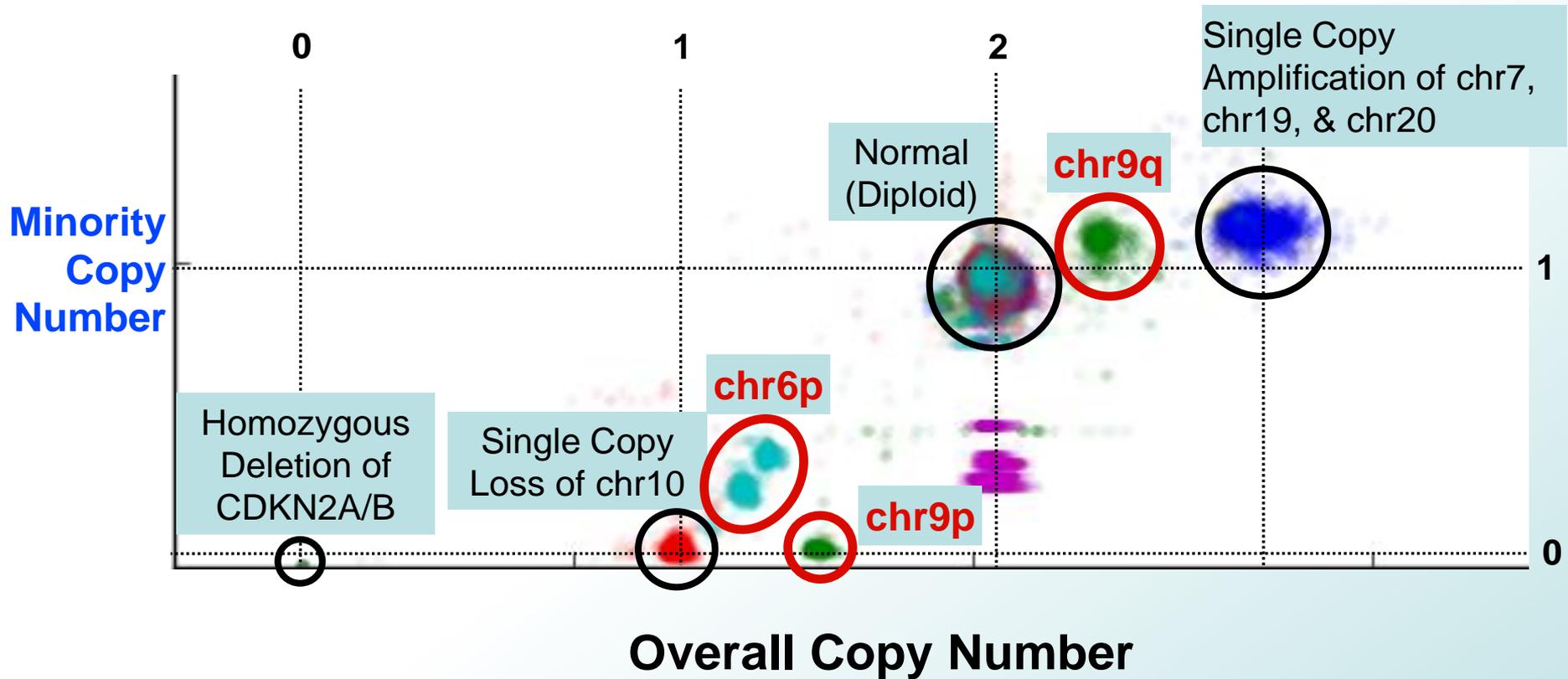
# Tumors exhibit multiple rounds of duplication, rearrangement and loss



# Copy Number Profile Analysis



# Copy Number States

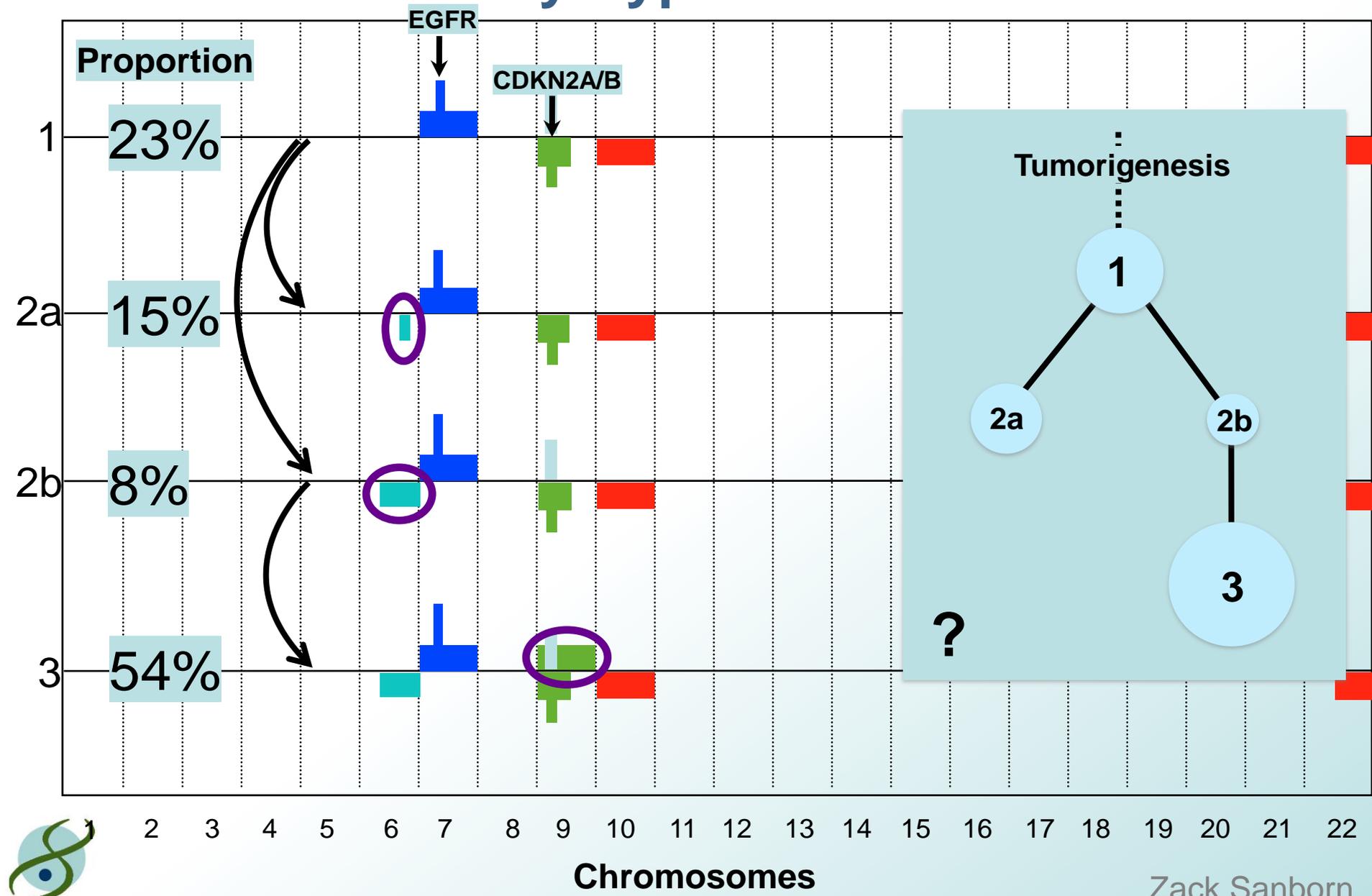


GBM: TCGA-06-0185

Zack Sanborn



# Simulated Progression Model to Infer Karyotype Mixture



# General model of genome evolution

A general model of structural variation should include (at least):

- substitution
- duplication
- rearrangement
- gain and loss

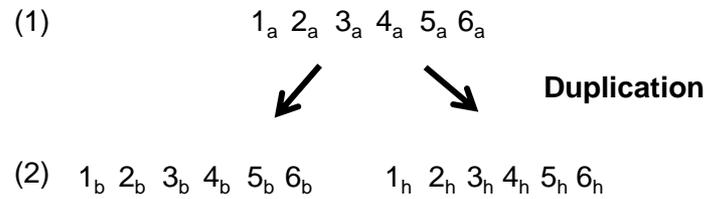
(1)

