

# Somatic mutations in tumors and normal tissues

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- Identifying Cancer Drivers
- Understanding Neutral Mutagenesis
- Identifying Clonal Hematopoiesis Drivers
- Chemotherapy effect in hematopoiesis
- Cancer Promotion

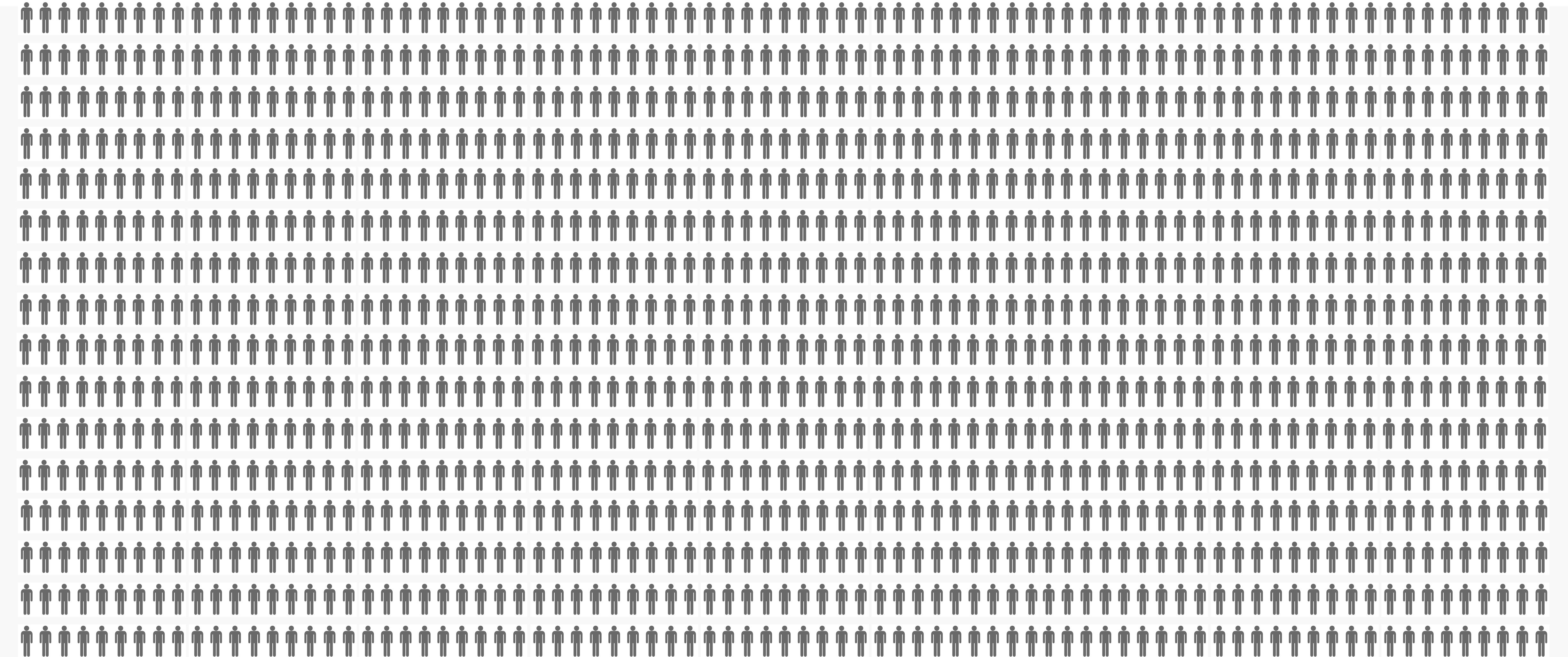
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Which are the genes that drive  
tumorigenesis upon mutations?

# Accumulated literature on cancer genes for decades

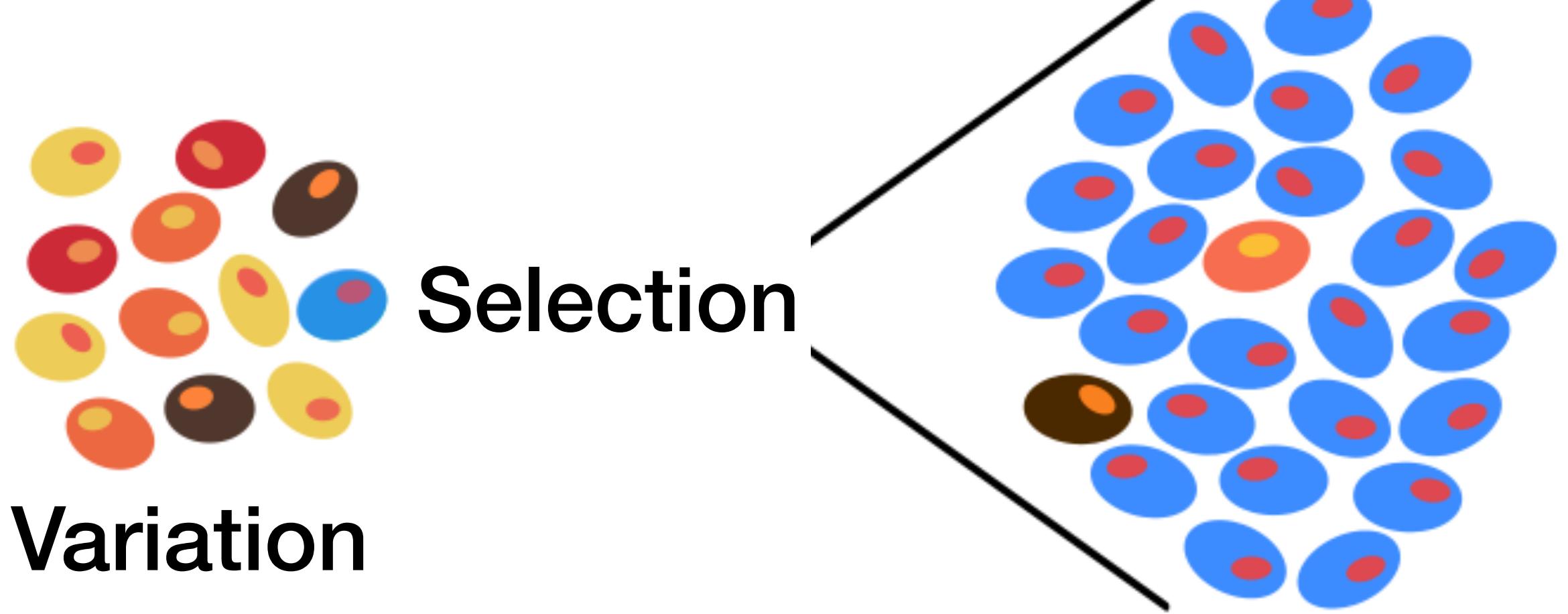


# Can we find cancer genes directly from tumors data?



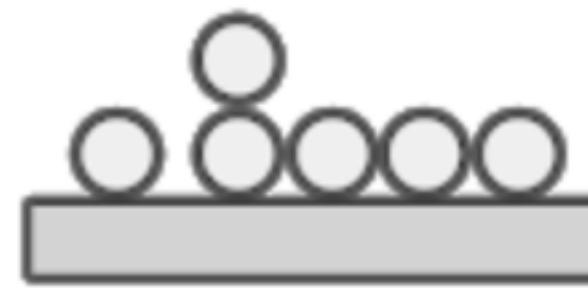
Thousands of tumor genomes sequenced

# Tumor development follows Darwinian Evolution

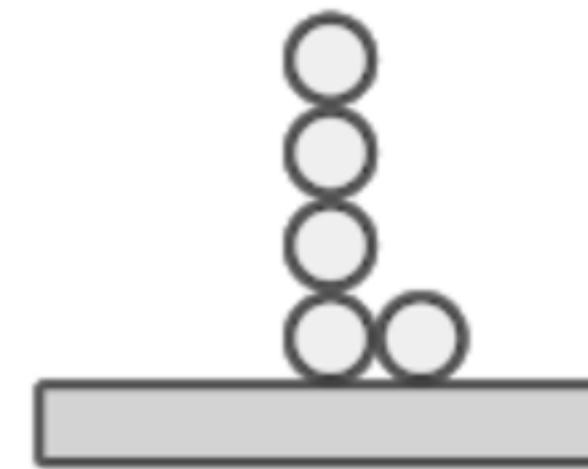


Drivers confer selective advantage to the cell

# Identifying signals of positive selection is an effective way to find cancer drivers



Identify genes mutated more frequently than the background mutation rate

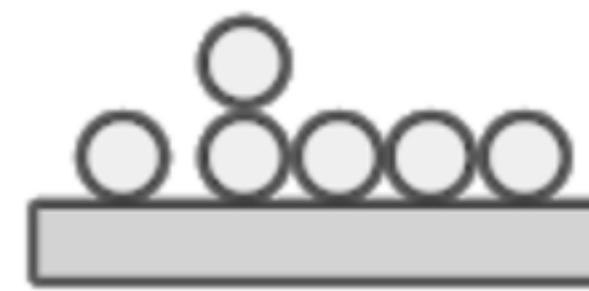


Identify genes with a significant regional clustering of mutations

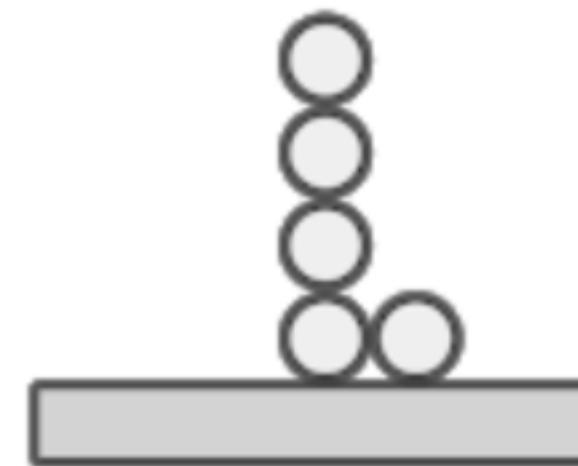


Identify genes with a bias towards high functional mutations (FM bias)

# Identifying signals of positive selection is an effective way to find cancer drivers



Identify genes mutated more frequently than the background mutation rate

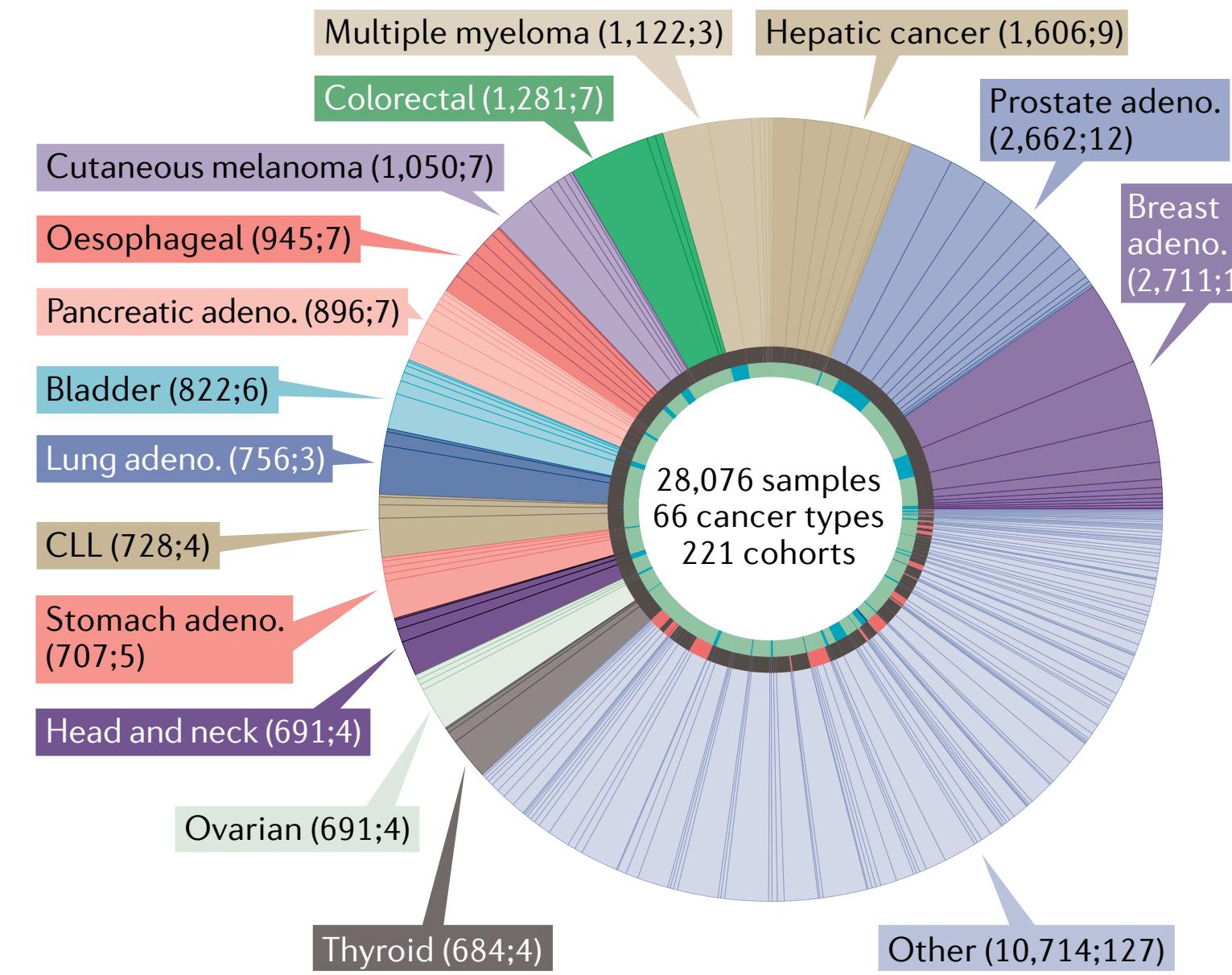


Identify genes with a significant regional clustering of mutations



Identify genes with a bias towards high functional mutations (FM bias)

# The Compendium of Mutational Cancer Driver Genes



28,076 Tumors · 221 cohorts · 66 Cancer Types  
203,003,747 Mutations

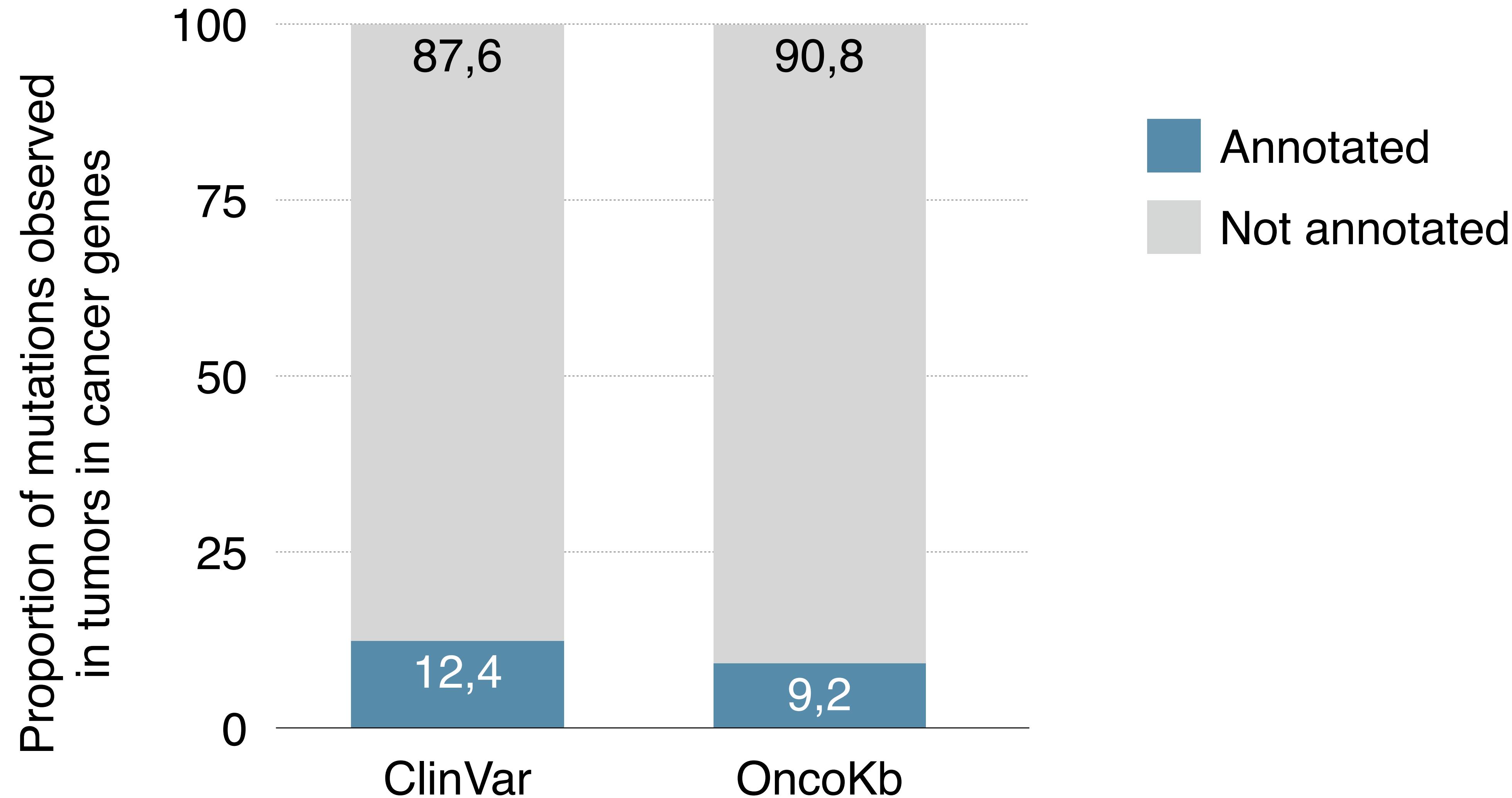
# Mutation Pattern Analysis to identify Cancer Genes

# 568 Cancer Genes across 66 Cancer Types

This approach recovers most known cancer genes and also identify new ones

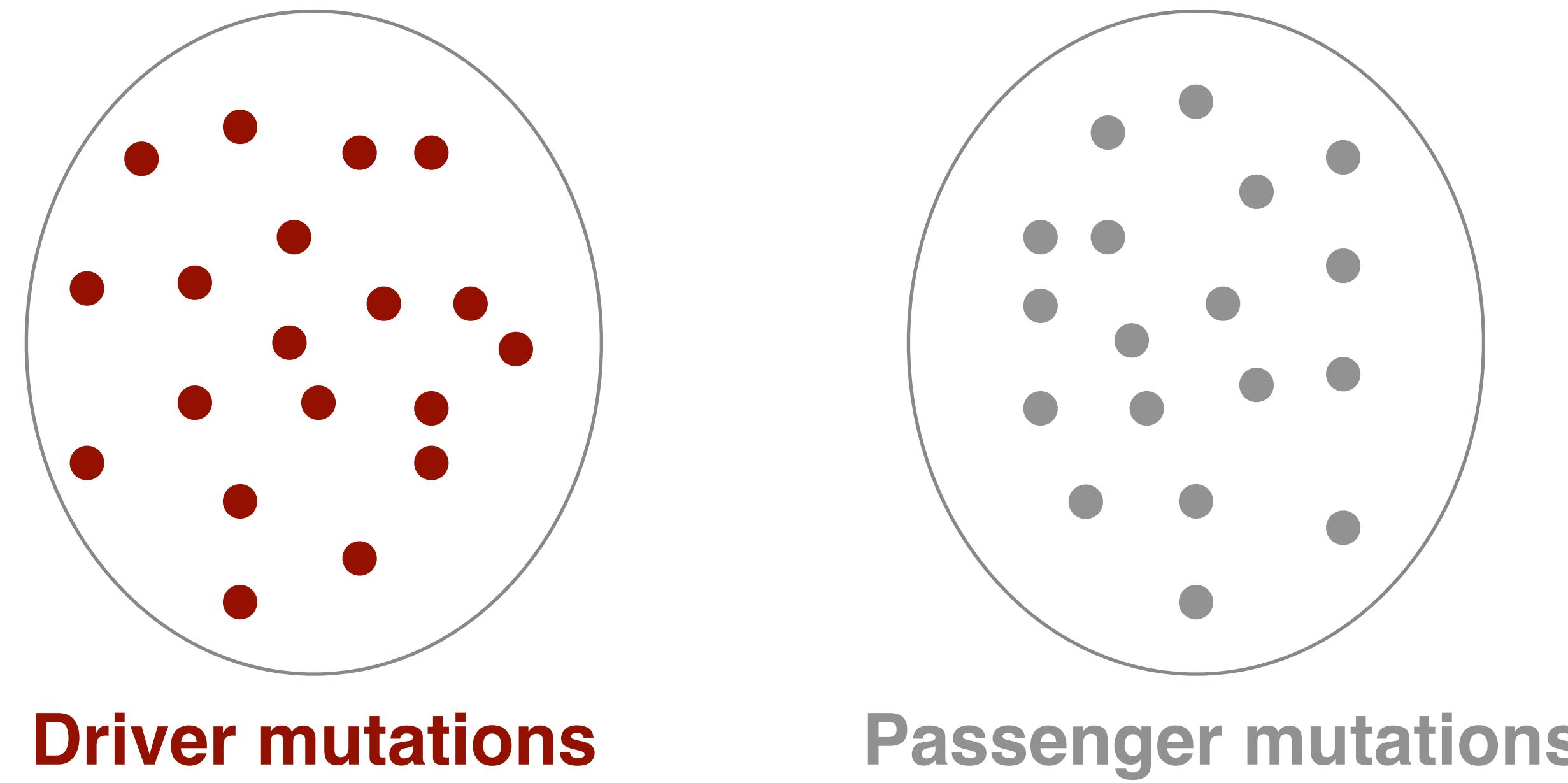


# Most mutations in cancer genes are of uncertain significance

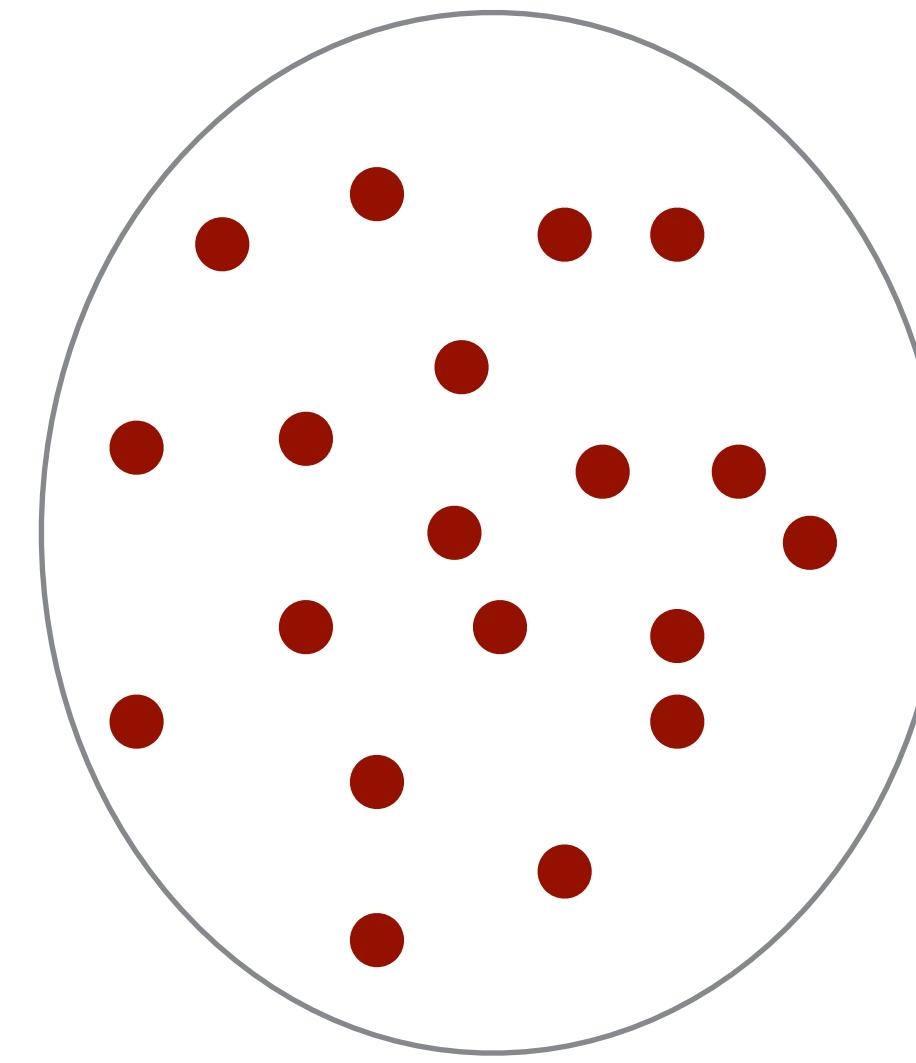


Which mutations in these cancer genes are capable of driving tumorigenesis?

# BoostDM: Learns feature combinations that define driver mutations in each gene/tumor type

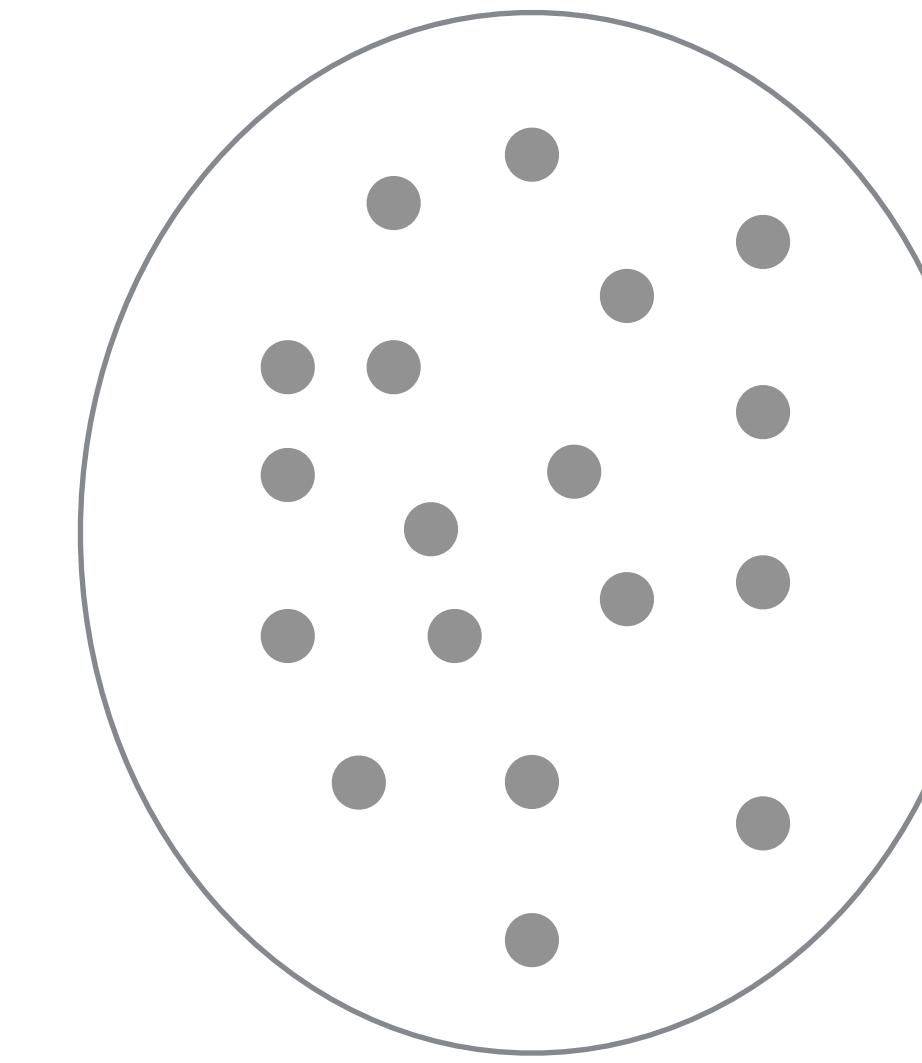


# BoostDM: Learns feature combinations that define driver mutations in each gene/tumor type



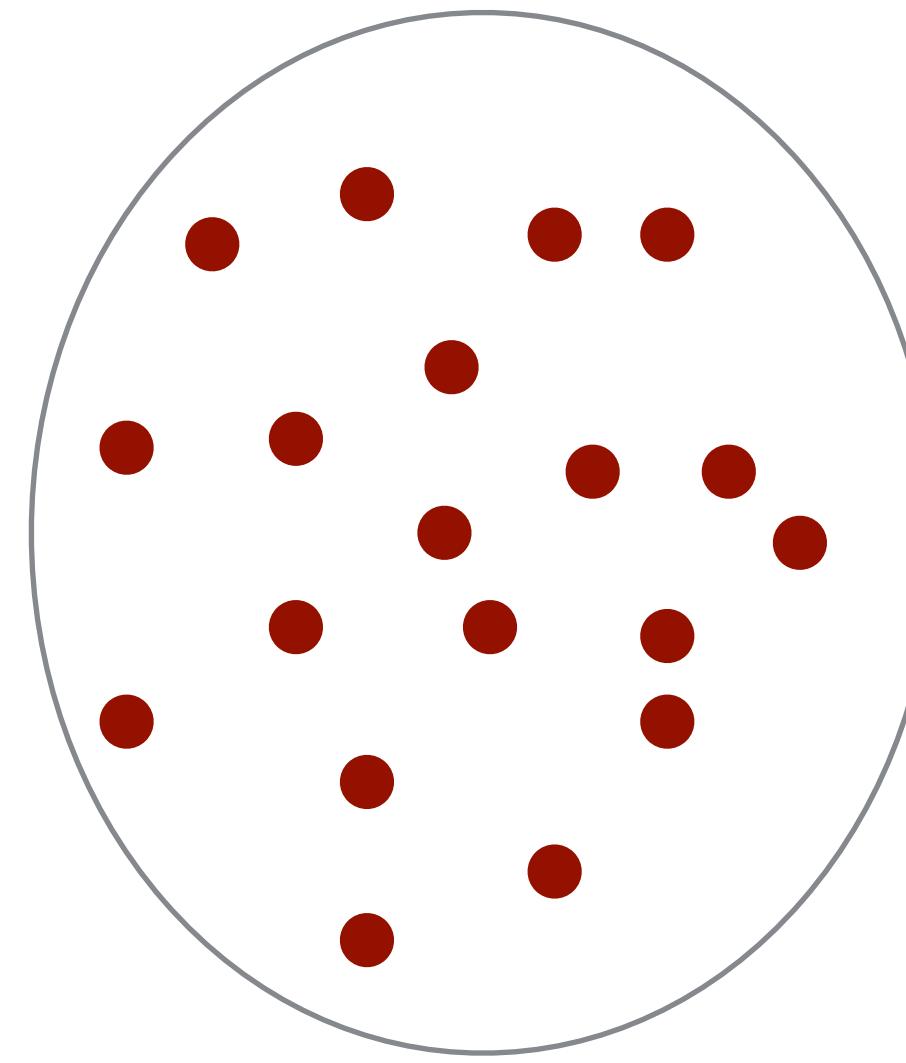
**Driver mutations**

Mutations observed in cancer genes in human tumors are enriched for drivers



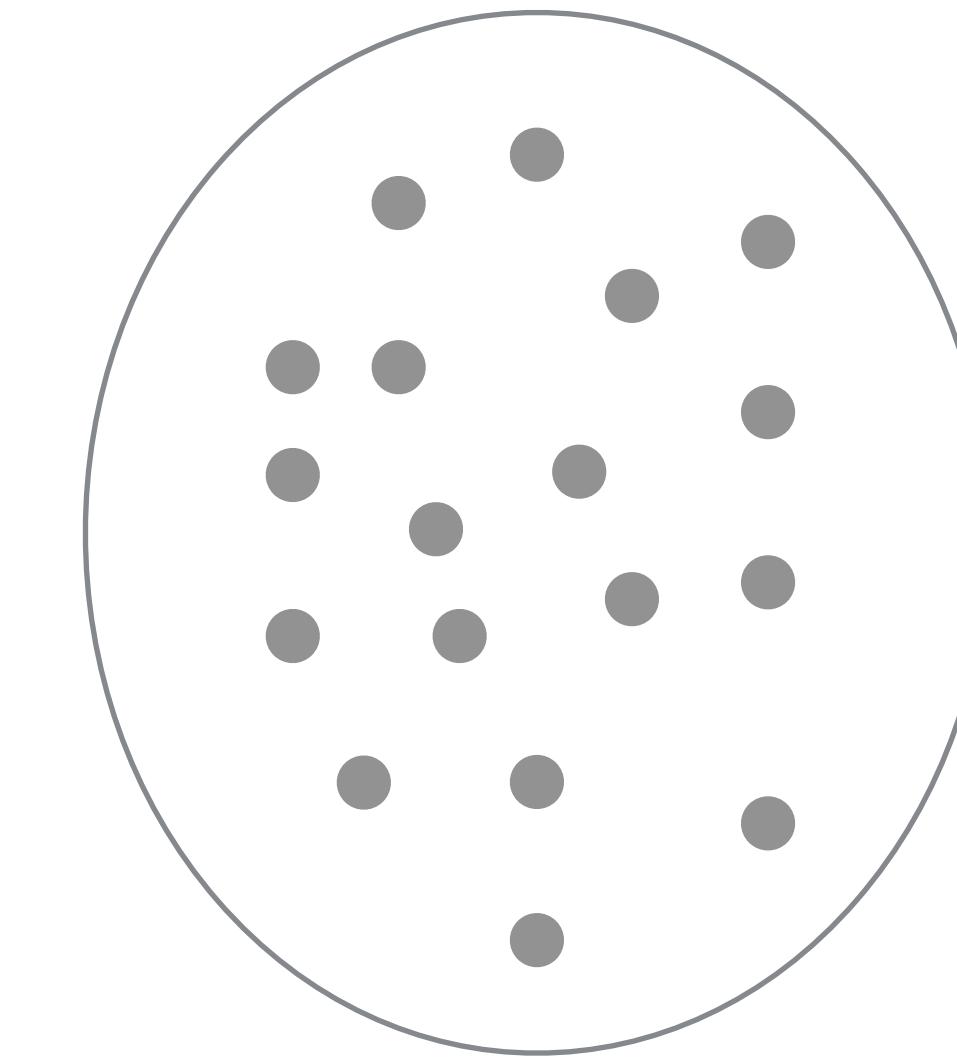
**Passenger mutations**

# BoostDM: Learns feature combinations that define driver mutations in each gene/tumor type



## Driver mutations

Mutations observed in cancer genes in human tumors are enriched for drivers



## Passenger mutations

Simulate neutral mutagenesis to create mutations enriched for passengers

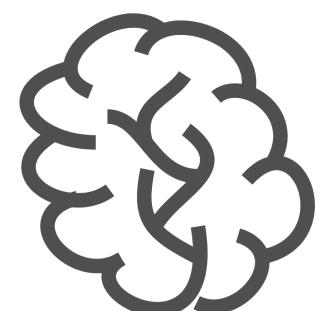
# BoostDM: Learns feature combinations that define driver mutations in each gene/tumor type



28,076 Tumors · 221 cohorts · 66 Cancer Types ·  
203,003,747 Somatic Mutations

- Gene-tissue specific models
- Interpretable models

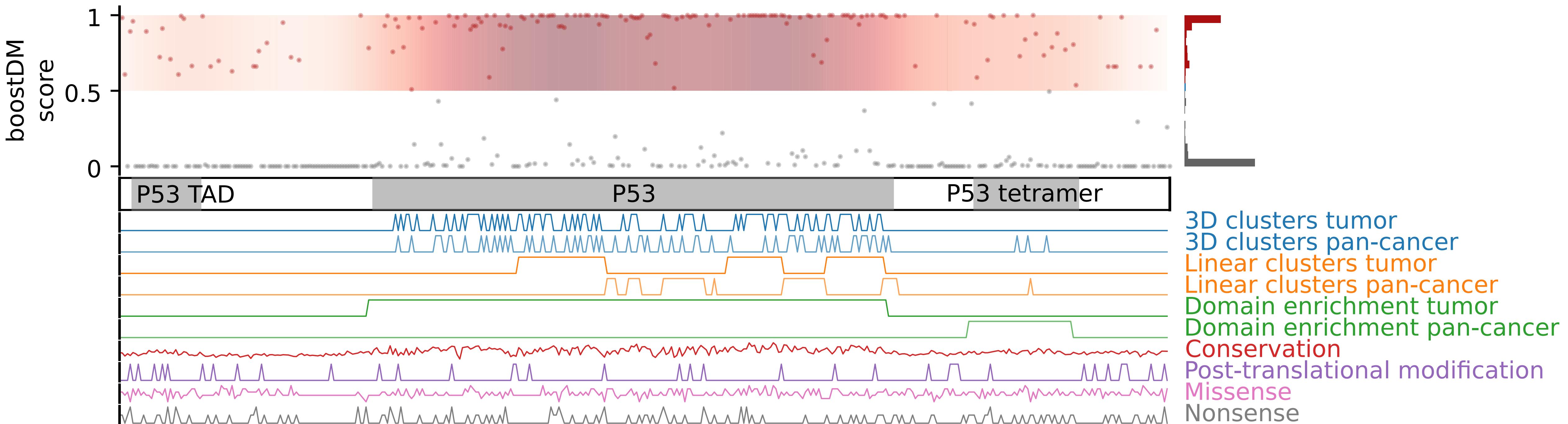
185 high quality models



BoostDM

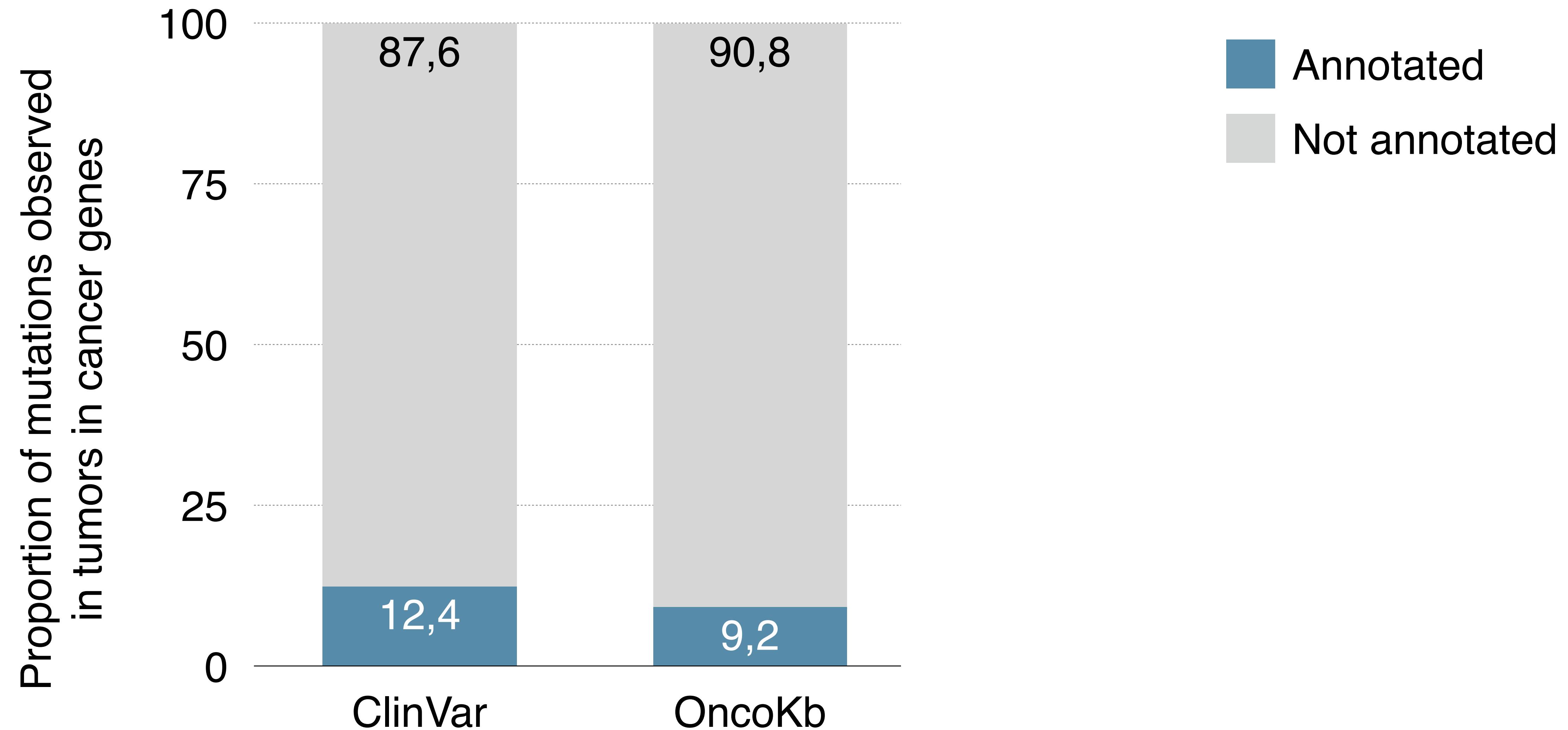
# In Silico Saturation Mutagenesis of Cancer Genes