$1_a 2_a 3_a 4_a 5_a 6_a$



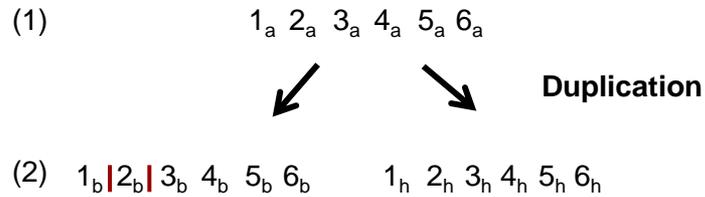
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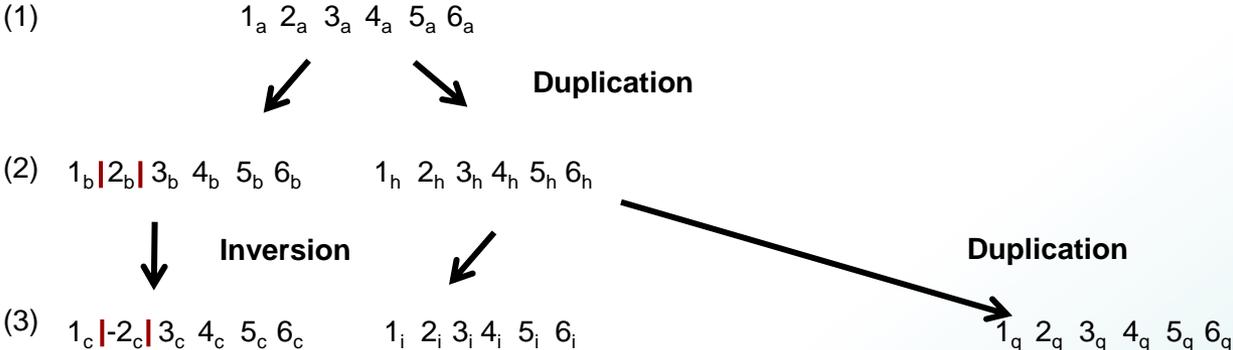
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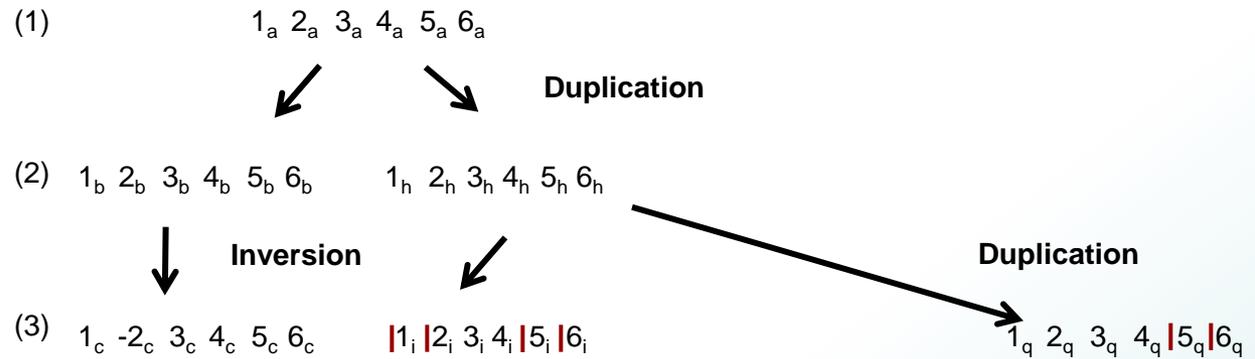
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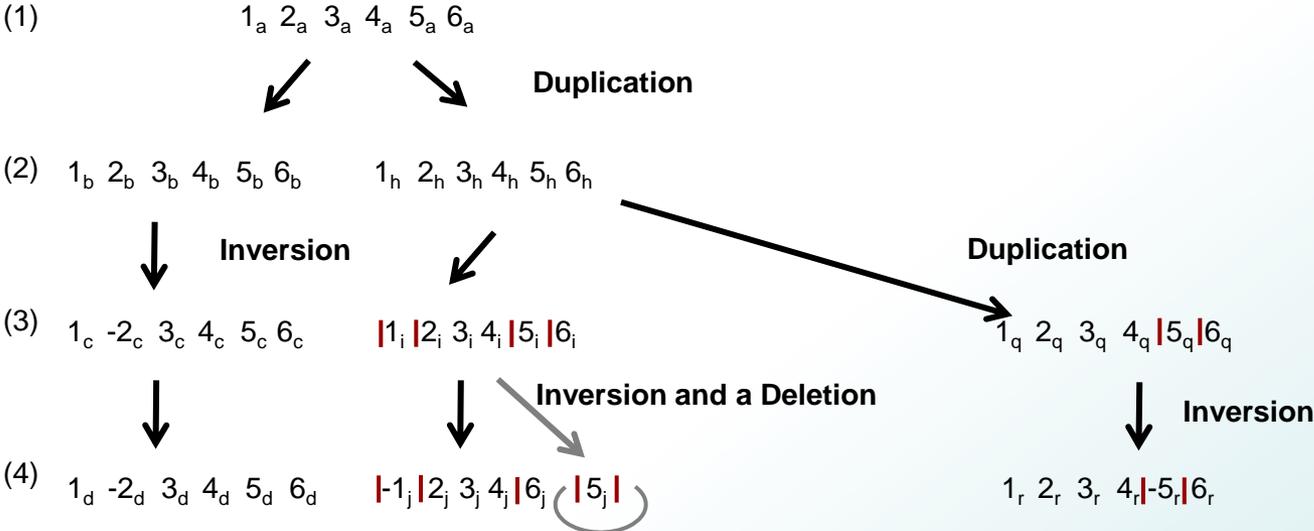
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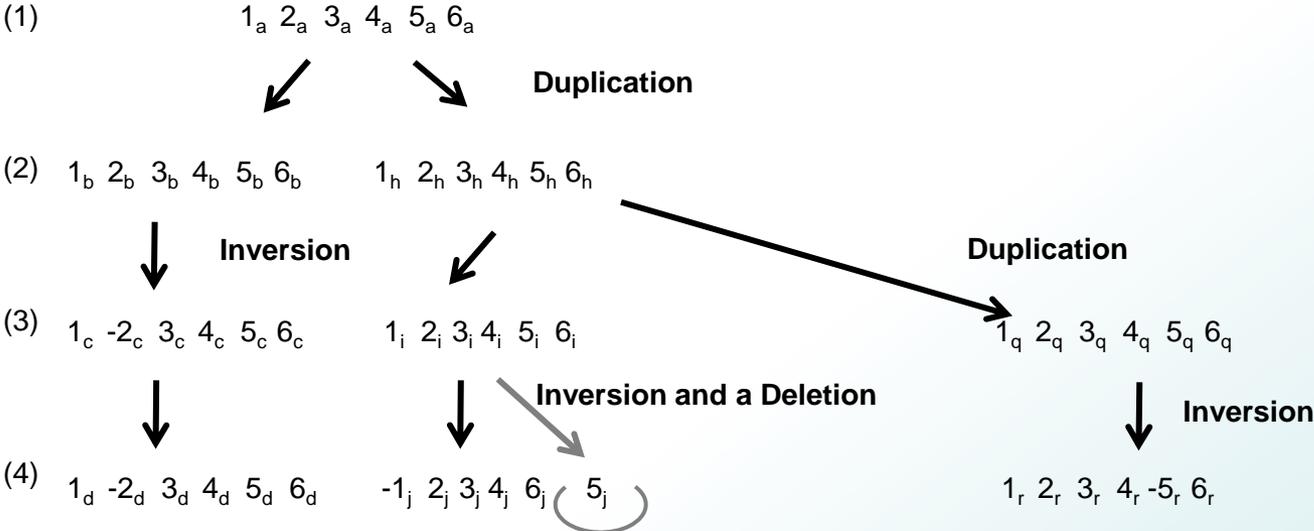
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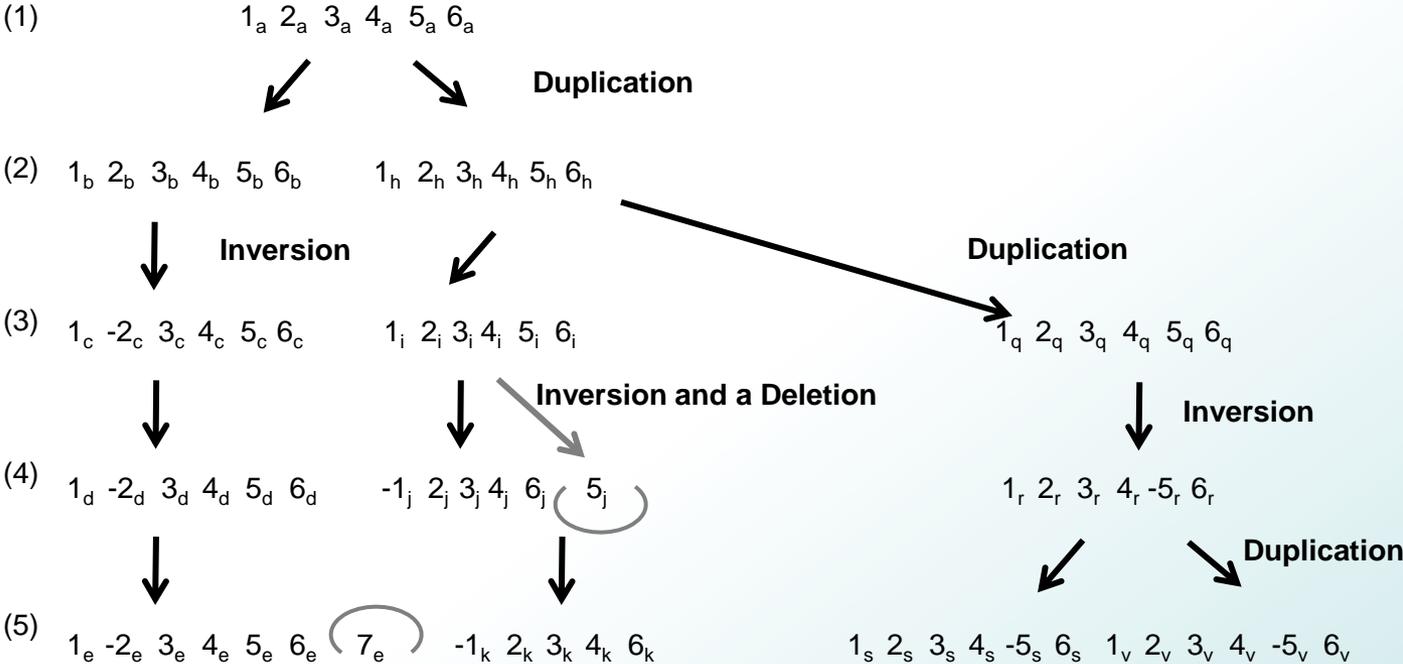