## TP53 Colorectal Cancer

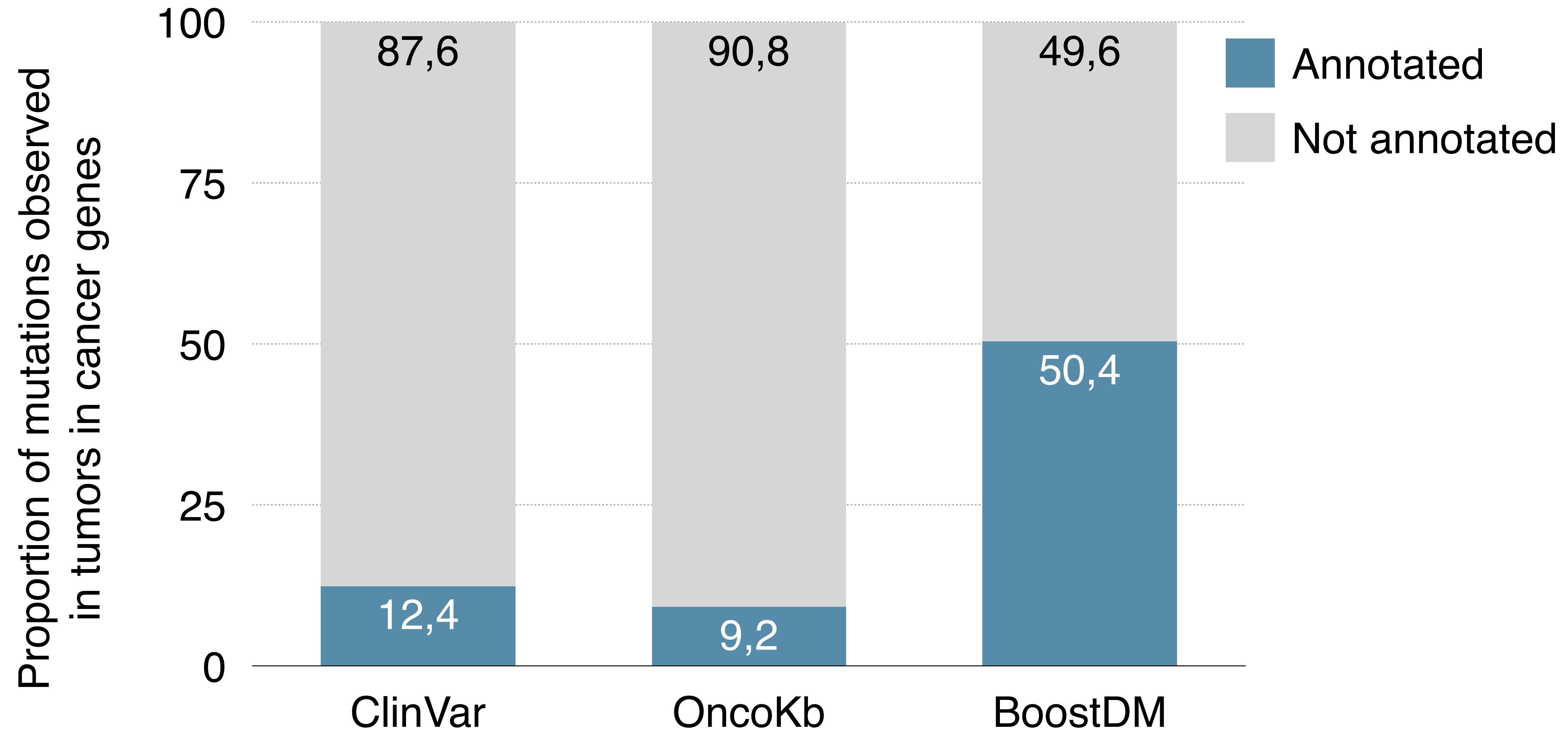


More blueprints at <http://intogen.org/boostdm>

# Most mutations in cancer genes are of uncertain significance



# Most mutations in cancer genes are of uncertain significance





# CANCER GENOME INTERPRETER

<http://www.cancergenomeinterpreter.org>



- Identifies potentially oncogenomic alterations
- Flags genomic biomarkers of drug response with different levels of clinical relevance

ALTERATIONS PRESCRIPTIONS

## Mutations

Show entries with:  Mutations identified as drivers  Mutations with oncogenic annotations  Other mutations

Sample ID	Gene	Protein Change	Oncogenicity	Mutation	Consequence	Oncog
Search here...						
TCGA-49-4494-01A-01D-	<a href="#">EGFR</a>	T790M	<span>driver</span>	chr7:55249071 C>T	missense variant	
TCGA-49-4494-01A-01D-	<a href="#">EGFR</a>	L858R	<span>driver</span>	chr7:55259515 T>G	missense variant	
TCGA-49-4494-01A-01D-	<a href="#">MGA</a>	E2115*	<span>driver</span>	chr15:42042148 G>T	stop gained	
TCGA-49-4494-01A-01D-	<a href="#">LRP1B</a>	R851P	<span>driver</span>	chr2:141751656 C>G	missense variant	
TCGA-49-4494-01A-01D-	<a href="#">LRPPRC</a>	splice acceptor variant	<span>driver</span>	chr2:44204416 C>A	splice acceptor variant	
TCGA-49-4494-01A-01D-	<a href="#">RBM10</a>	splice donor variant	<span>driver</span>	chrX:47034492 G>T	splice donor variant	
TCGA-49-4494-01A-01D-	<a href="#">ARHGAP21</a>	E724*	<span>passenger</span>	chr10:24908654 C>A	stop gained	

# Clinical Implementation



**CGI-Clinics**  
Cancer Genome Interpreter

Data-driven cancer genome interpretation  
for personalized cancer treatment

<https://www.cgiclinics.eu/>

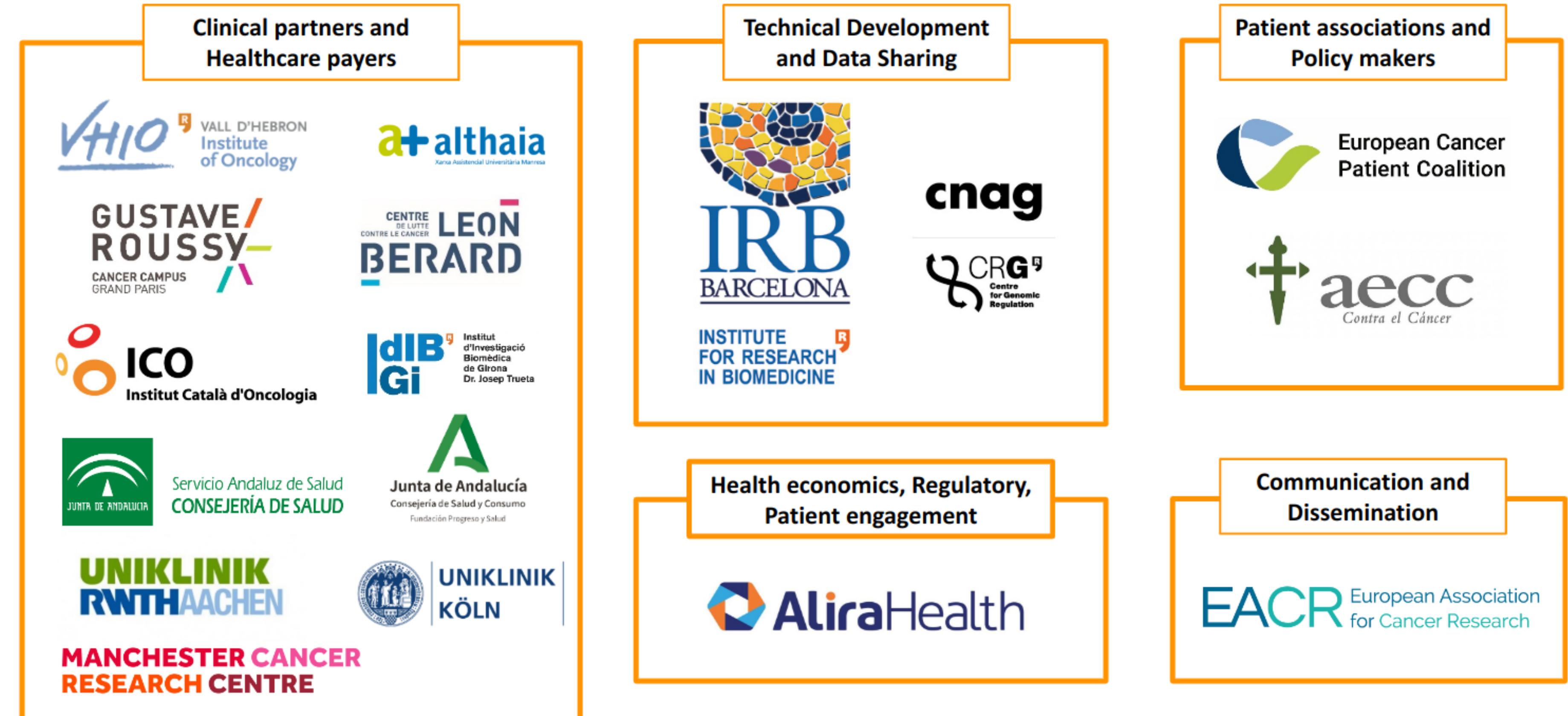
HORIZON-HLTH-2021-CARE-05  
5 years EU project, started November 2022

**CGI-Clinics** is an international multidisciplinary project with 17 partners involving biologists, bioinformaticians, oncologists, patients,...



4 EU Countries  
5 years  
10 M€

[www.cgiclinics.eu](http://www.cgiclinics.eu)



9 Hospitals + 3 collaborators

30 hospitals in implementation phase (from 2026)

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- Chemotherapy effect in hematopoiesis
- Cancer Promotion

# Modeling neutral mutagenesis

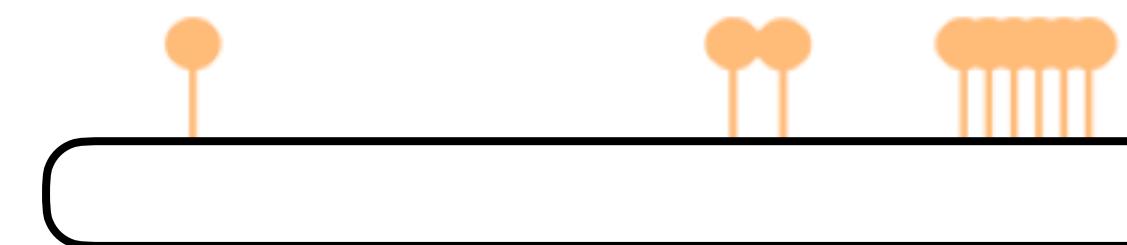
# Modeling neutral mutagenesis

- Variable mutation rate along the genome

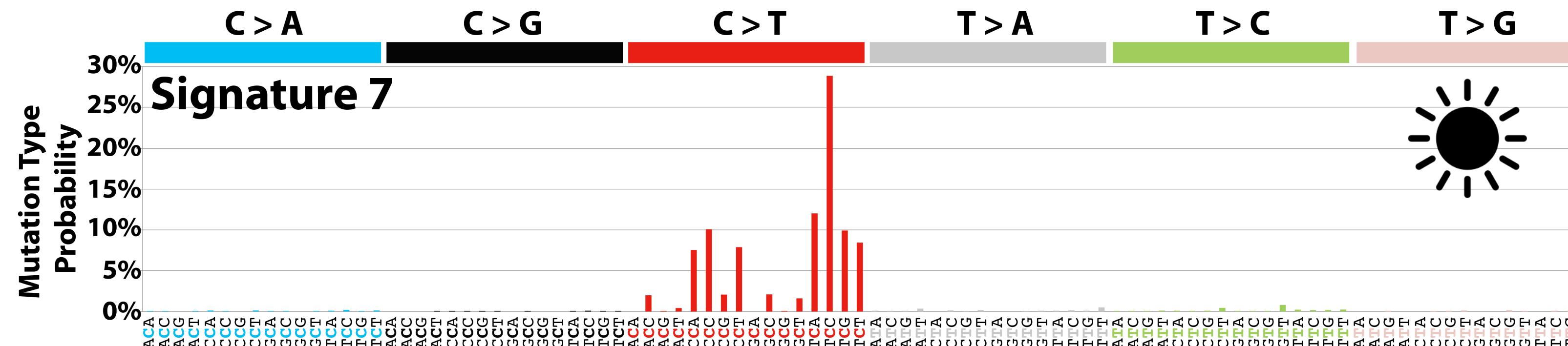


# Modeling neutral mutagenesis

- Variable mutation rate along the genome



- Different probability for different sequence context (mutational signatures)



# Mutational signatures of cancer treatments

## DNA damaging agent

Chemotherapy



e.g. alkylating agents



# Mutational signatures of cancer treatments

DNA damaging agent

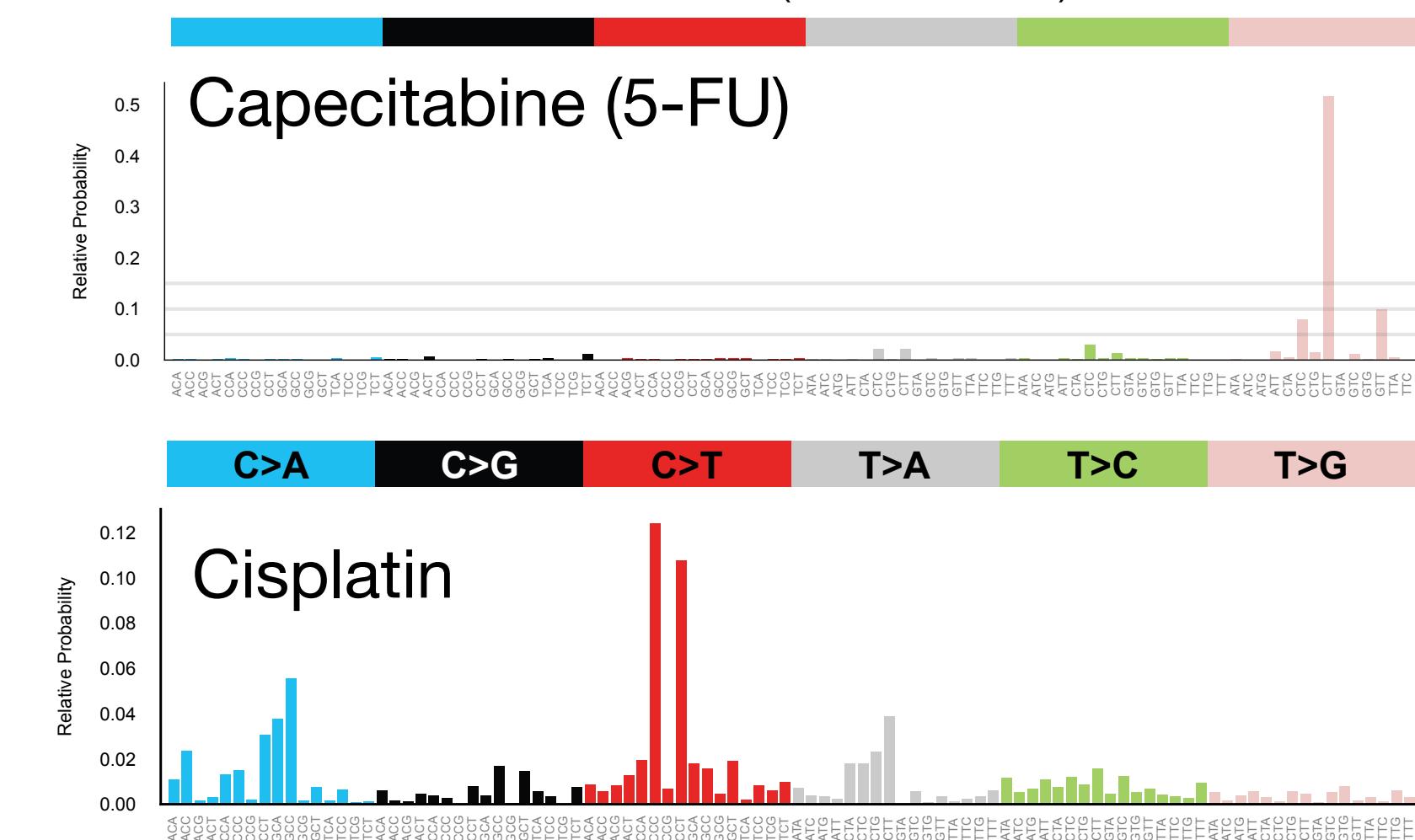
Chemotherapy



e.g. alkylating agents



## Mutational signatures of cancer treatments

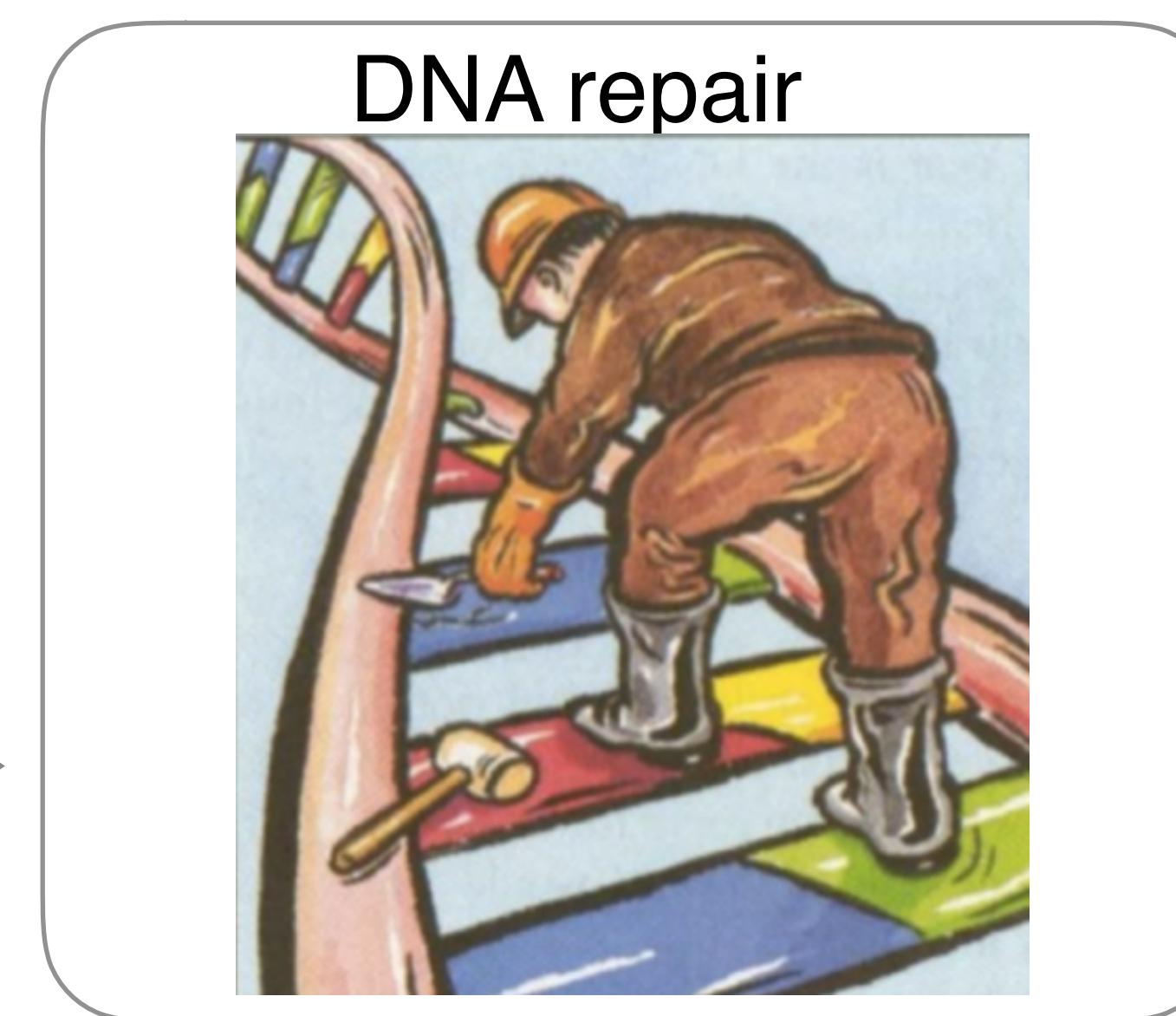
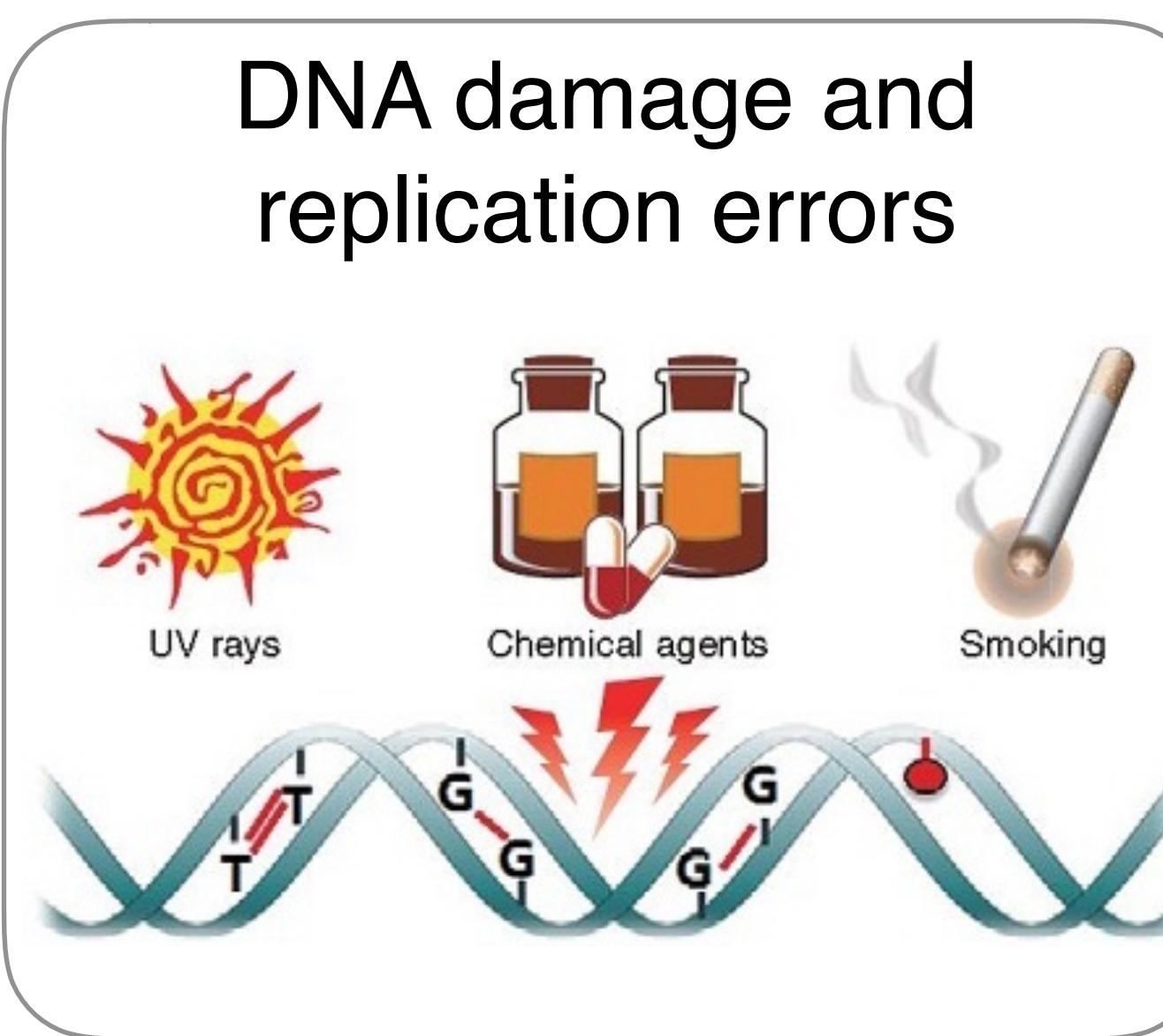


Pich et al., Nature Genetics 2019



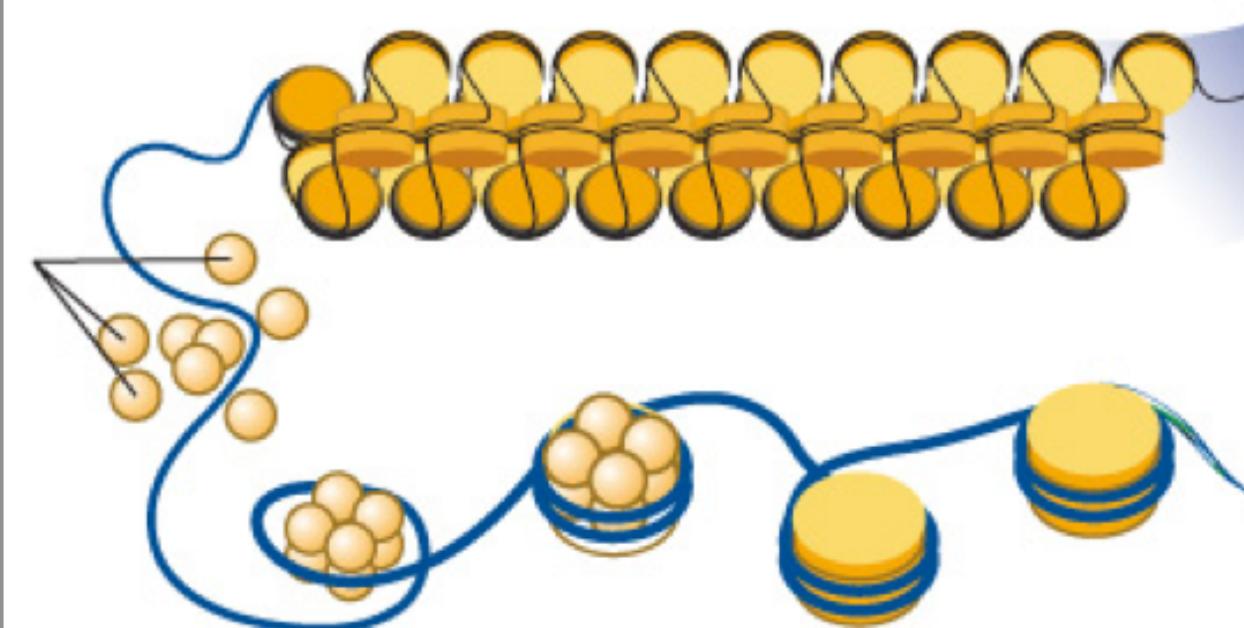
Oriol Pich Abel Gonzalez-Perez Ferran Muiños