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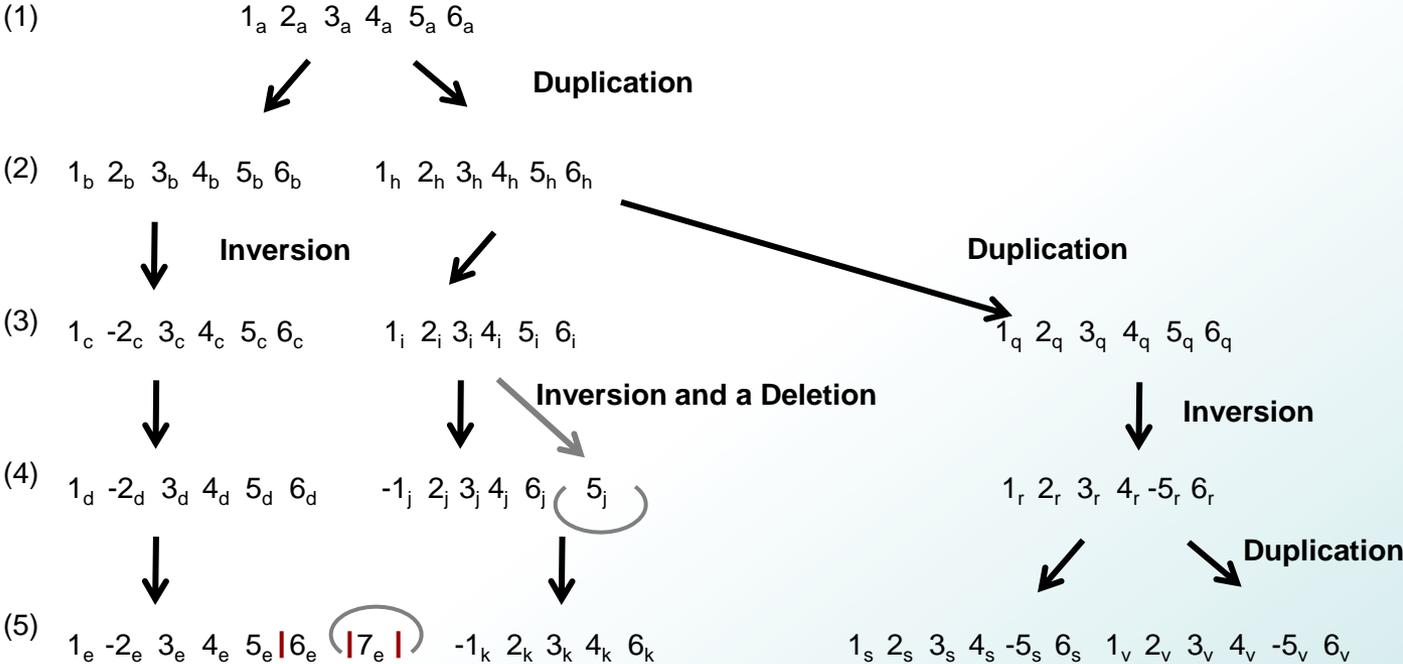
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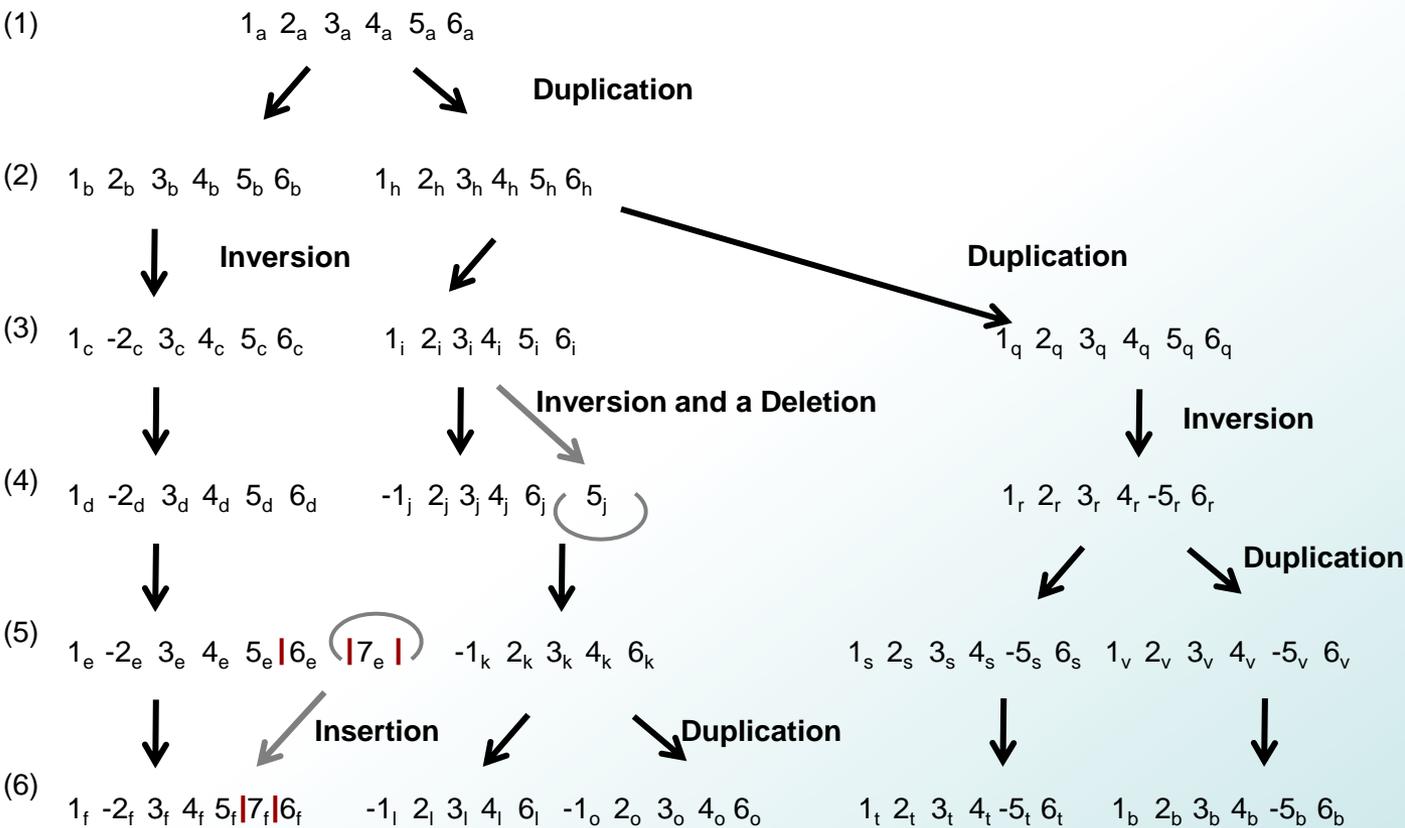
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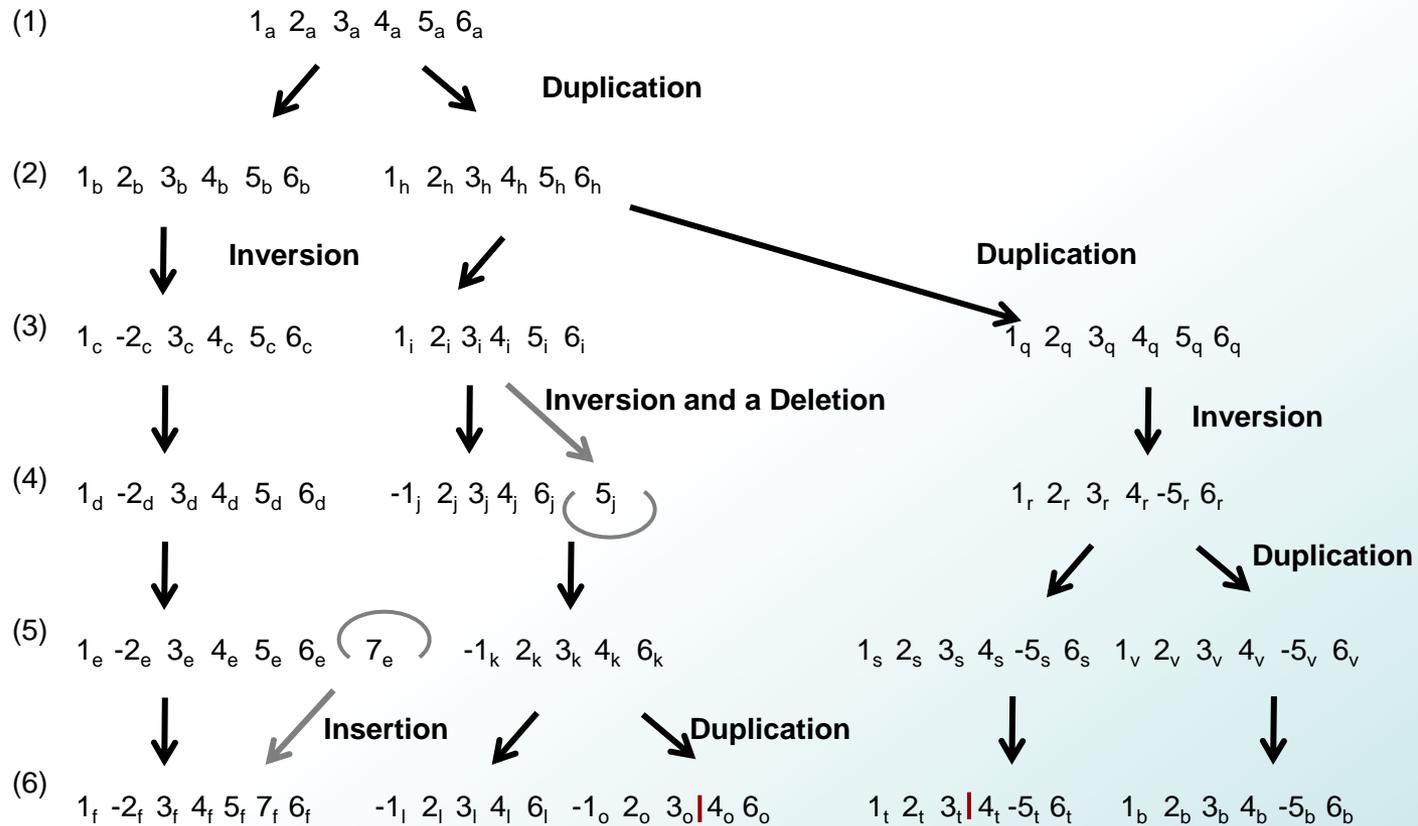
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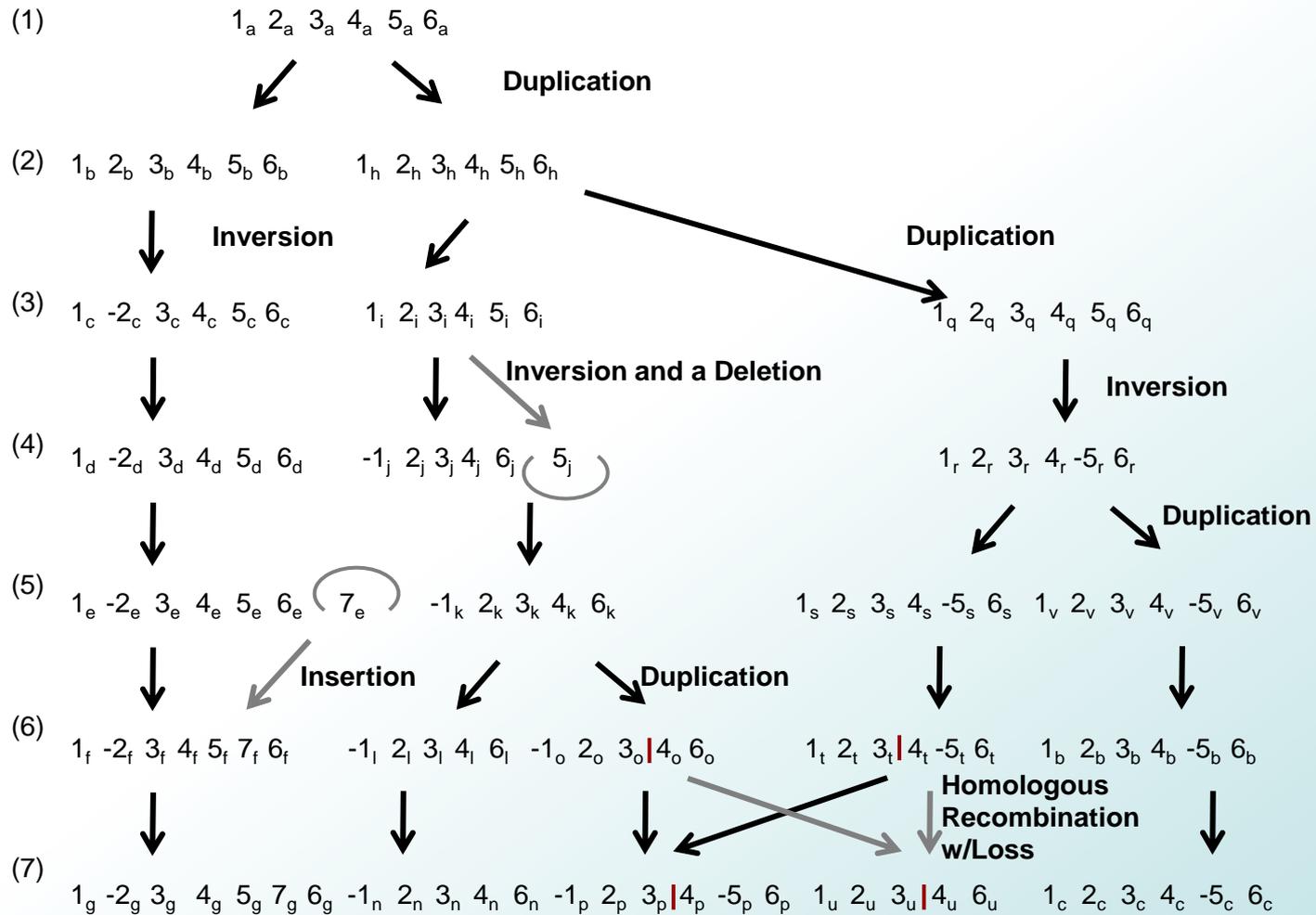
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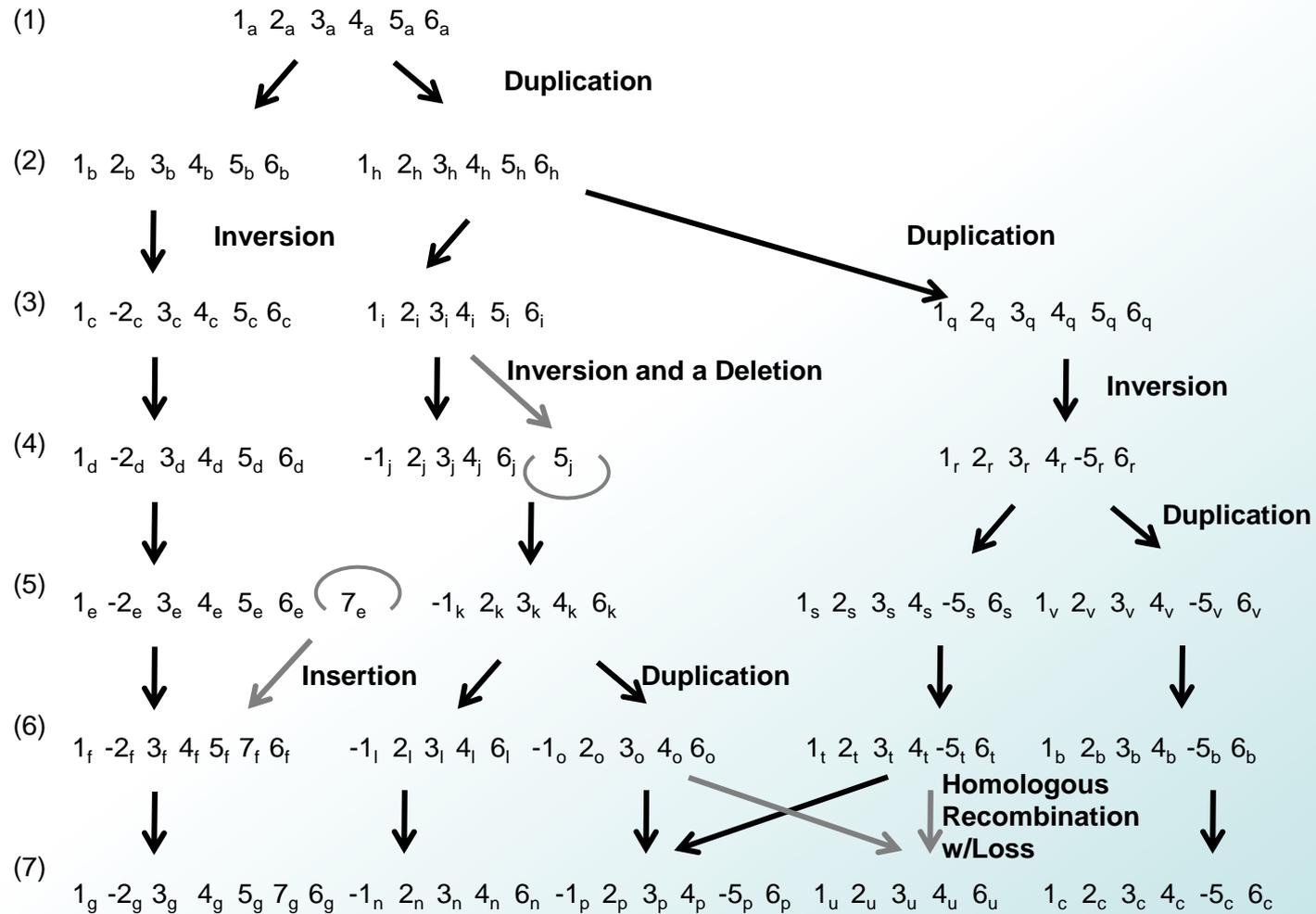
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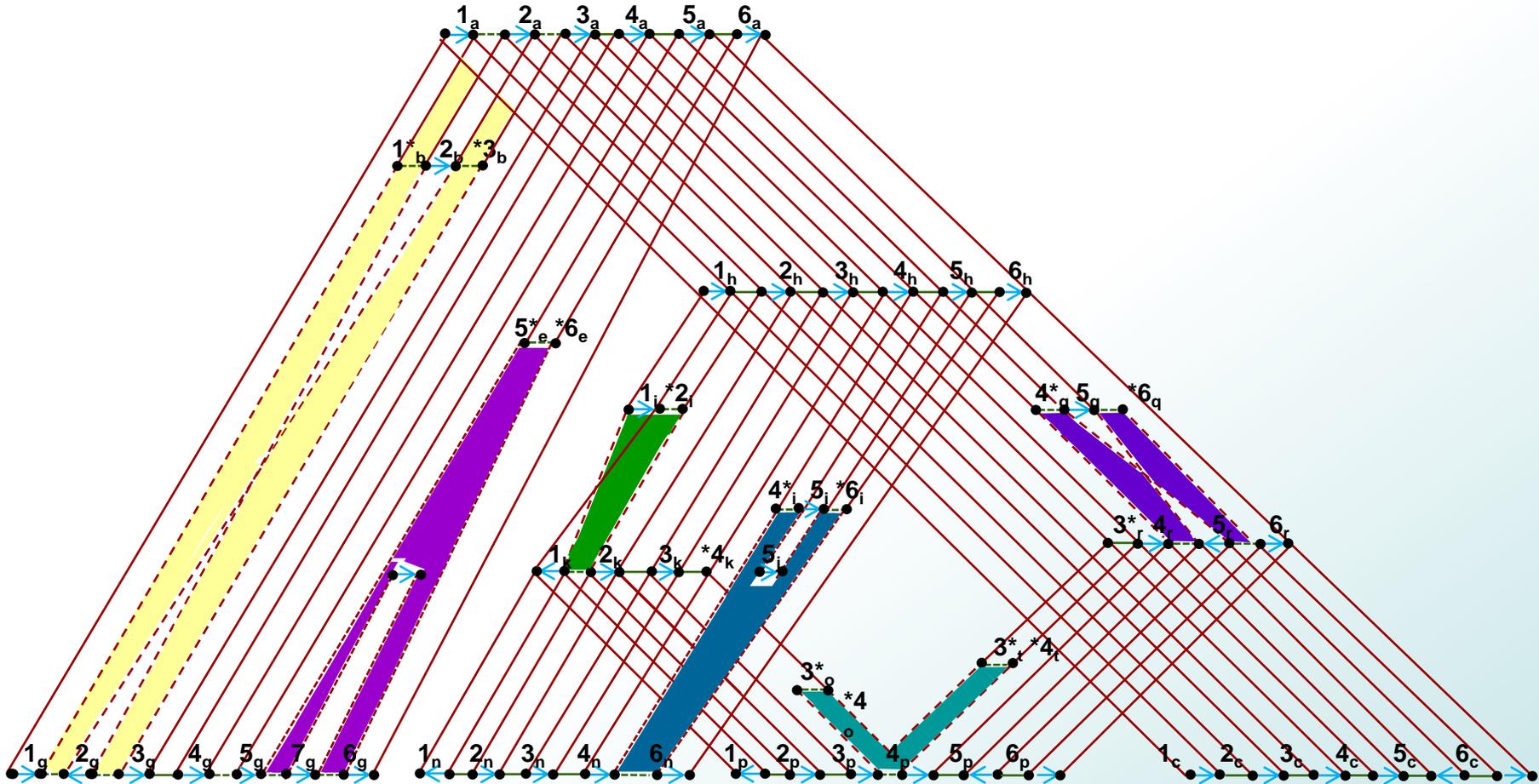