# Interplay between DNA damage and DNA repair

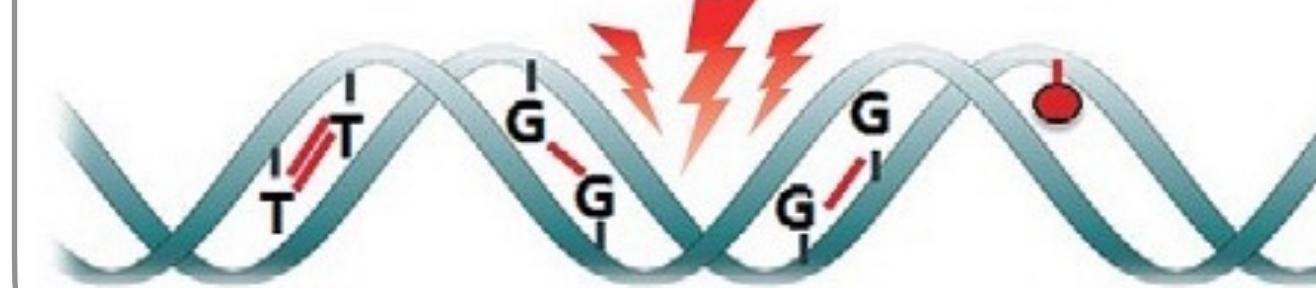


# Interplay between DNA damage and DNA repair and chromatin

## Chromatin conformation



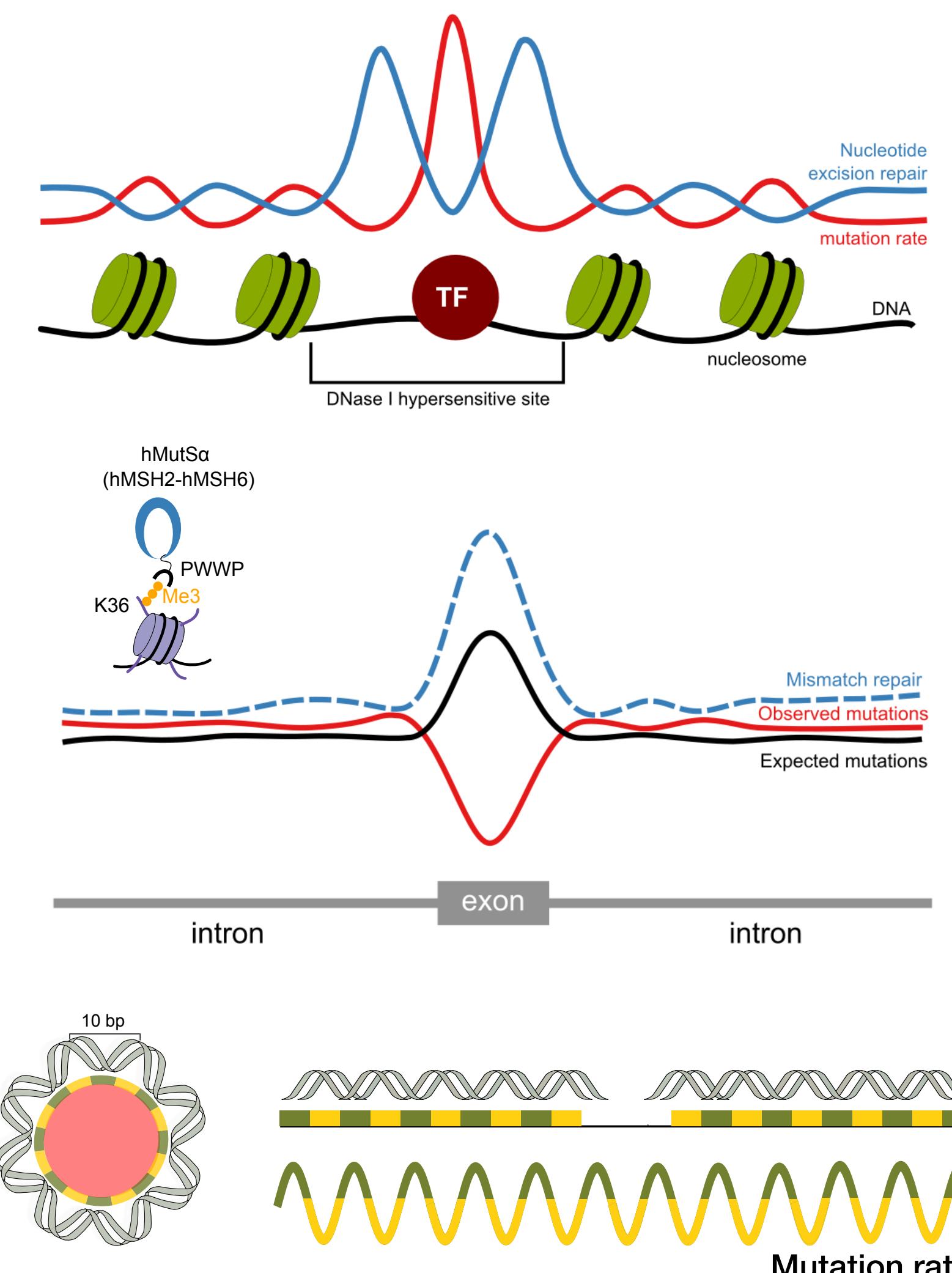
## DNA damage and replication errors



## DNA repair



# Mutation rate variability at local scale



High mutation rate in TFBS due to impaired Nucleotide Excision Repair

Sabarinathan et al., Nature 2016



Differential mismatch repair leads to reduced mutation rate in exons

Frigola et al., Nature Genetics 2017

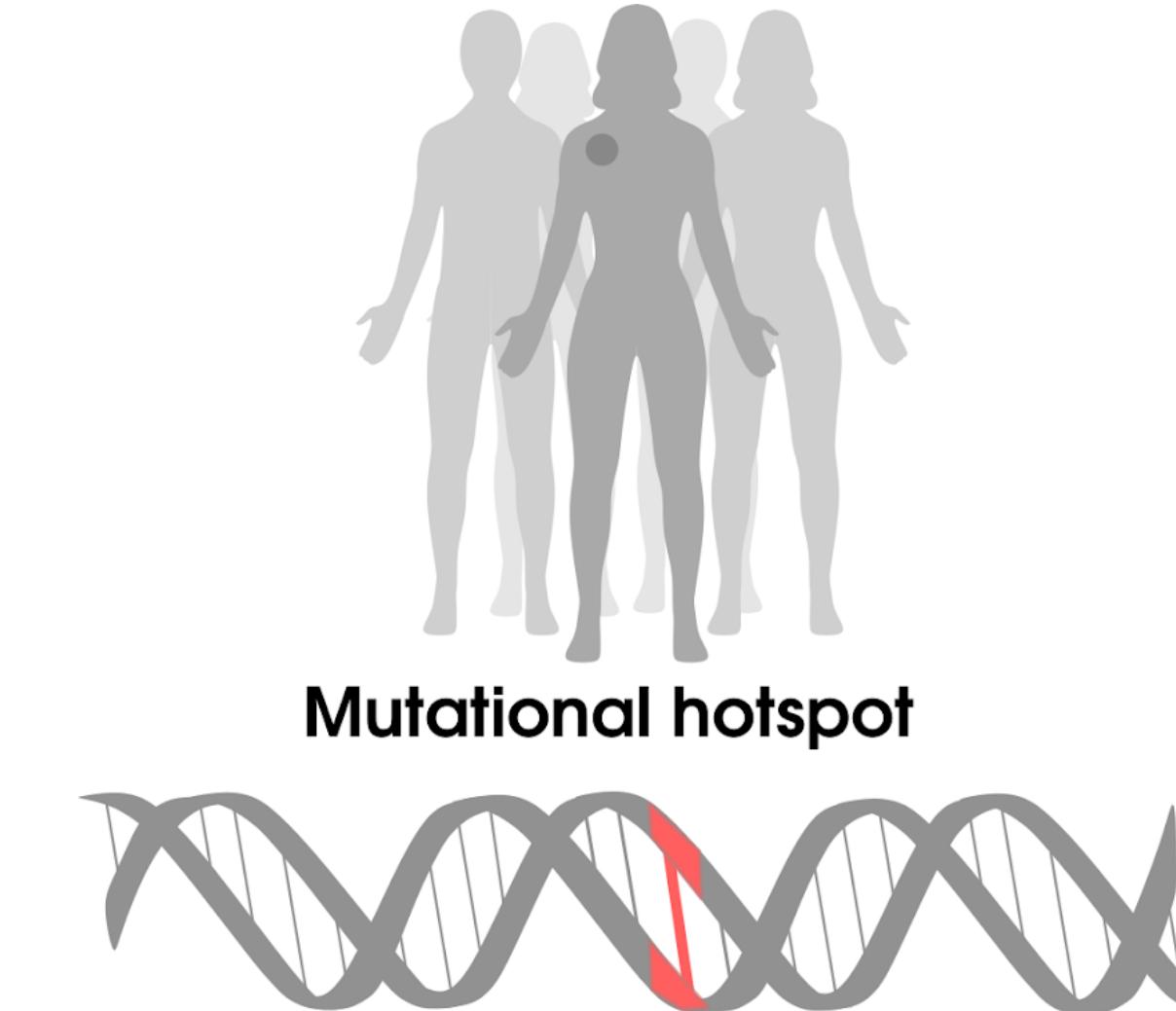


10-bp mutation rate periodicity in nucleosome covered DNA

Pich et al., Cell 2018



# How well do we estimate mutation rate at single-nucleotide resolution?



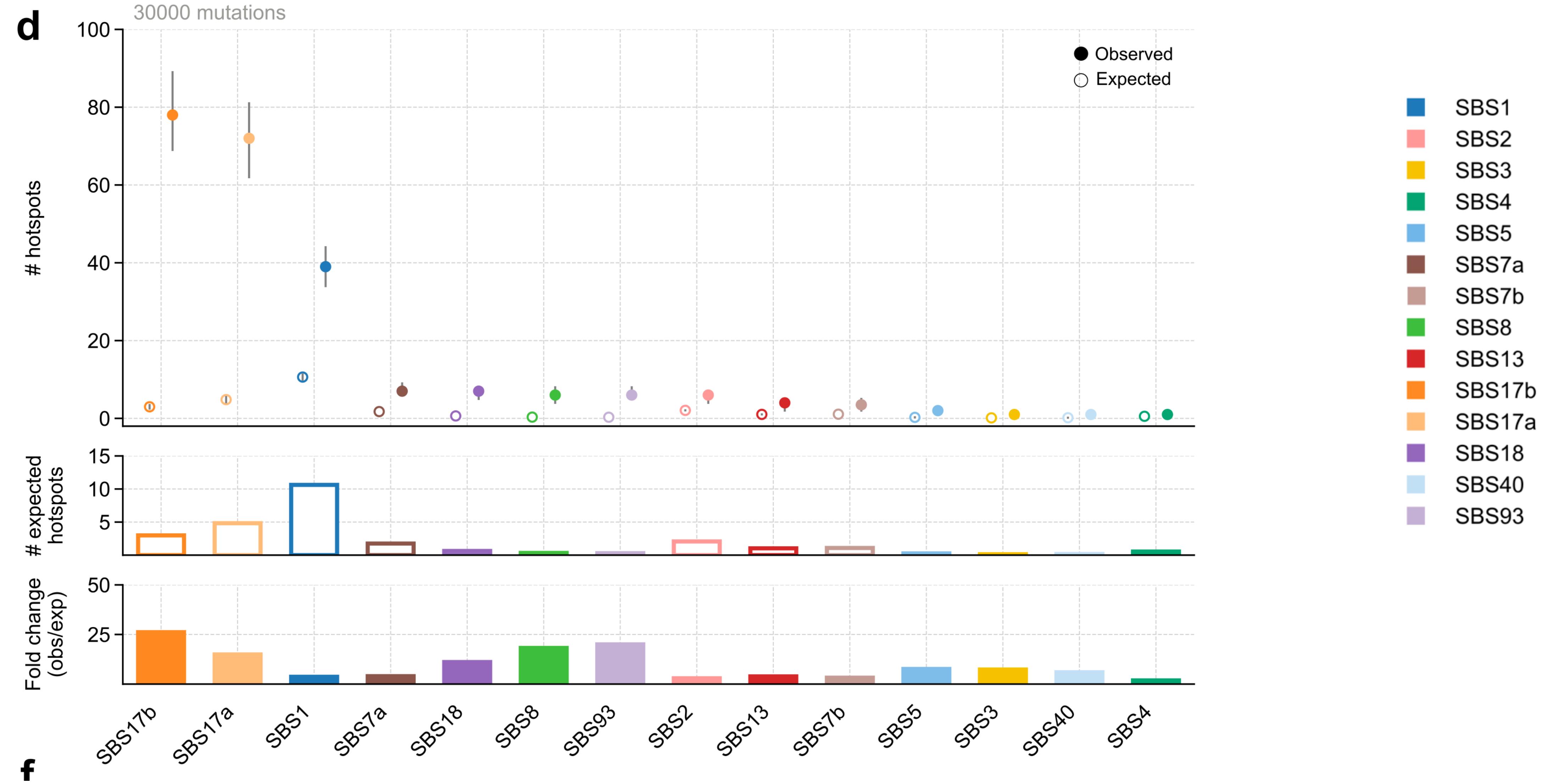
Identification of somatic mutation hotspots across 7,507 whole genomes



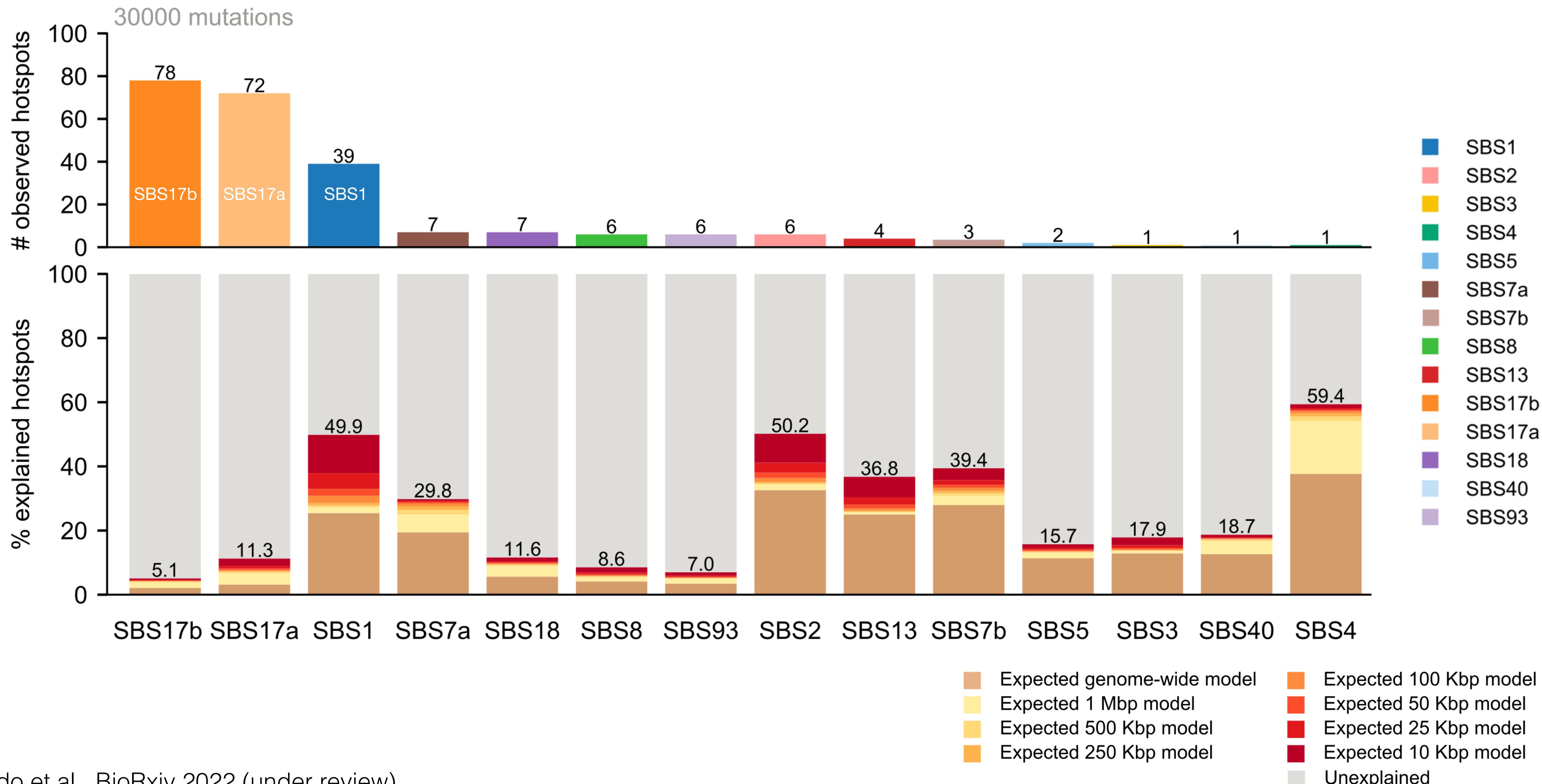
Claudia Arnedo

Which processes create hotspots? Can we predict those with current models?

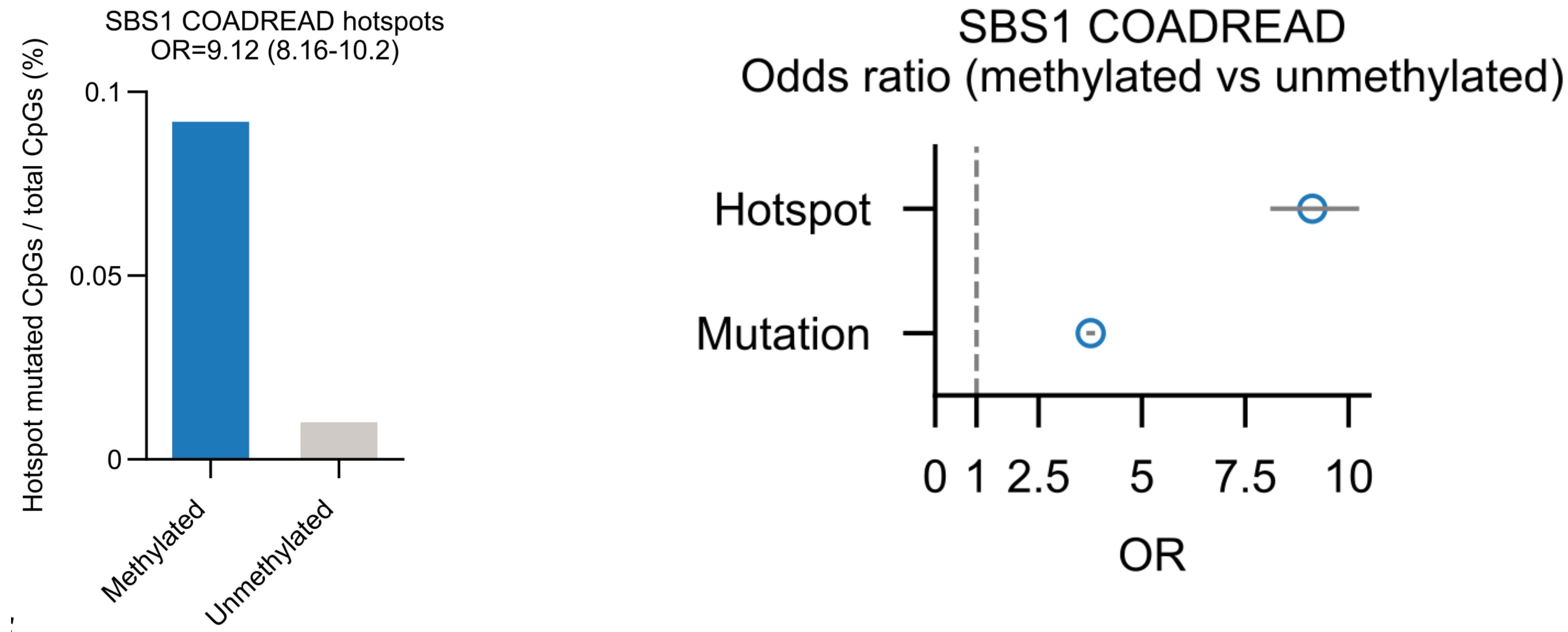
# SBS1 and SBS17a, b have the highest propensity to hotspot formation



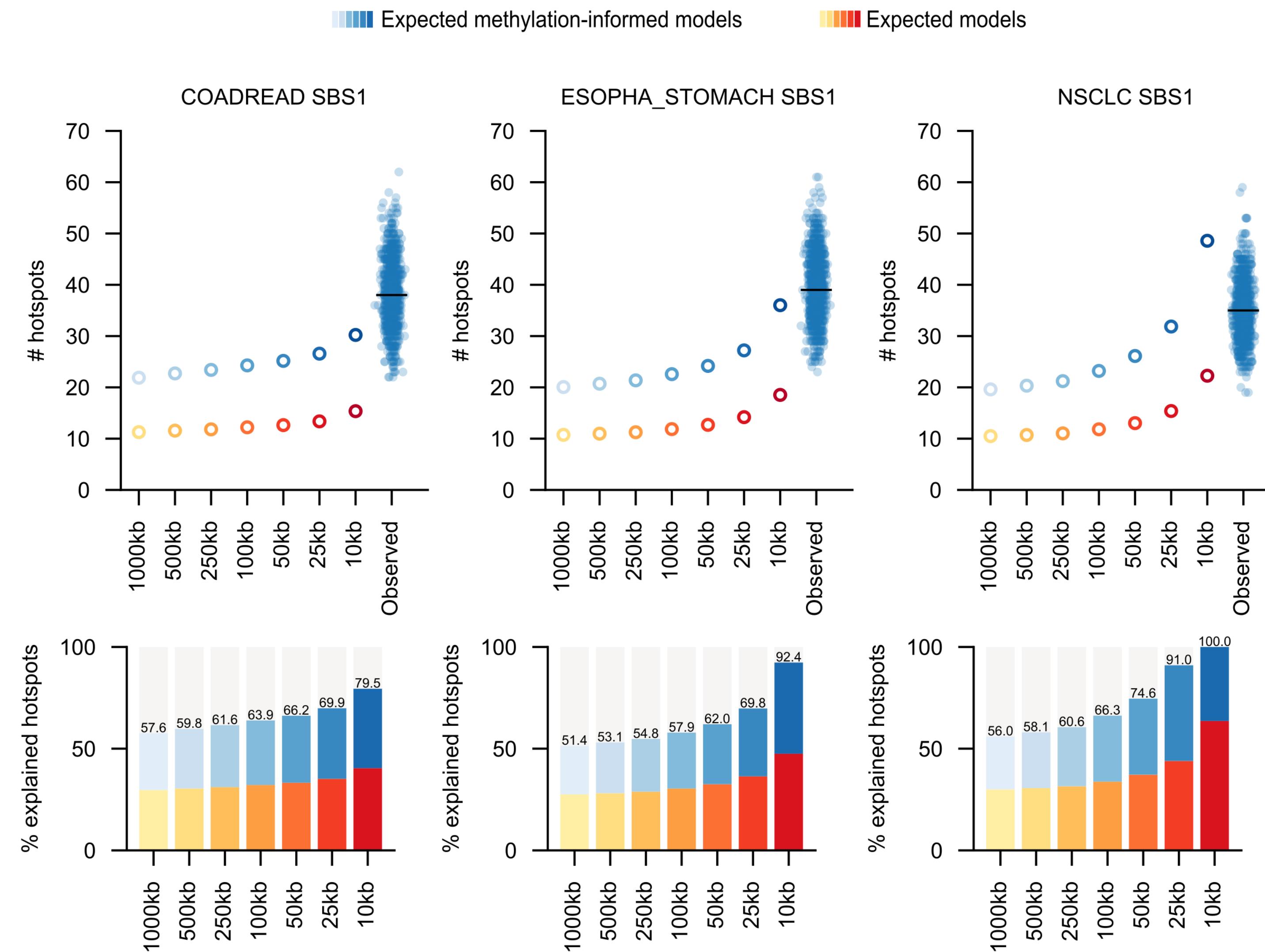
# Large proportion of hotspots remain unexplained



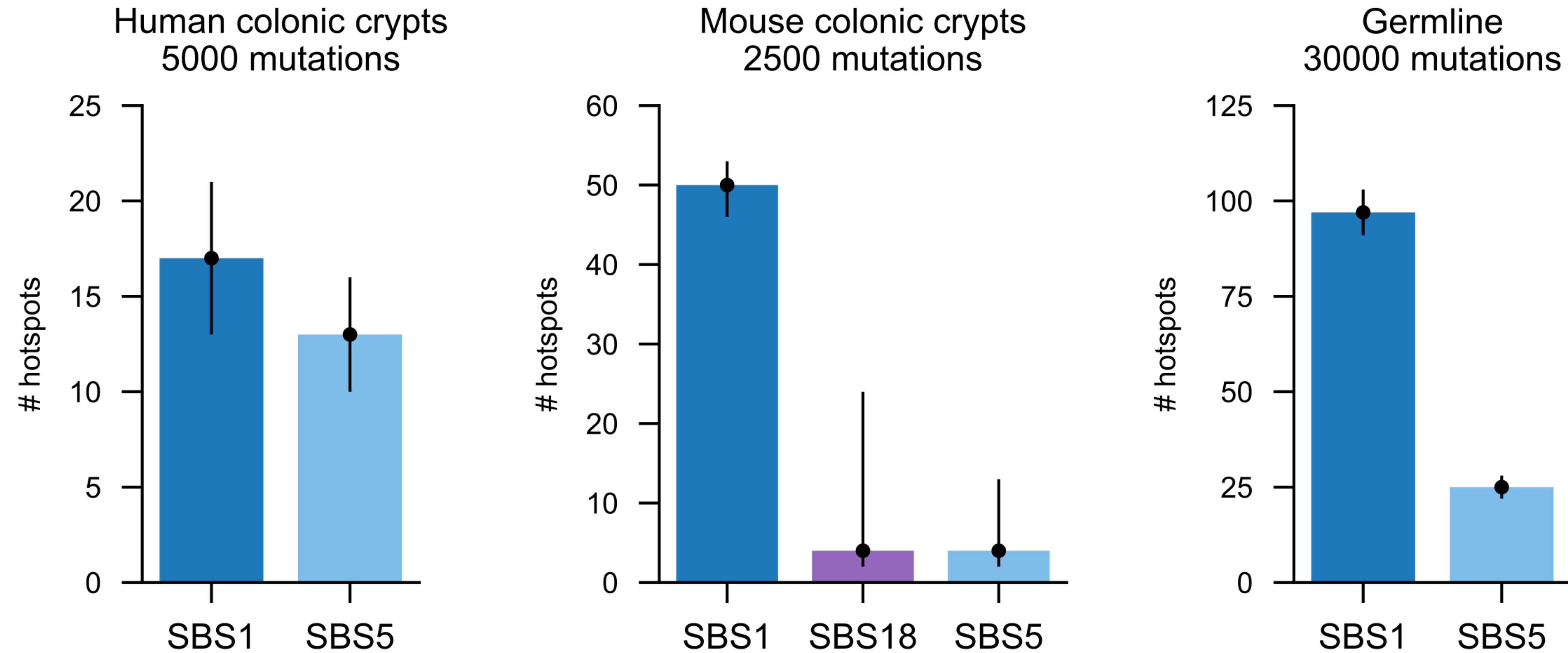
# High proportion of hotspots in methylated CpGs