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- rearrangement
- gain and loss



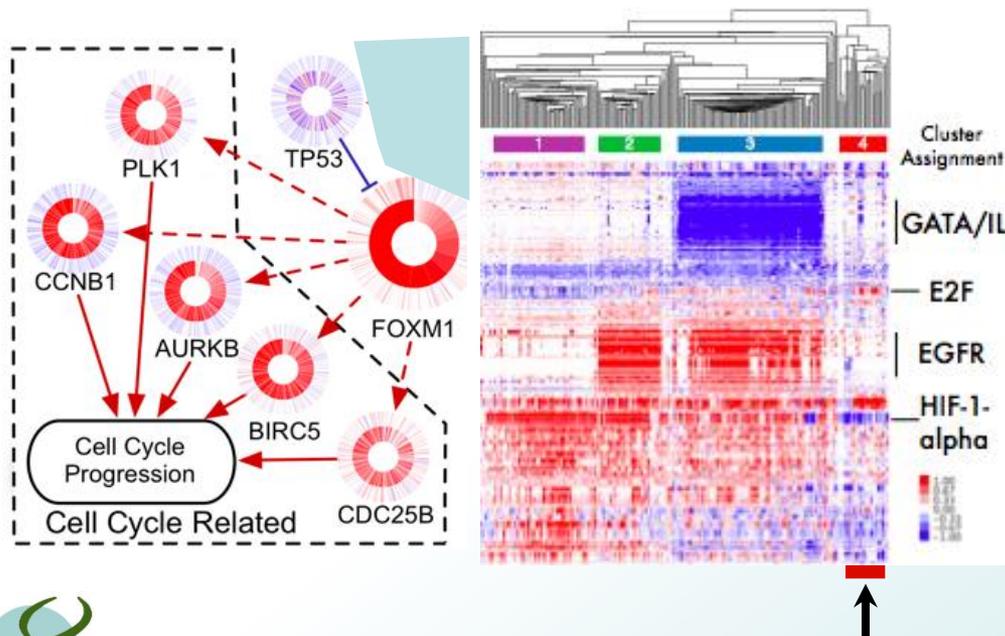
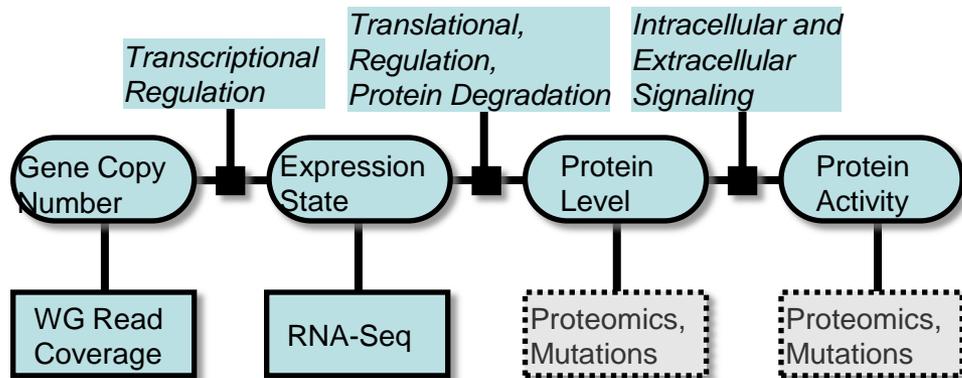
# Ancestral Variation Graphs (AVGs)



- Graph theoretic model
- Tractable framework for inference, modeling and reasoning
- Allows missing data and partial inference



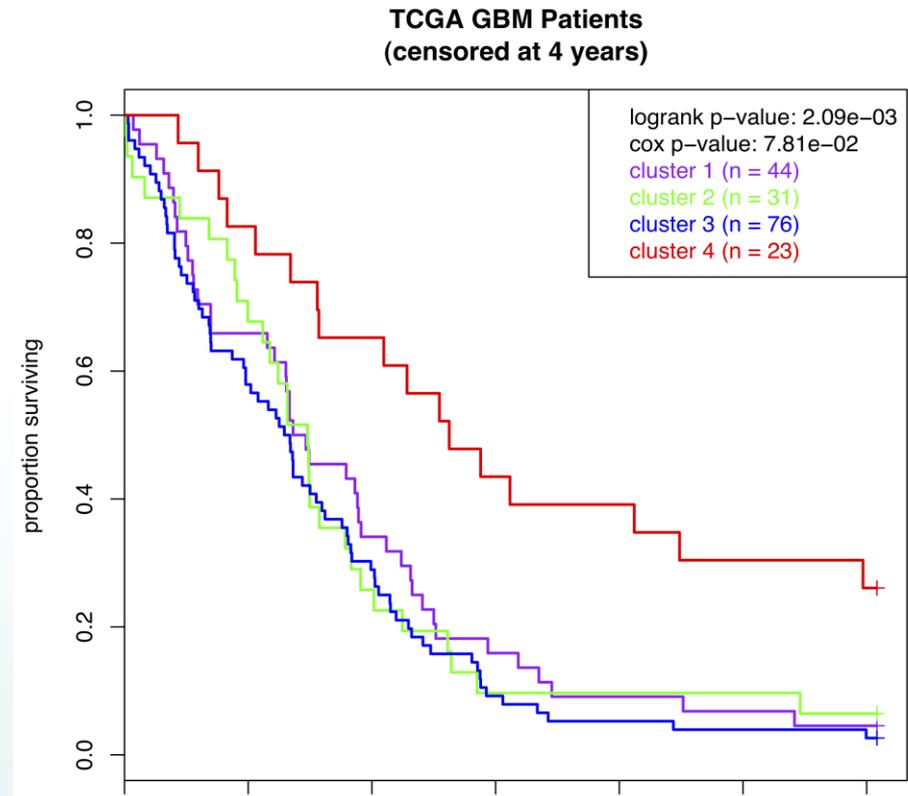
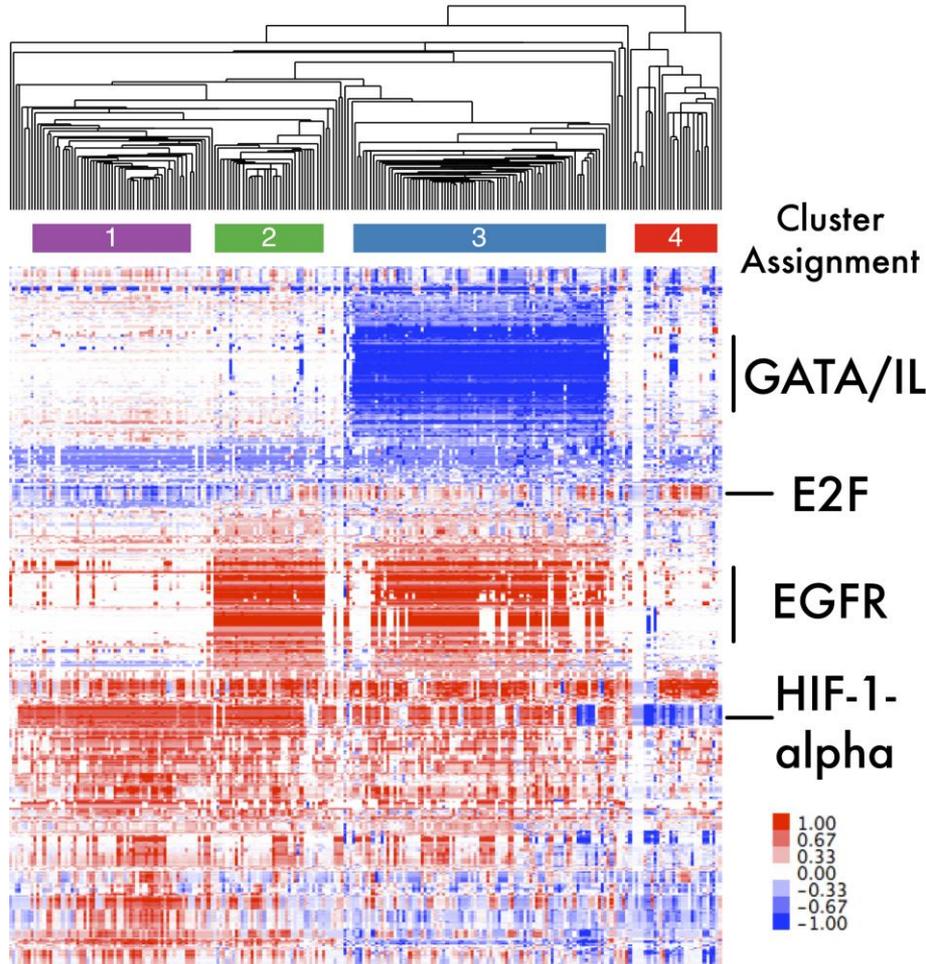
# Next: Biological and Clinical interpretation of the data