# Genome-wide distribution of methylated CpGs sites can explain most of SBS1 hotspot propensity

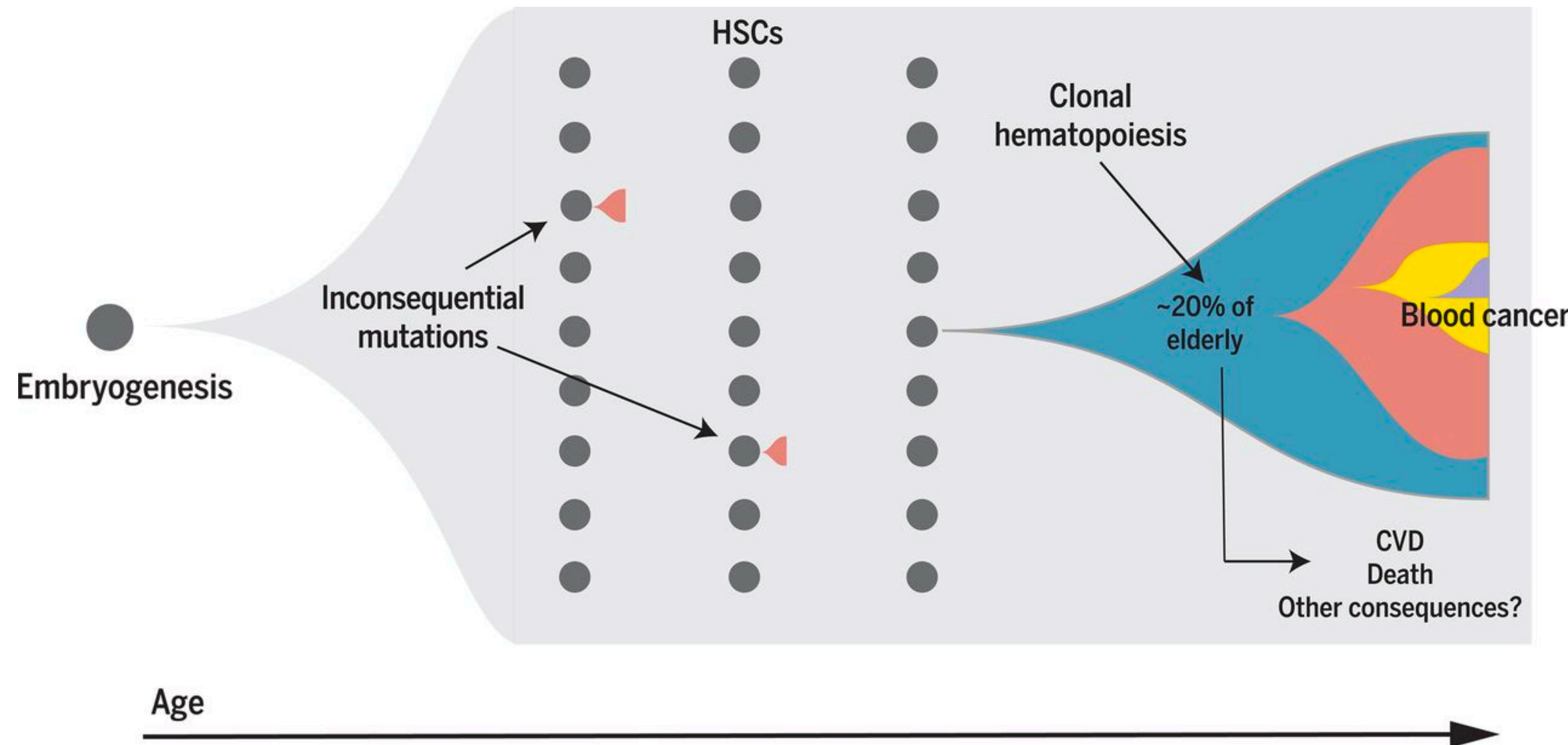


# Beyond cancer: high SBS1 hotspot propensity in normal tissues and germline variants



- Identifying Cancer Drivers
- Understanding Neutral Mutagenesis
- Identifying Clonal Hematopoiesis Drivers
- Chemotherapy effect in hematopoiesis
- Cancer Promotion

# Clonal expansions in normal tissue

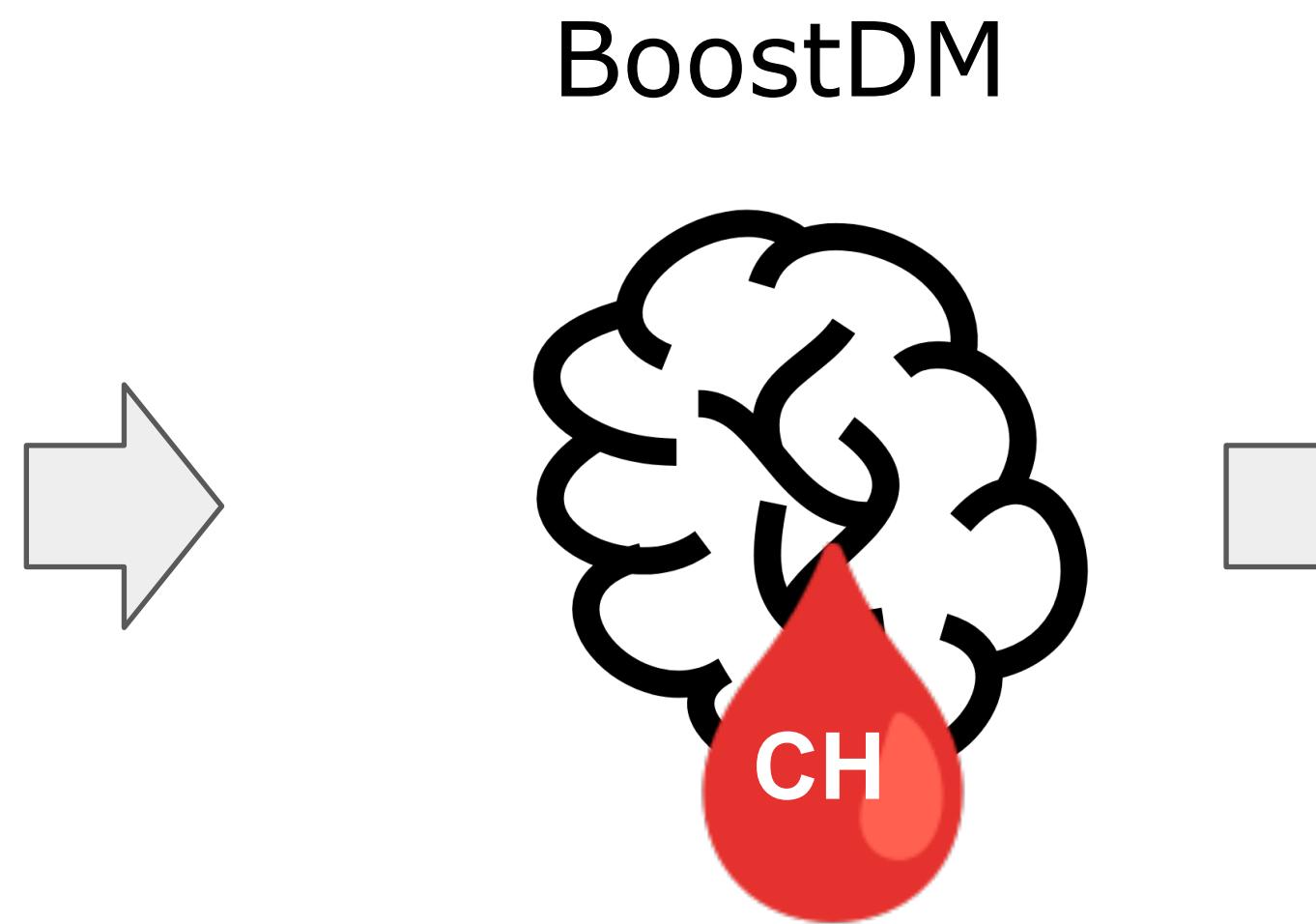


# Identification of clonal hematopoiesis driver genes and driver mutations



<https://www.intogen.org/ch/>

CH driver  
genes



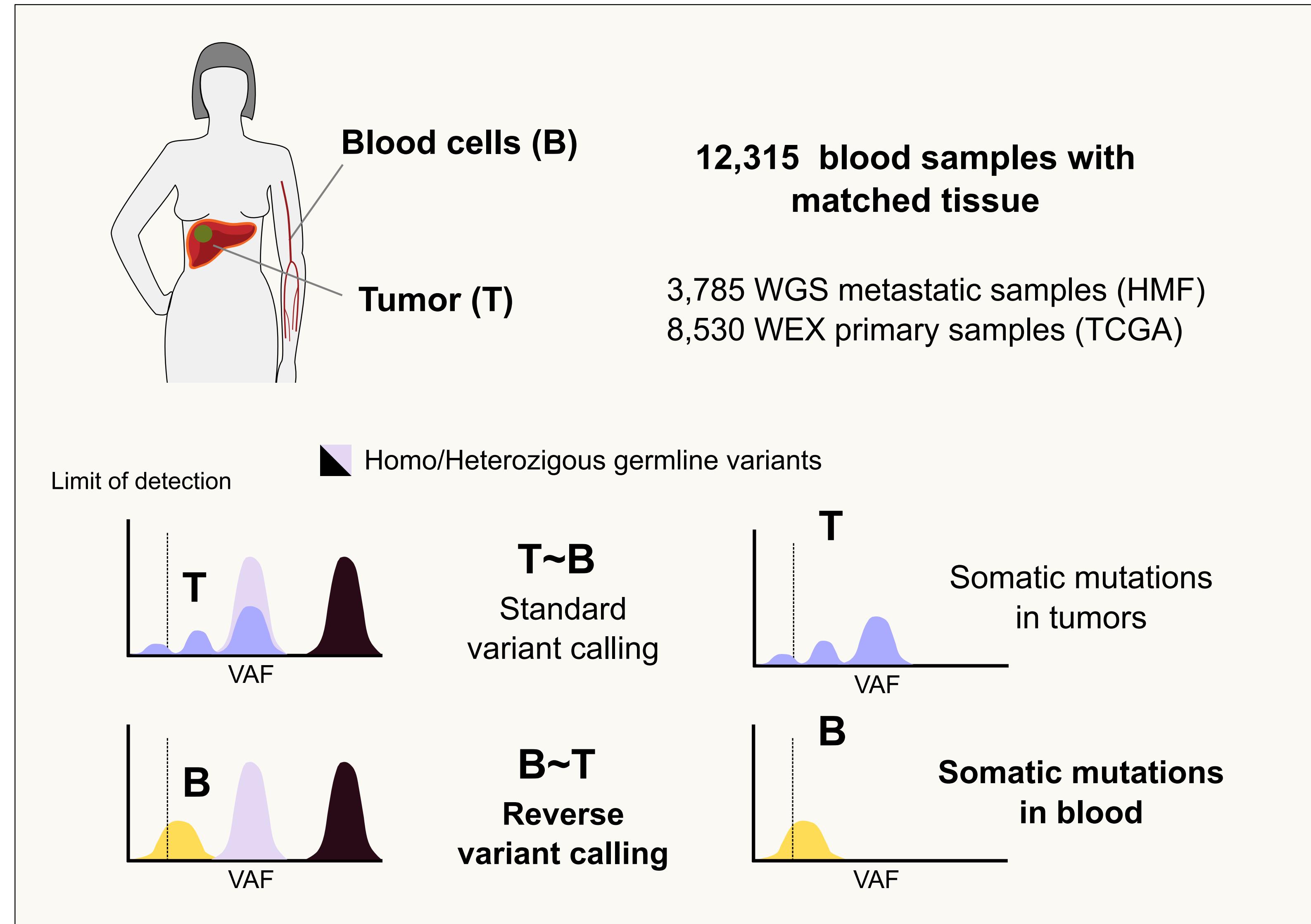
CH driver  
mutations



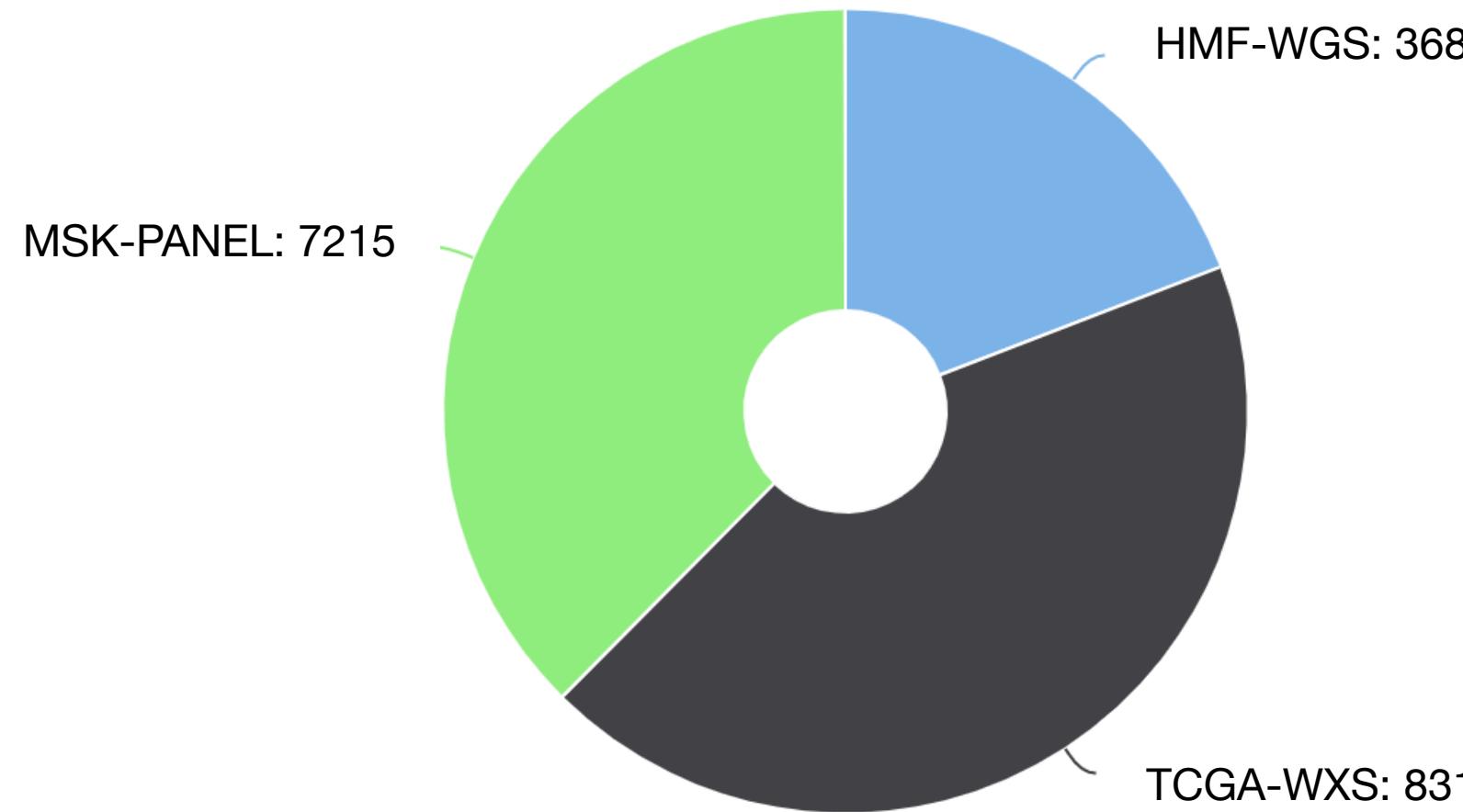
Clinical interpretation  
of CH mutations



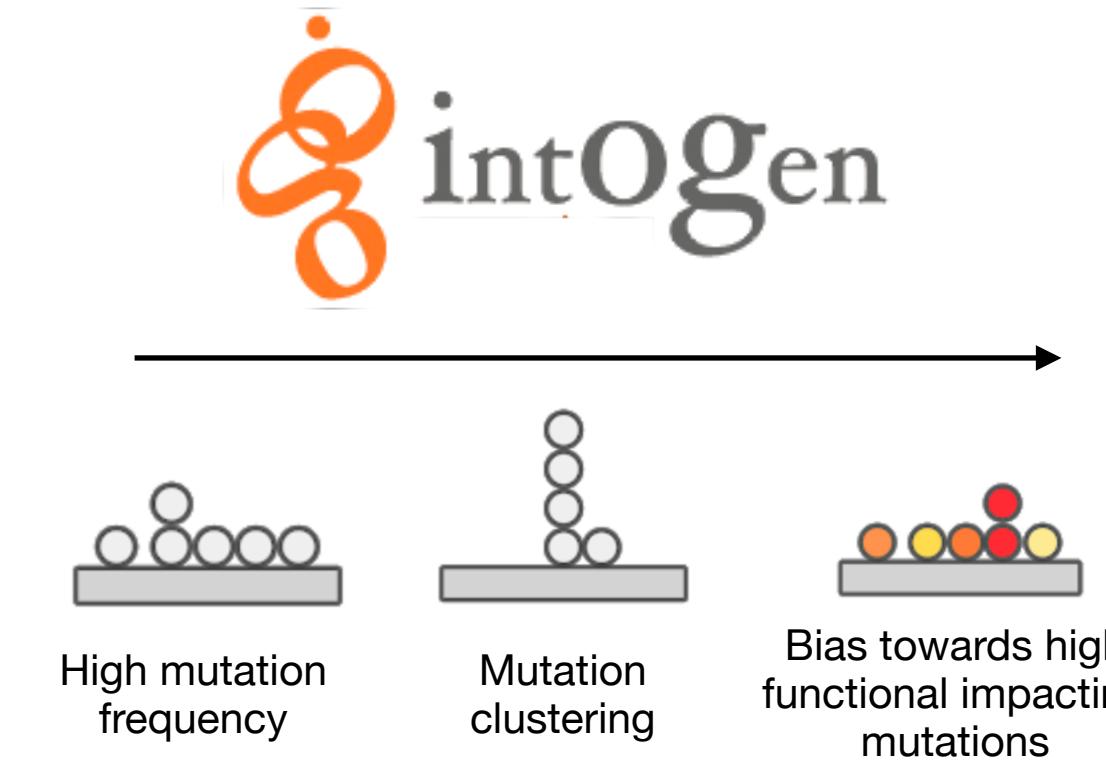
# Exploiting cancer genomics data to identify blood somatic mutations



# Discovering Clonal Hematopoiesis Driver Genes



19,202 Tumors · 3 cohorts



Mutation Pattern Analysis  
to identify Cancer Genes

A grid of 64 gene names, color-coded by category:

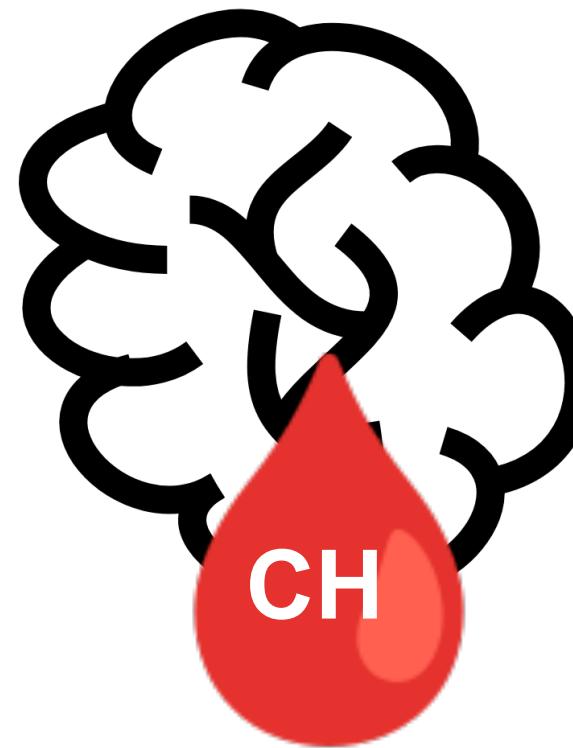
KDM5C	PABPC1	FOXP1	NOTCH1	SDHAF2	MYO5A	CUX1	=
MDM4	LZTR1	MGA	RAD21	TMEM127	KDM6A	PTPN11	
SUZ12	ERCC2	MPL	RET	NF1	TET2	CDKN1B	
PTPRD	IDH2	JAK2	ATM	TP53	DNMT3B	GNB1	
KRAS	CHEK2	MYCN	DNMT3A	MYC	AFF3	STAT5B	
EZH2	GNAS	ASXL1	CBL	KMT2C	ZRSR2		
NRAS	STAG2	STAT3	ARID2	PPM1D	SF3B1	U2AF1	
CALR	CTCF	SRSF2	MYD88	AR	DNM2	ERF	
		ABL2	SH2B3	RUNX1	ATE1	IDH1	
		MKL1	TP63				