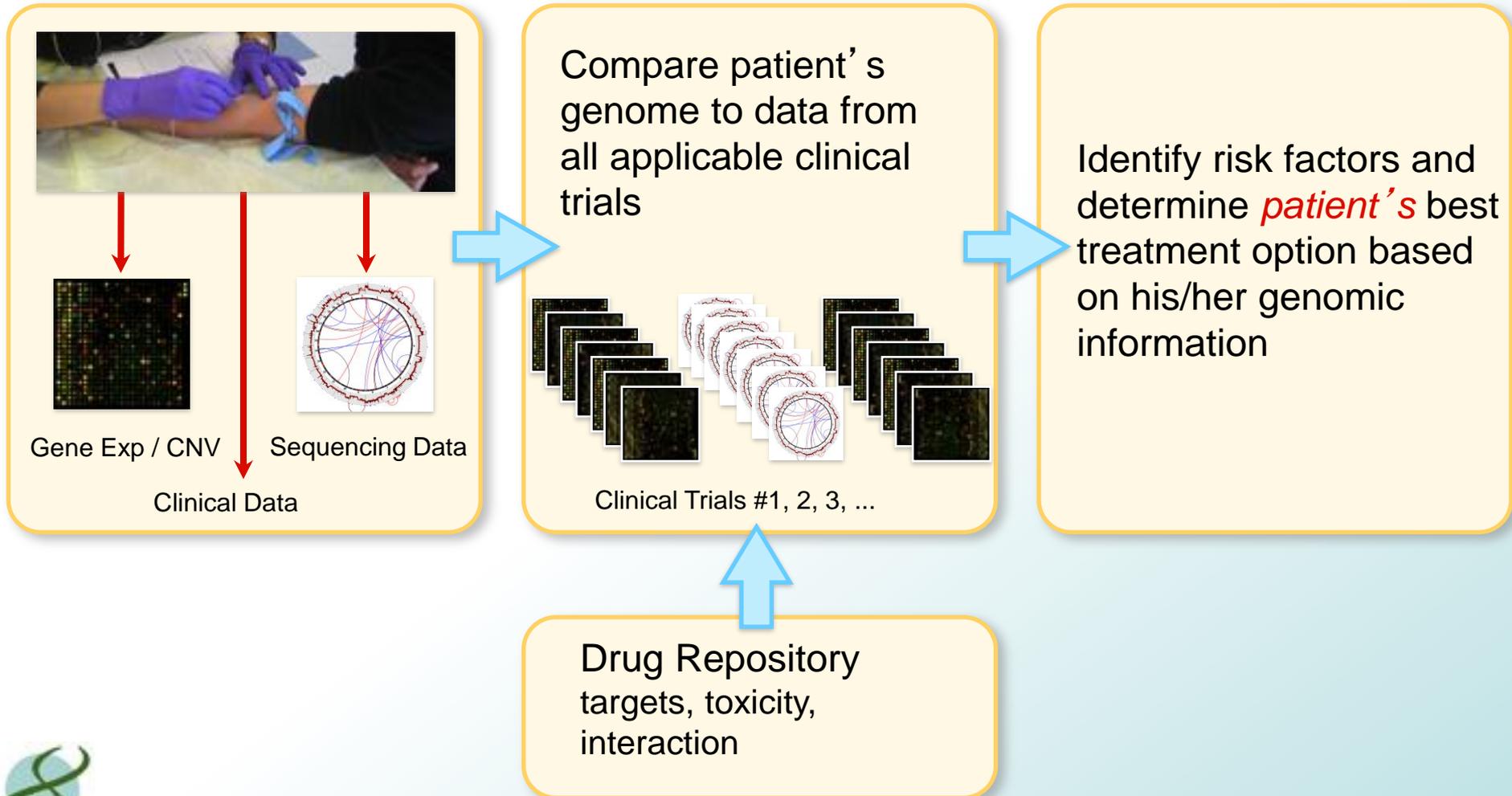
Patients with Good Prognosis

- PARADIGM is an example of a patient-specific inference model
- Identifies biological processes that are abnormally activated or suppressed in each patient
- Many types of genomics information aggregated in a biologically relevant manner
- “Central Dogma”-based graphical model
- Various gene interactions incorporated including transcriptional and post-transcriptional.

# Clustering Activity Vectors Stratifies Glioblastoma Patients by Survival Time

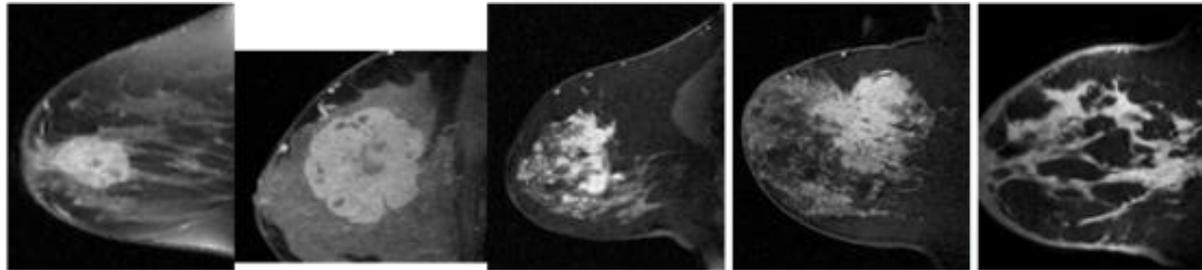


# One Goal: Targeted Cancer Treatment

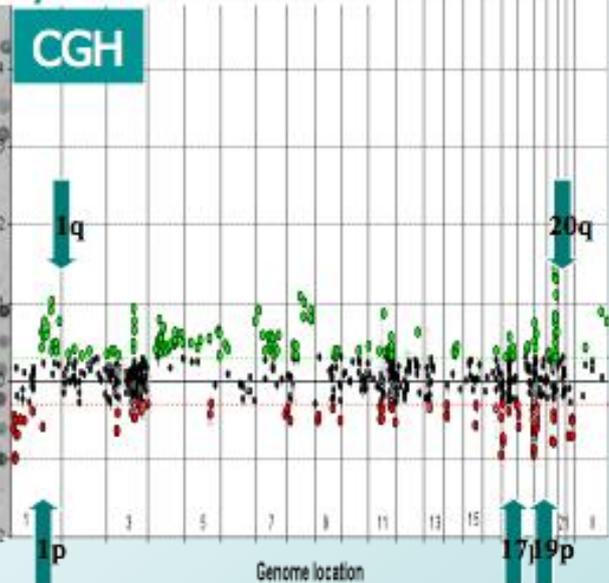
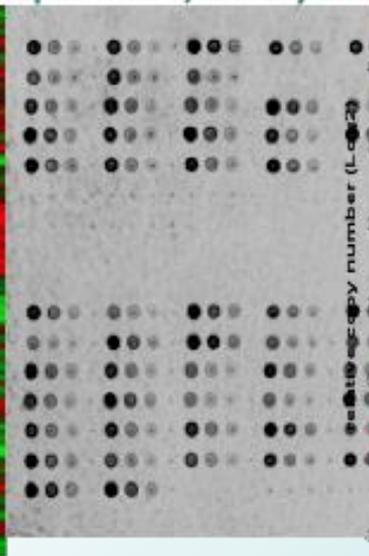
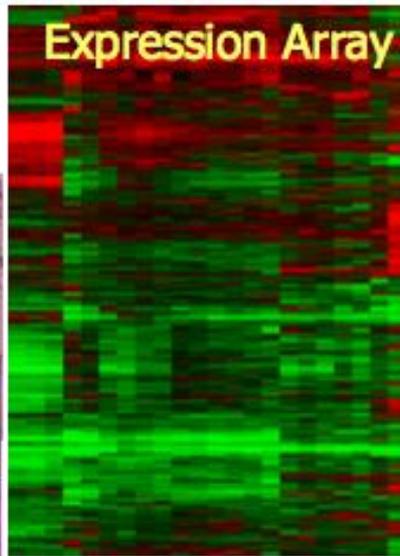
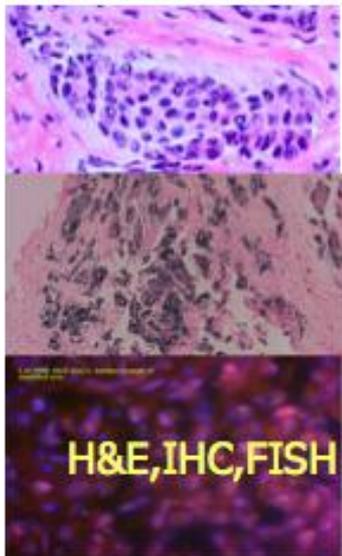




# Too Many Biomarkers and Treatment Strategies to Test in Conventional Clinical Trials

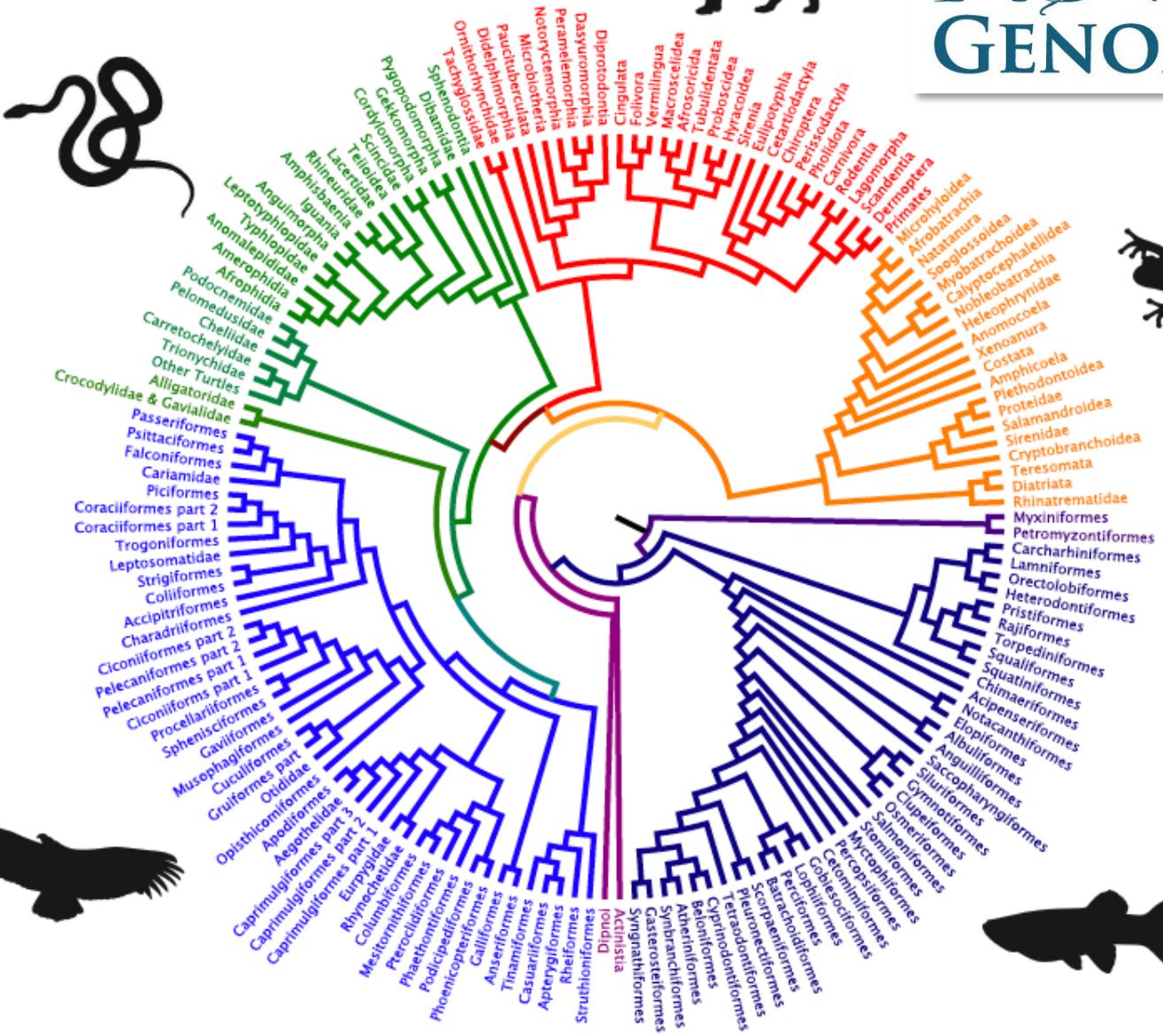


Tissue Markers: 2996 cores from 211 patients; Analysis by 12 Laboratories



**Laura Esserman - I-SPY Adaptive Trial**  
breast surgeon and oncologist at UCSF





# The Genome 10K Project:

*To understand how complex animal life evolved through changes in DNA and use this knowledge to become better stewards of the planet.*