64 Clonal Hematopoiesis Driver Genes  
(All known + new candidates)

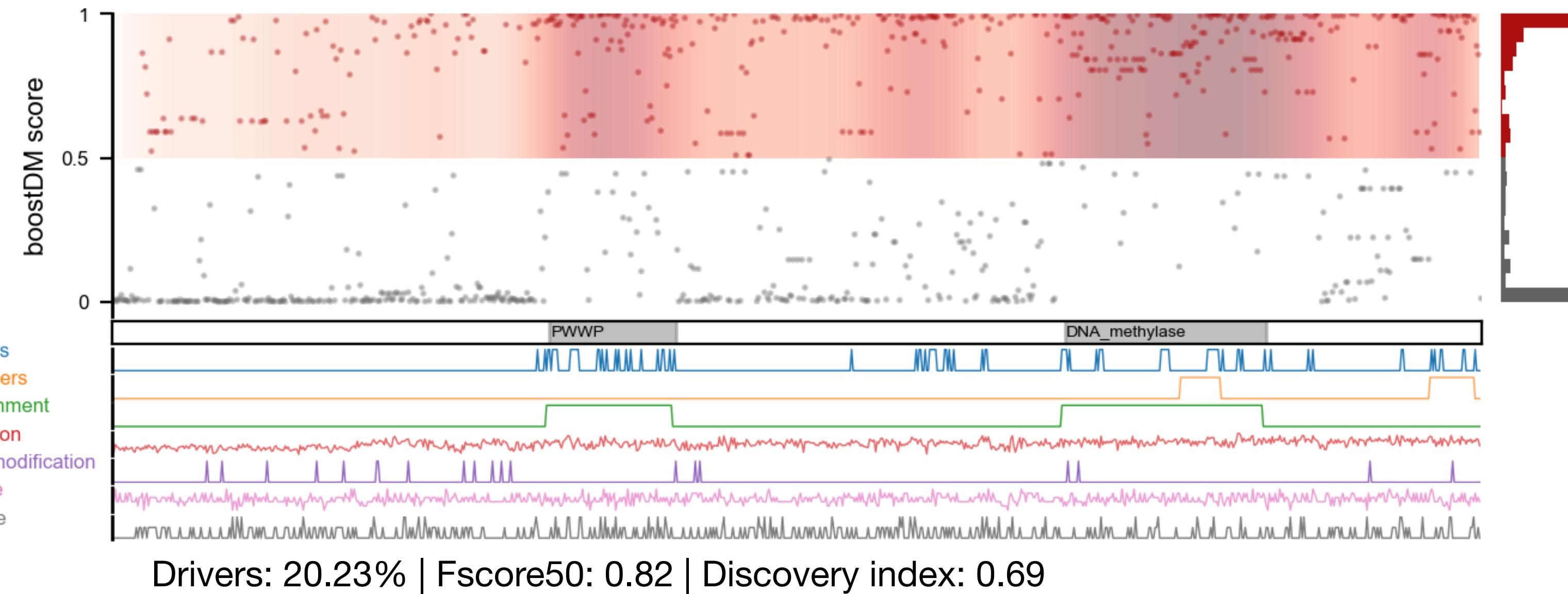


# Identification of Clonal Hematopoiesis Driver Mutations through In Silico Saturation Mutagenesis

BoostDM

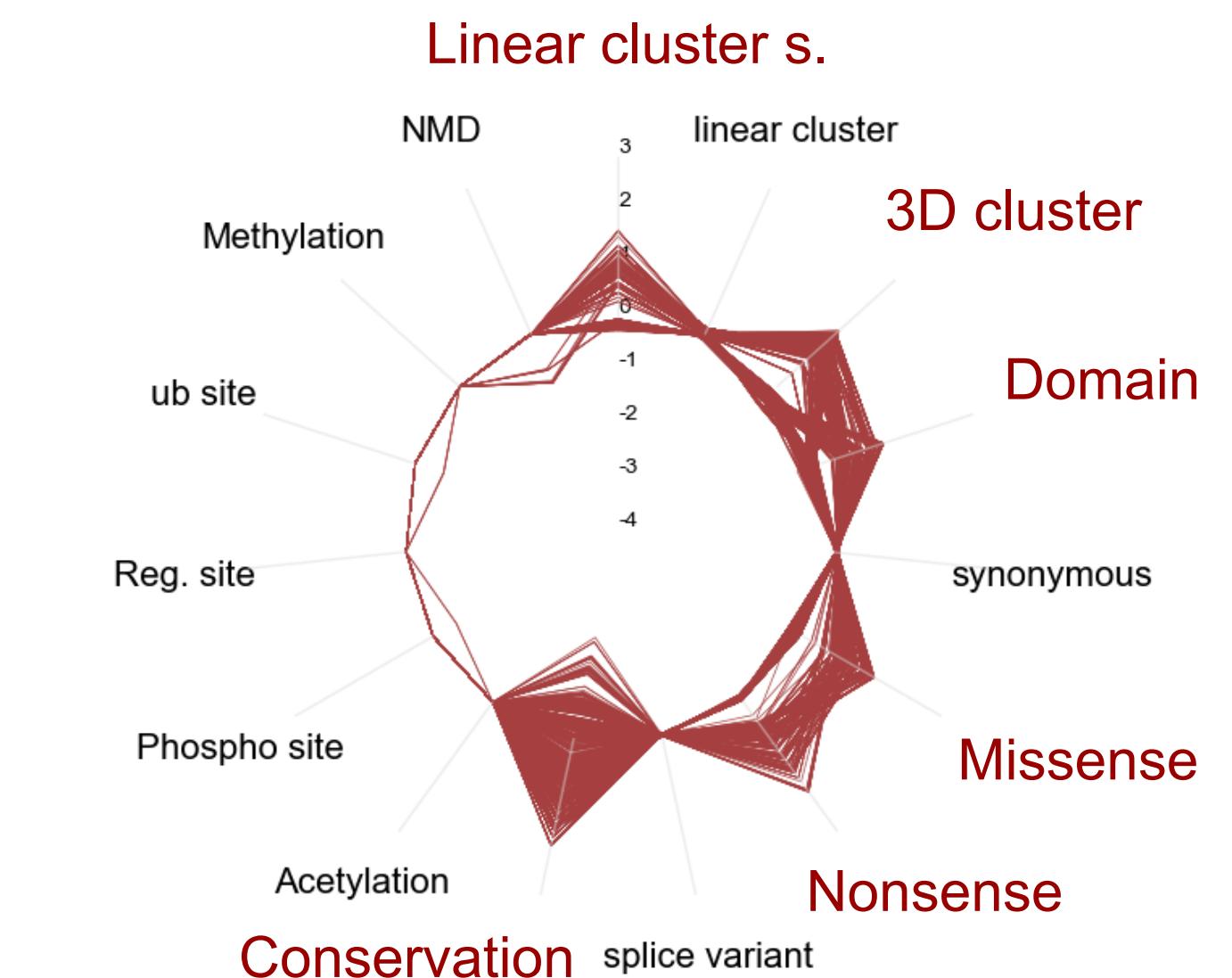


# In silico saturation mutagenesis of DNMT3A



**All predicted DNMT3A drivers:**  
missense & nonsense mutations  
in two functional domains and two clusters

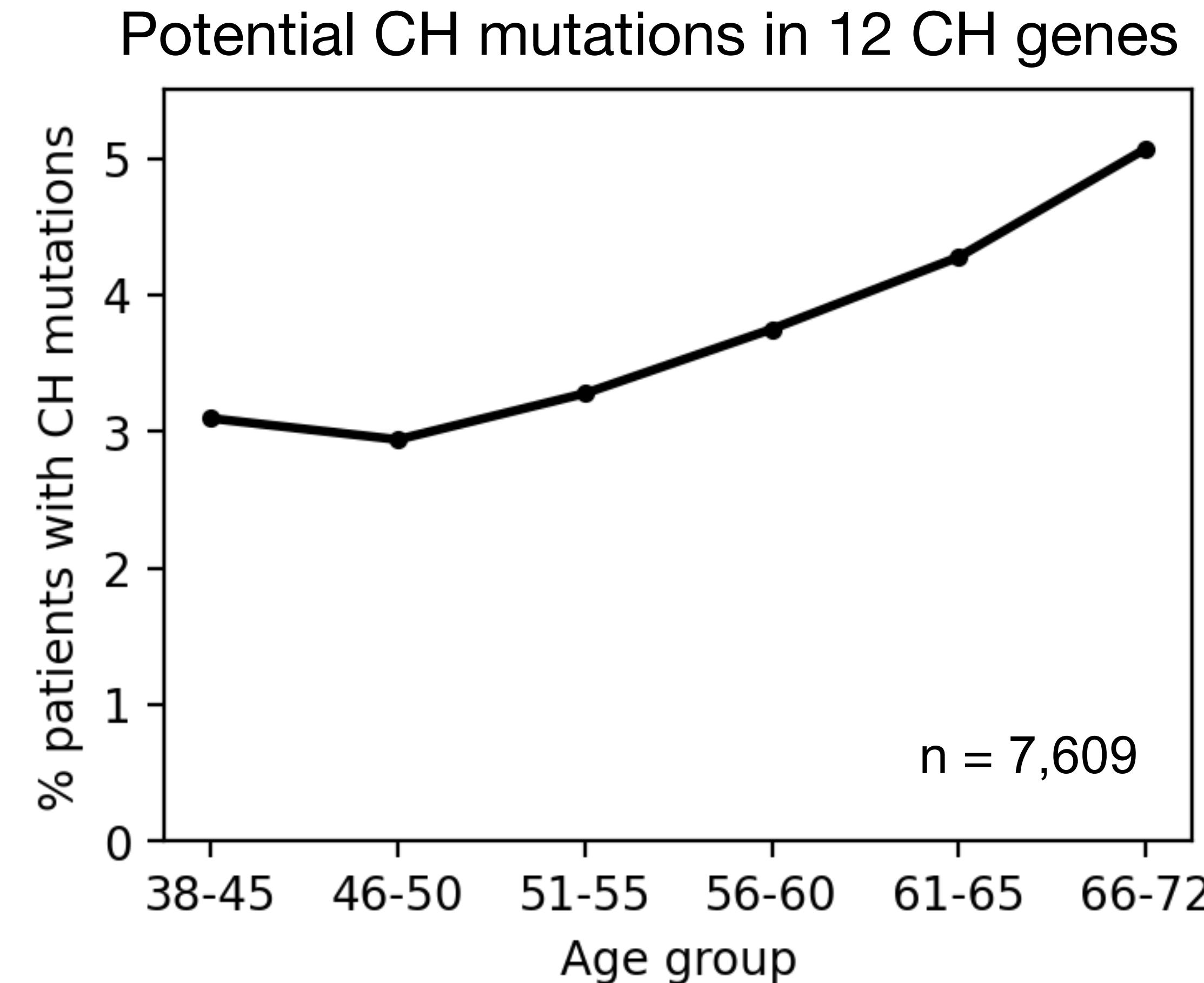
Explanation  
**Observed DNMT3A drivers**



# Finding CH mutations in 200,000 individuals (UK Biobank)

Potential CH mutations are associated with age but show a high rate of false positives

**biobank<sup>uk</sup>**

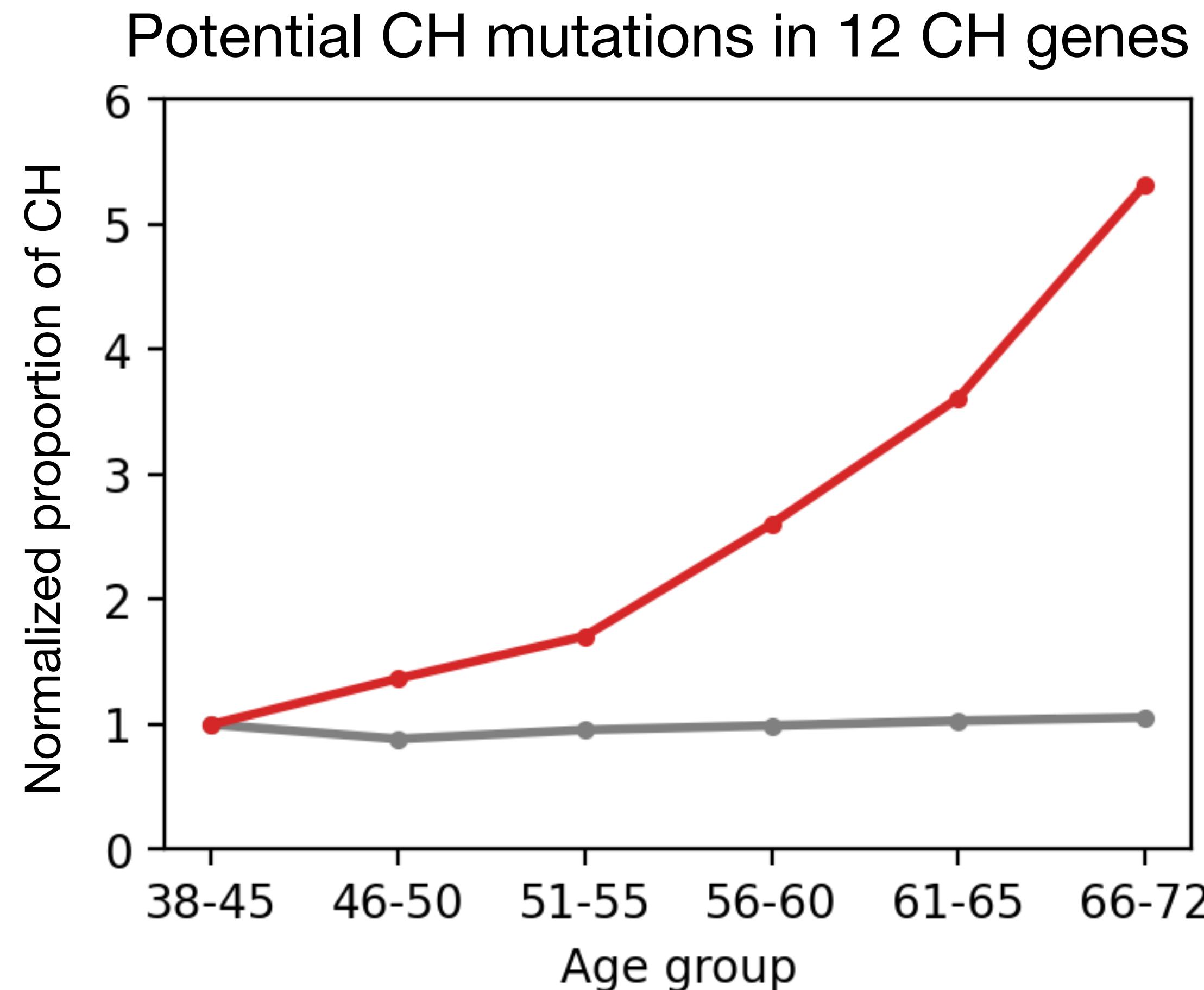


Some method to select specific mutations is needed to eliminate false positive mutations

Whole exome sequencing: DeepVariant filtered by AD > 3, VAF < 0.30, non-synonymous, SNVs, low gnomAD,...

# Only CH mutations predicted as drivers by BoostDM-CH highly correlate with age

Identification of driver mutations from the potential CH mutations by BoostDM-CH

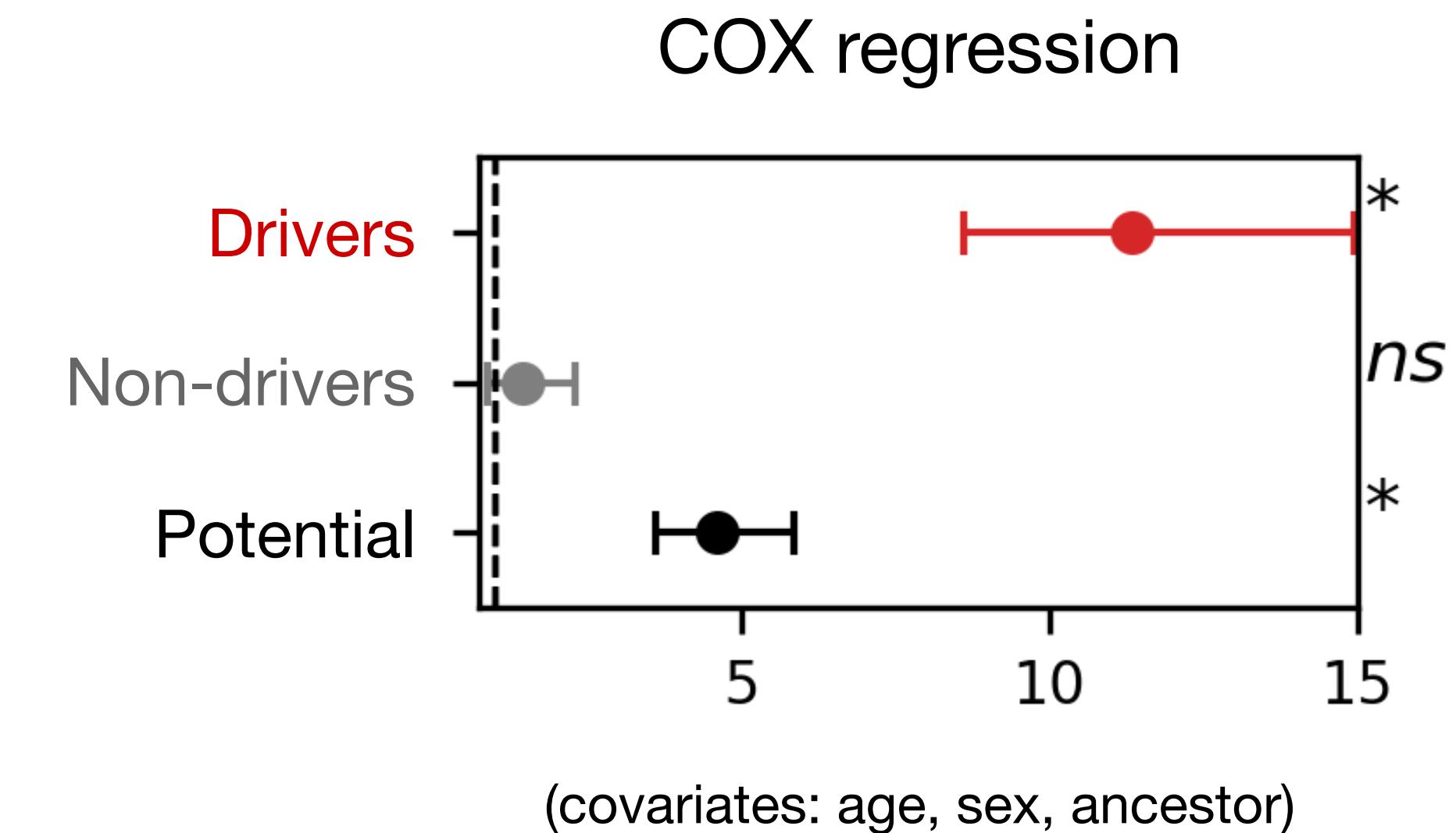
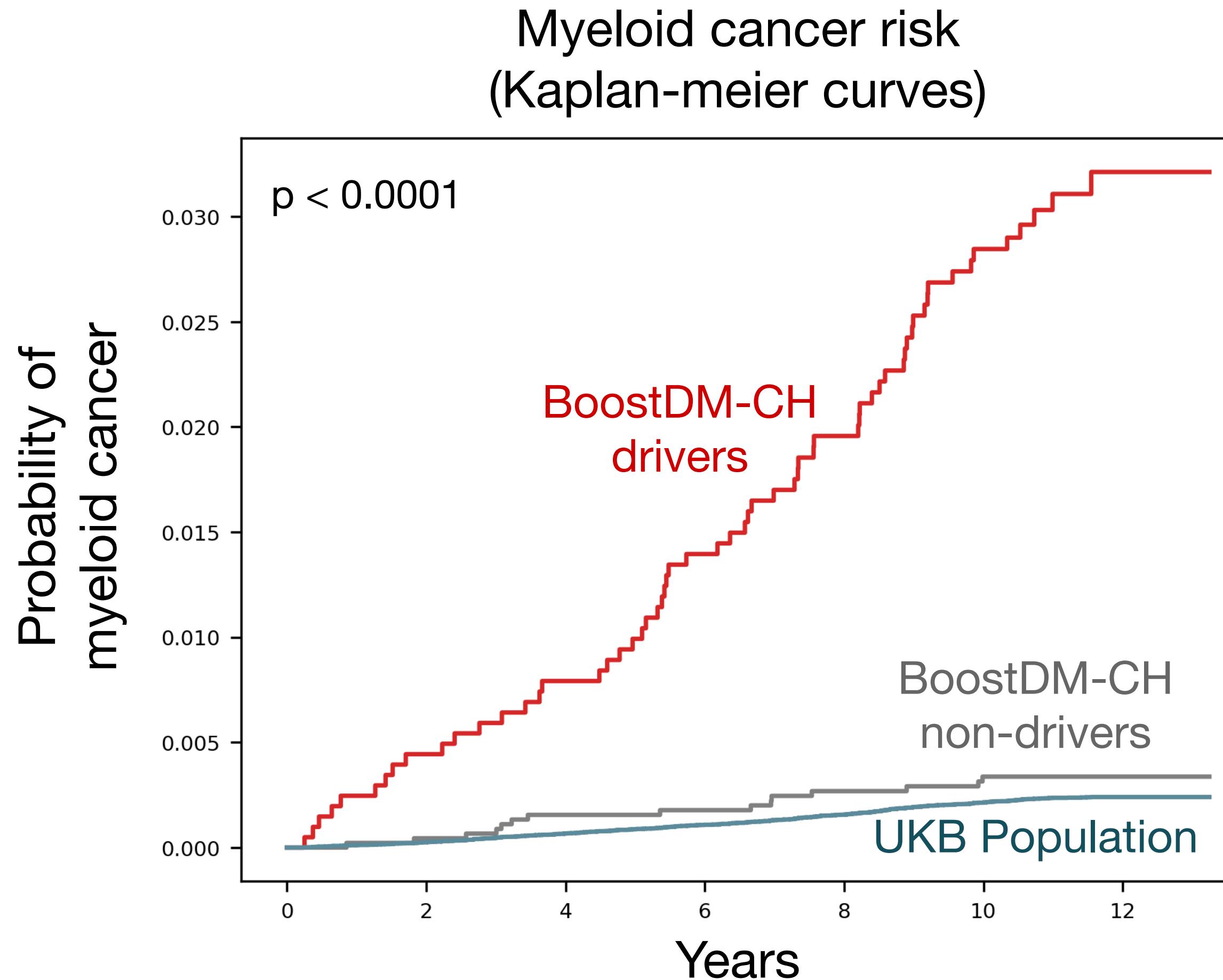