- Collect samples and sequence at least 10,000 different vertebrate species, bank fibroblast cell lines and make iPS lines for > 1,000. Currently ~200 genomes and ~20 iPS lines in progress.
- Annotate genomes, map and interpret genetic differences between species, and compute the evolutionary record of genetic changes on each lineage
- Correlate with ecologic, biologic and geologic data for deep study of vertebrate diversity, biology, evolution, and for species conservation

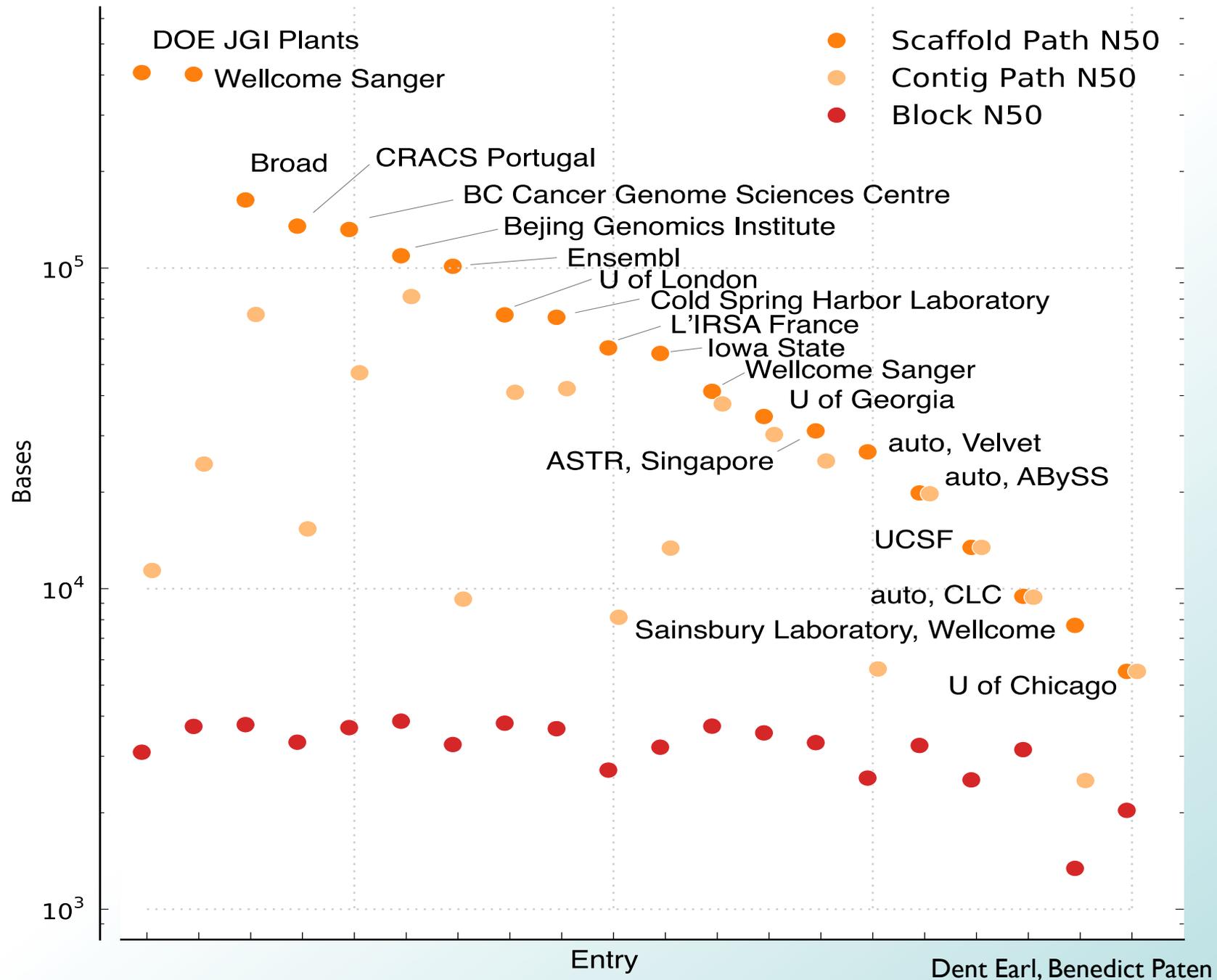


# Assemblathon 1: Assembly teams competed in March to assemble a novel genome from short reads

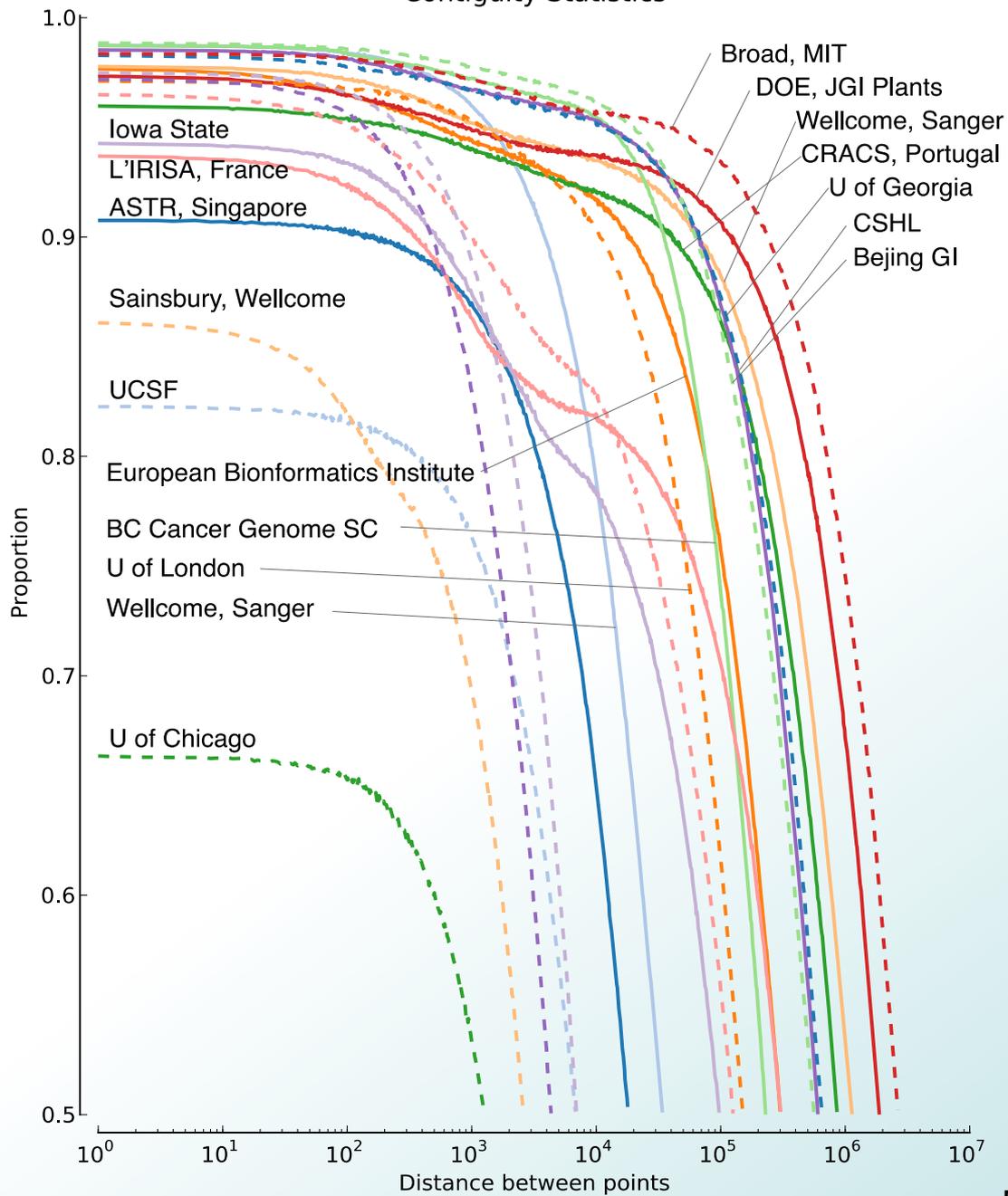
- Organized by Joe DeRisi (UCSF), Jasper Rine(UCB) and David Haussler (UCSC), lead by Ian Korf, UCD and Benedict Paten, UCSC.
- 39 assemblies from 17 teams, ~150 attendees
- Simulated Illumina reads were used, planned follow-up challenge to include other technologies.
- Revealed limitations of short reads in genome sequencing and highlighted software challenges



# Average size of assembled piece (N50)



# Contiguity Statistics

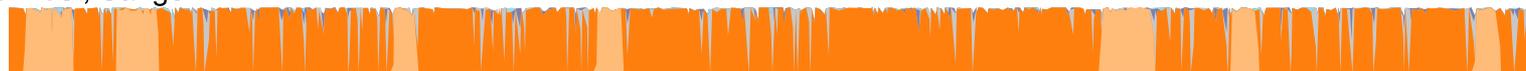


# Chromosome 0 (76.25 Mb)

Genes



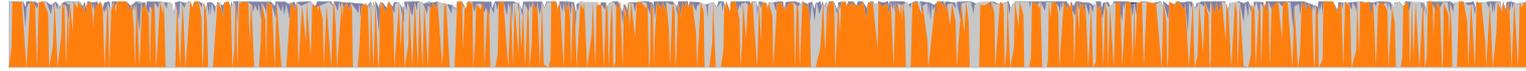
Wellcome Trust, Sanger



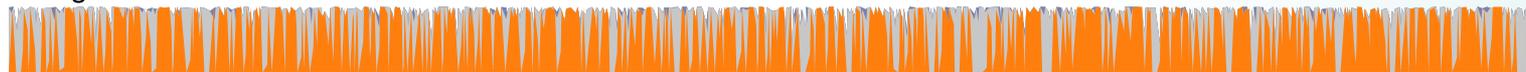
DOE Joint Genome Institute, Plants



Broad, MIT



CRACS, Portugal



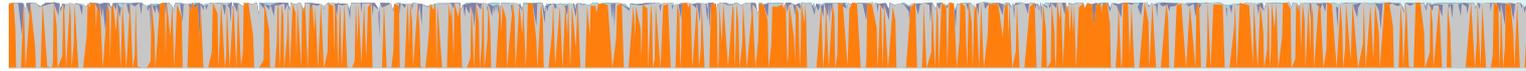
Beijing Genomics Institute



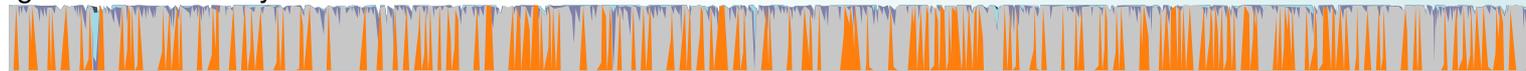
British Columbia Cancer Genome Sciences Centre



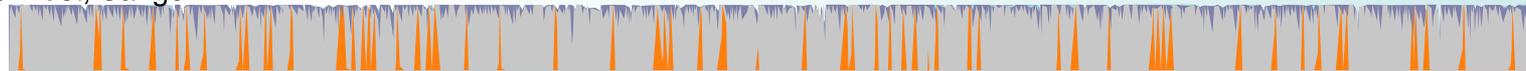
European Bioinformatics Institute, Ensembl



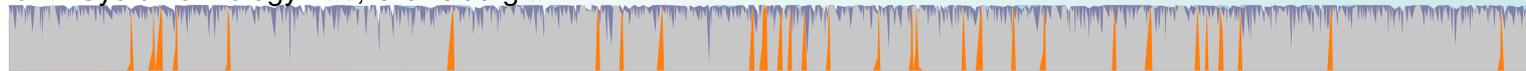
Cold Spring Harbor Laboratory



Wellcome Trust, Sanger

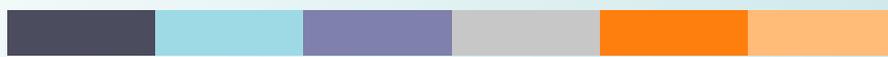


Computational Systems Biology Lab, U of Georgia



Fill Color Key

Item >=



1

1e2

1e3

1e4

1e5

1e6



## UCSC Cancer Genomics & Genome Analysis

- **Josh Stuart**
- Jingchun Zhu
- Zack Sanborn
- Steve Benz
- Charles Vaske
- Brian Craft
- Christopher Szeto
- Larry Meyer
- Sofie Salama
- Tracy Ballinger
- Mia Grifford
- Benedict Paten
- Daniel Zerbino
- Kord Kober
- Kyle Ellortt
- Mary Goldman
- James Durbin
- Amy Radenbaugh
- Chris Wilks
- Jim Kent
- UCSC Genome Browser Staff

## Collaborators

- Stand Up To Cancer
- The Cancer Genome Atlas
- Intl. Cancer Genomics Consortium
- Christopher Benz, Buck Institute
- Laura Esserman, UCSF
- Joe Gray, LBL
- Eric Collisson, UCSF

## Funding Agencies

- NCI/NIH
- NHGRI
- American Association for Cancer Research
- UCSF Comprehensive Cancer Center
- California Institute for Quantitative Biosciences (QB3)

# UCSC Cancer Integration Group

Josh Stuart, Co-PI



Jing Zhu



Charlie Vaske



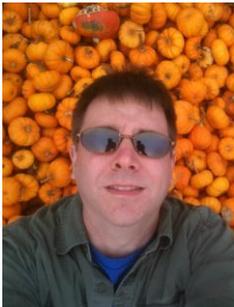
Steve Benz



Zack Sanborn



James Durbin



Larry Meyer



Chris Szeto



Sam Ng



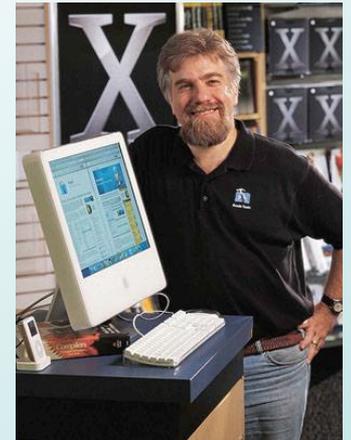
Mia Grifford



Amie Radenbaugh



Ted Golstein



CENTER FOR BIOMOLECULAR SCIENCE & ENGINEERING  
promoting discovery and invention for human health and well-being



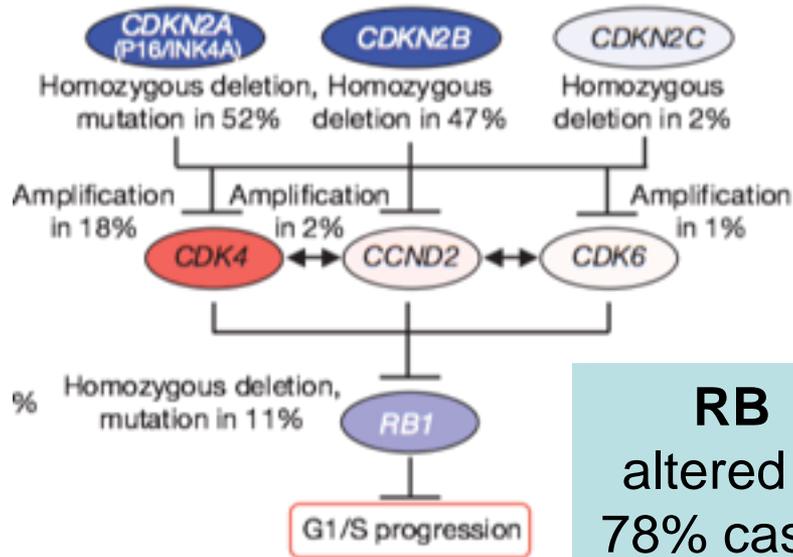
# The UCSC team



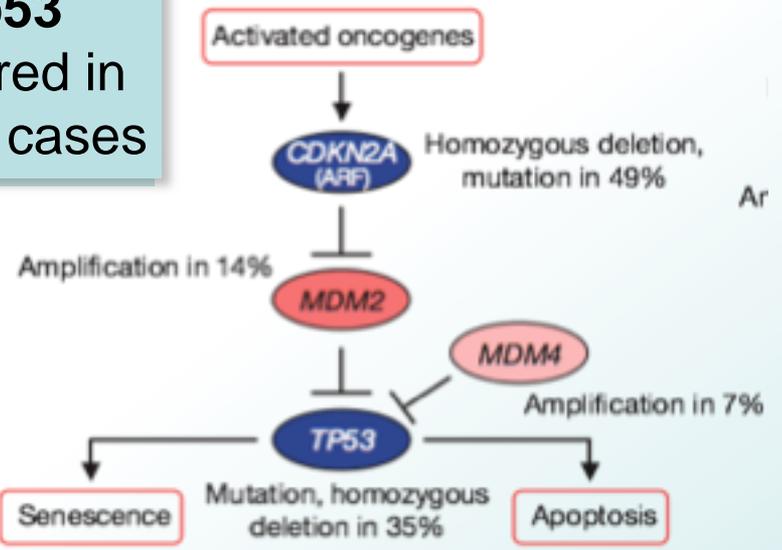
**CENTER FOR BIOMOLECULAR SCIENCE & ENGINEERING**  
promoting discovery and invention for human health and well-being



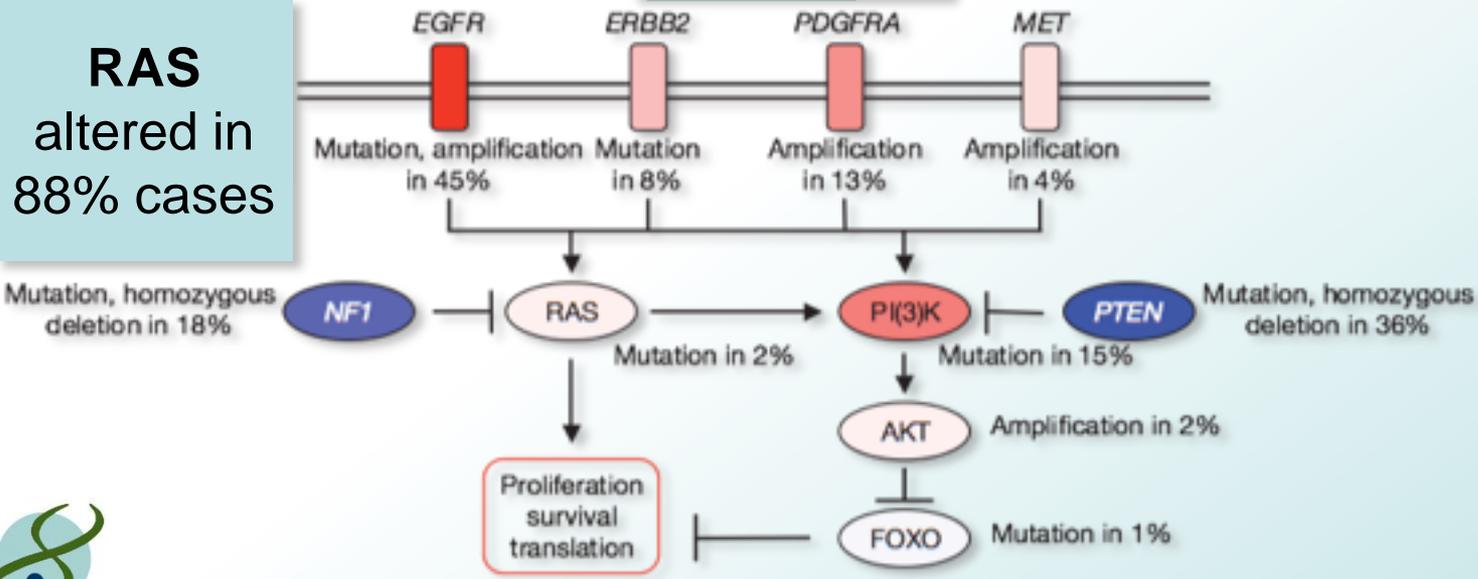
# Pathways as Genetic Units: GBM analysis



**p53**  
altered in  
87% cases



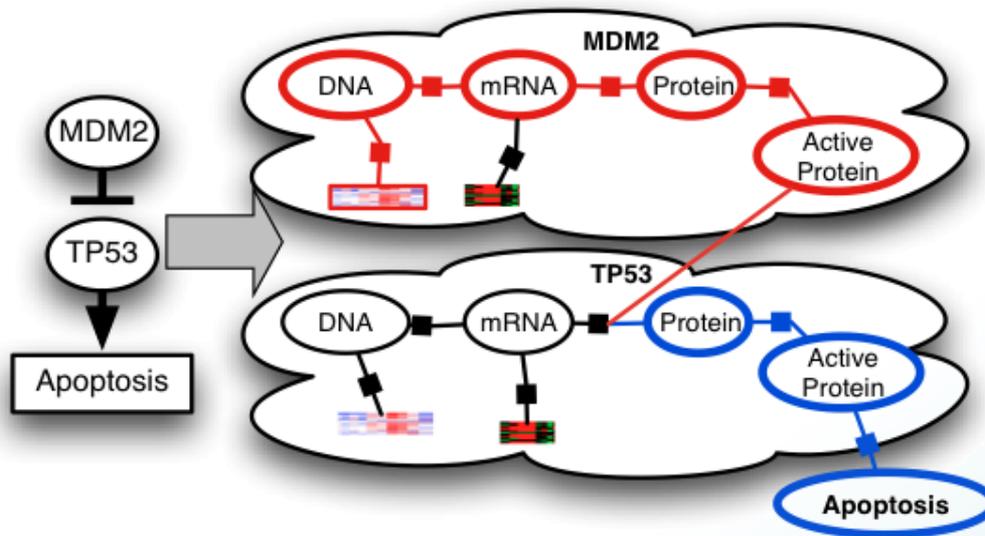
**RAS**  
altered in  
88% cases



**RB**  
altered in  
78% cases



# Integrated Pathway Activity (IPA)



- Abstract notion of a biological entity's activity within a pathway context
- Calculate log-likelihood ratio (LLR) of *up* (red), *same* (white), and *down* (blue) states
- IPA is the largest of the three LLRs, multiplied by the sign of the state

$$\log_{10} \frac{P(\text{Data} | TP53 = up, \Phi)}{P(\text{Data} | TP53 \neq up, \Phi)} = \log_{10} \frac{P(\text{Data}, TP53 = up | \Phi)}{P(\text{Data}, TP53 \neq up | \Phi)} - \log_{10} \frac{P(TP53 = up | \Phi)}{P(TP53 \neq up | \Phi)}$$

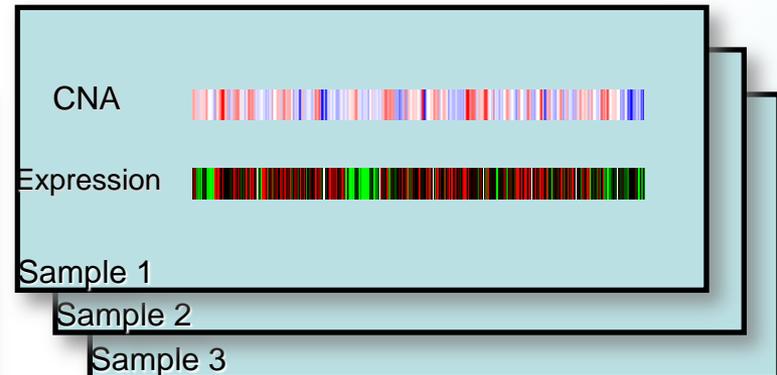
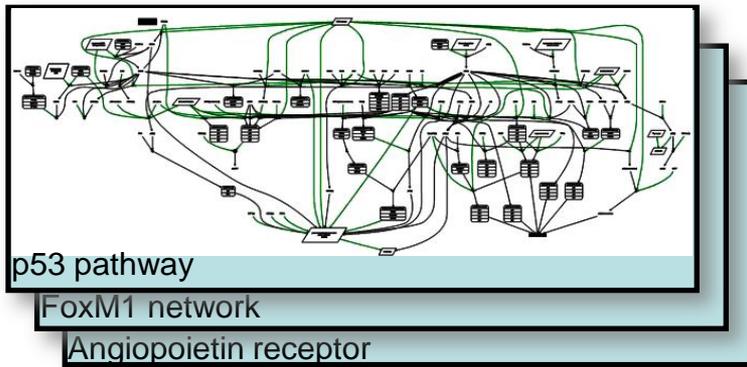
log odds of state  
and data

prior log odds



# Pathway Interpretation of Omics Data

## PARADIGM Pathway Analysis

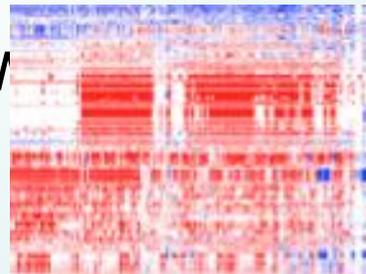


~100  
Pathways

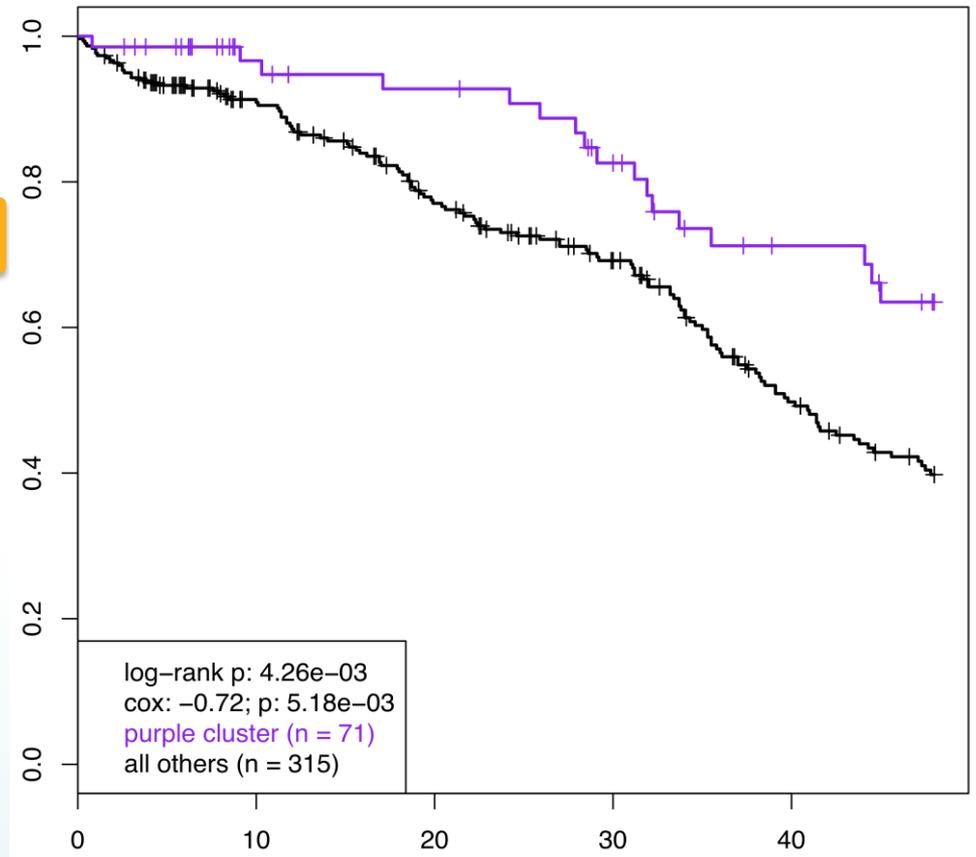
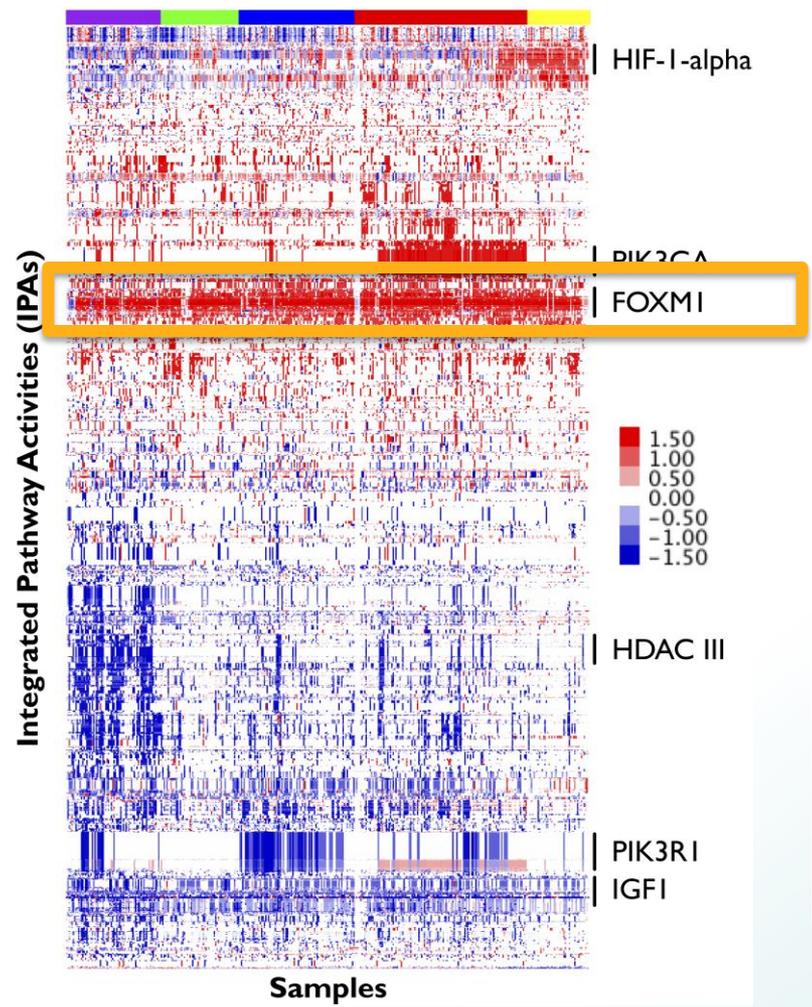


316 TCGA Ovarian  
Samples

Per-sample  
integrated pathway  
activities



# IPAs identify FOXM1 as key player and stratify ovarian cancer patients by survival time



# Pathway Markers of Drug Response

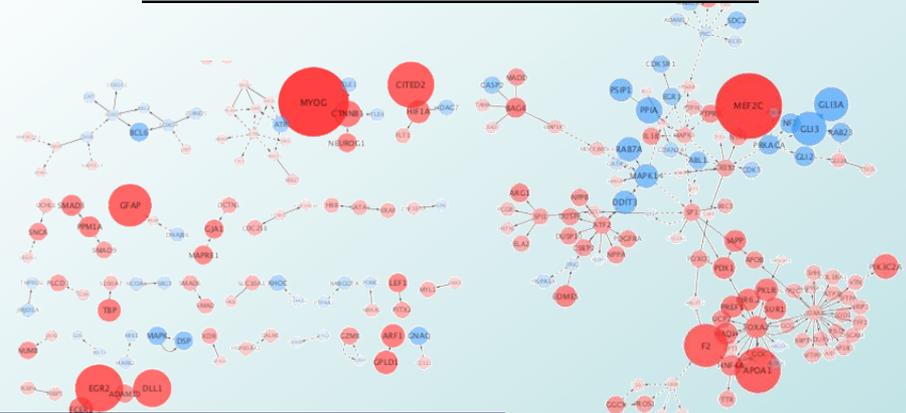
- Infer activities in a global “super pathway”
- Associate activities with drug sensitivity to find activity markers; similar for resistance
- Search for focused subnetworks with interconnected markers.

Super Pathway Overview of Sensitivity and Resistance of breast cell lines to gemcitabine

correlated with sensitivity

correlated with resistance

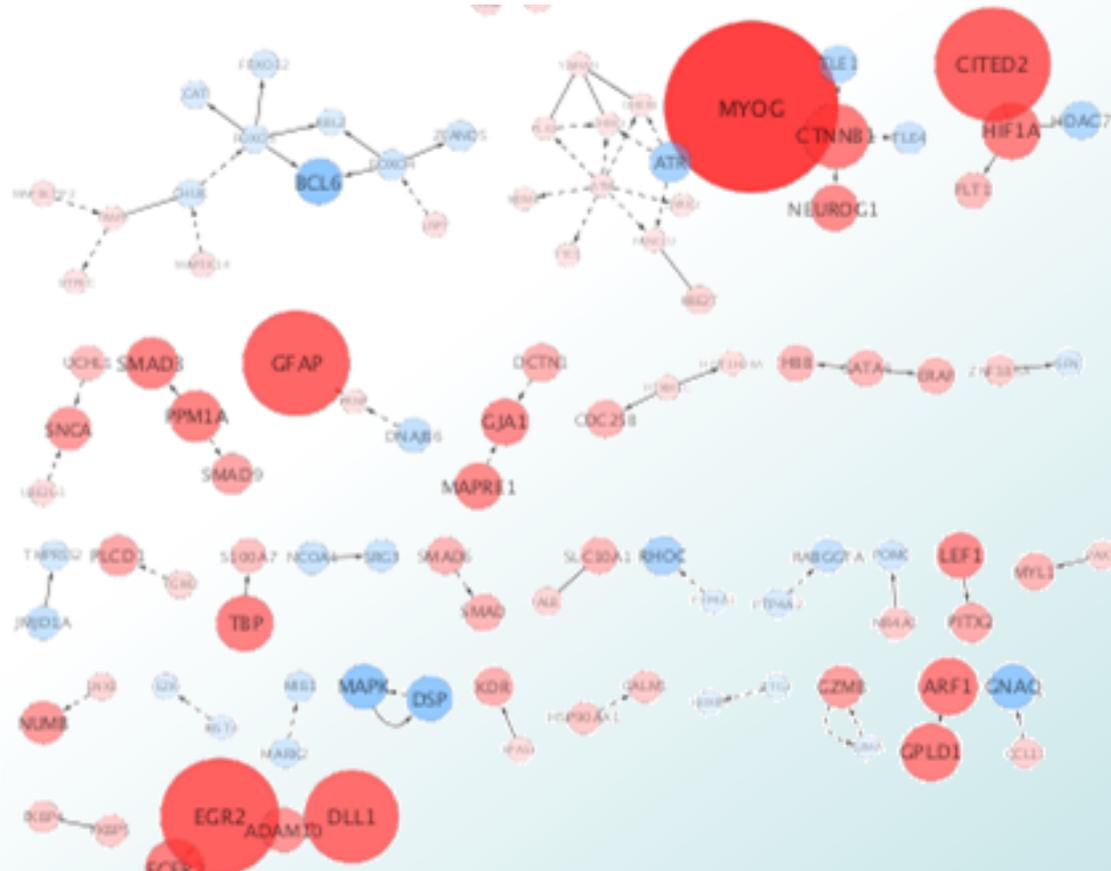
Gemcitabine subnet markers



# Pathway Markers of Drug Response

## Gemcitabine subnet markers

- Infer activities in a global “super pathway”
- Associate activities with drug sensitivity to find activity markers; similar for resistance
- Search for focused subnetworks with interconnected markers.



# Pathway Markers of Drug Response

## Gemcitabine subnet markers

- Infer activities in a global “super pathway”
- Associate activities with drug sensitivity to find activity markers; similar for resistance
- Search for focused subnetworks with interconnected markers.