BoostDM-CH drivers  
n = 2,298 (~30%)

BoostDM-CH non-drivers  
n = 5,311 (~70%)

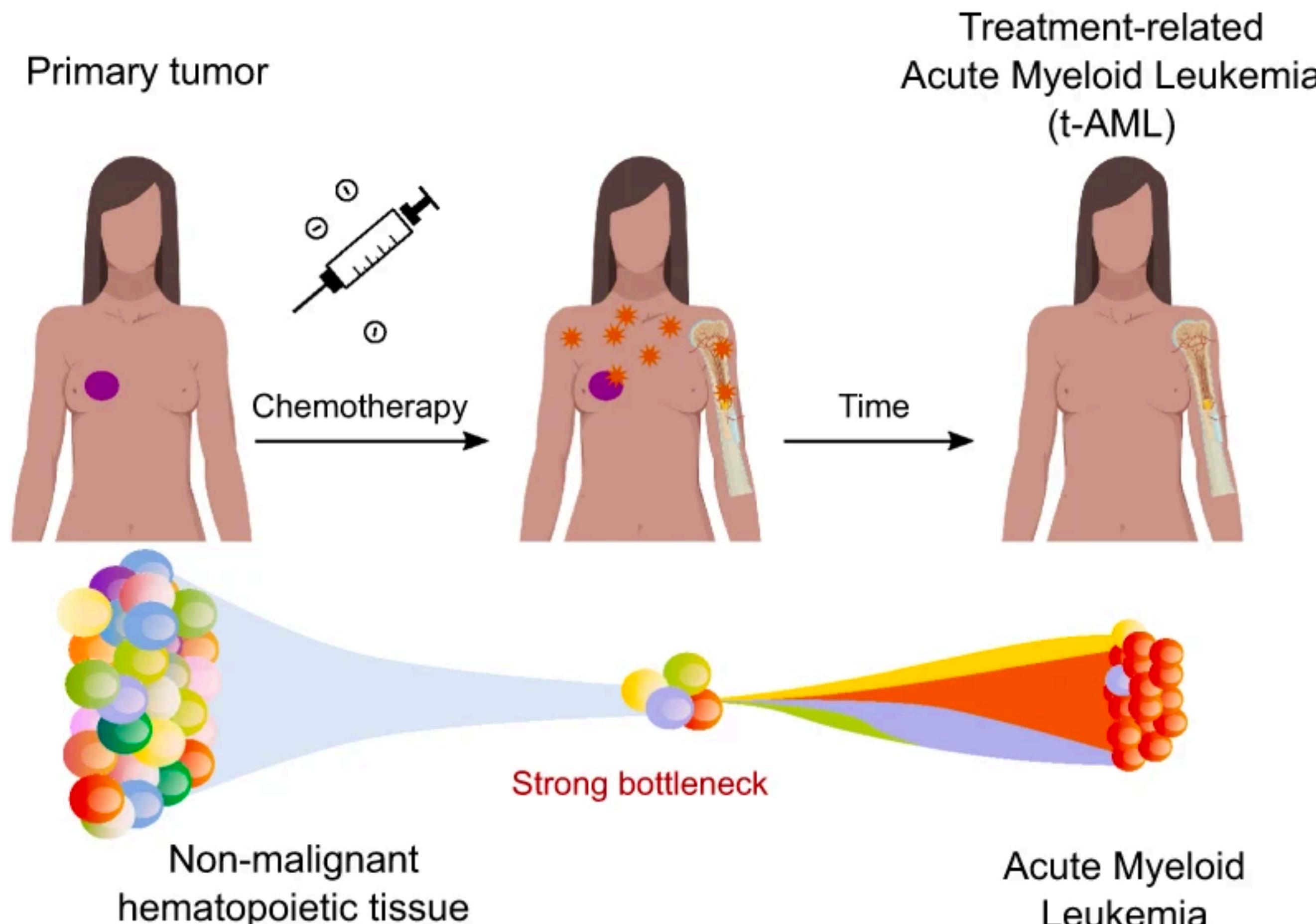
Logistic regressions:  
Drivers p-val = 6e-72  
Non-drivers p-val = ns

# Only CH mutations predicted as drivers by BoostDM-CH are associated with an increased risk of hematological cancer



- Identifying Cancer Drivers
- Understanding Neutral Mutagenesis
- Identifying Clonal Hematopoiesis Drivers
- Chemotherapy effect in hematopoiesis
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# Treatment-related Acute Myeloid Leukemia (tAML)

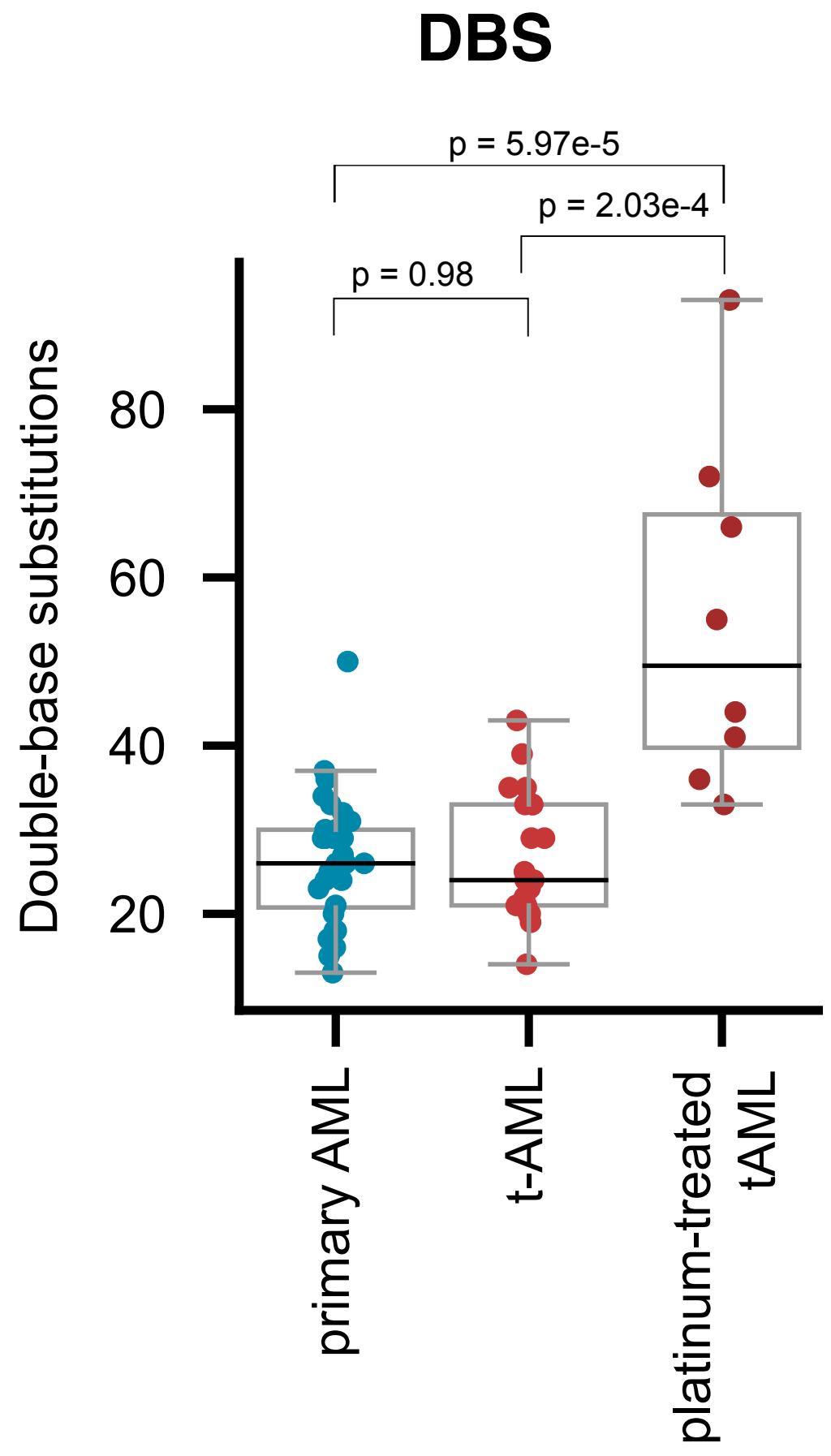
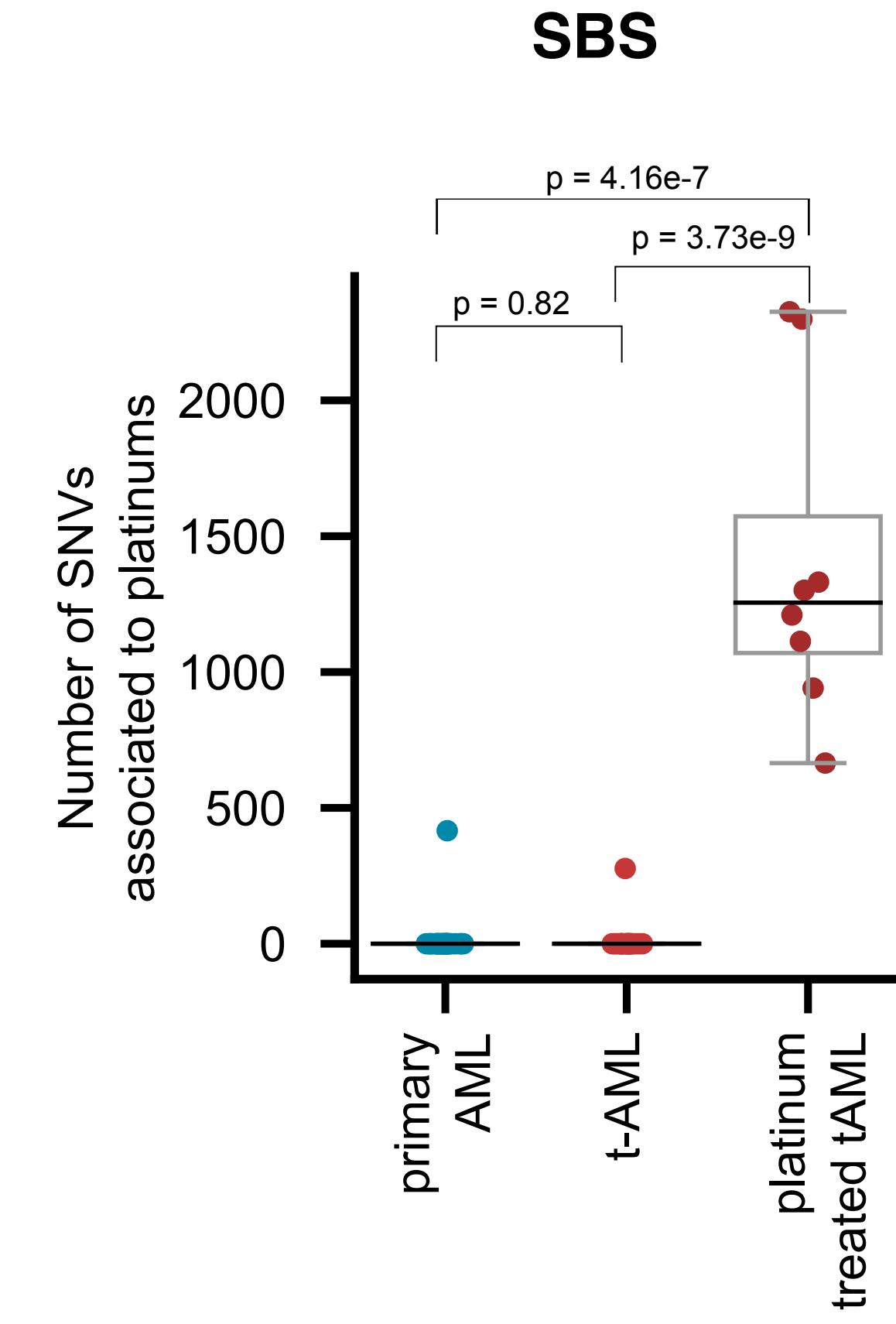
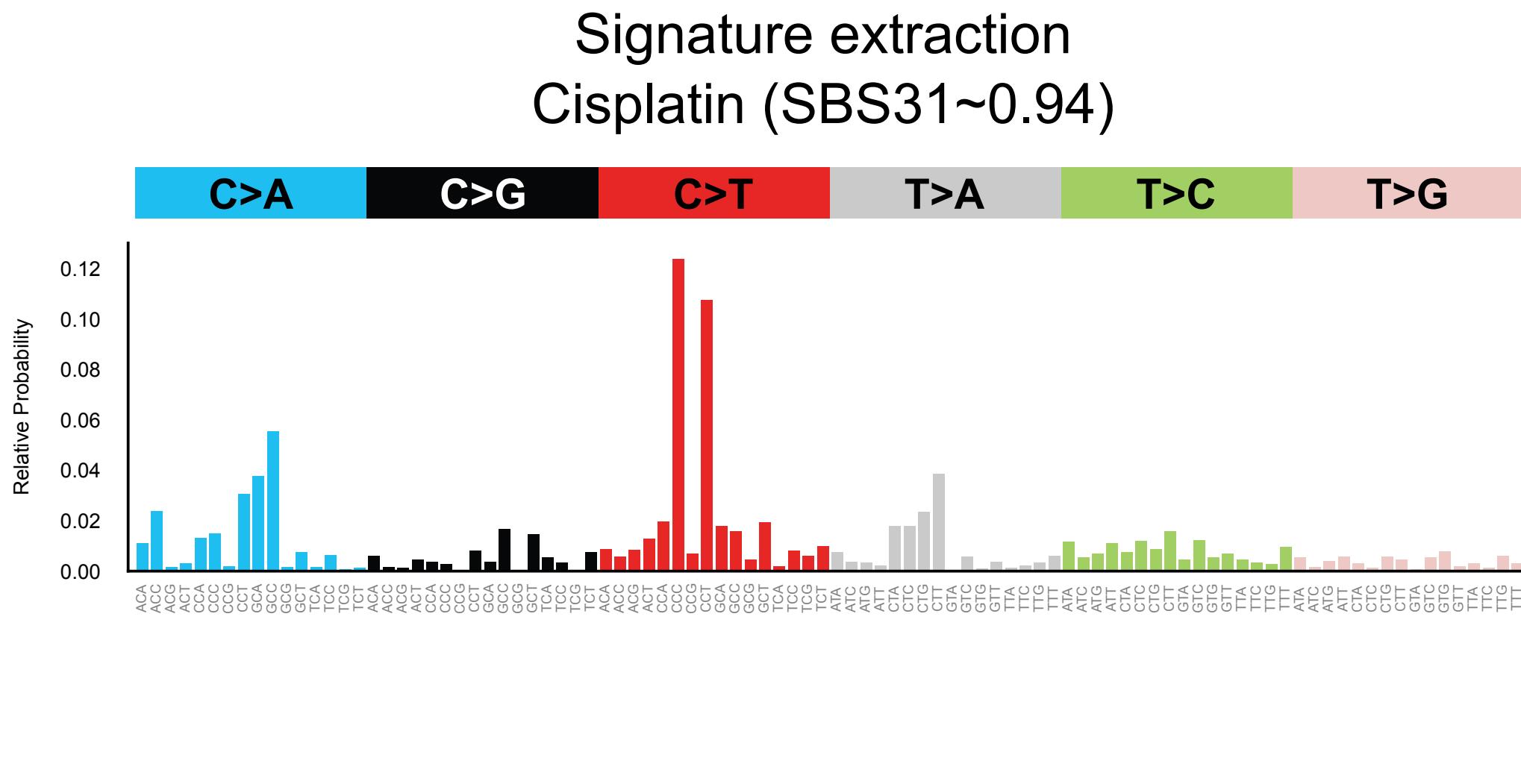


Albert Cortés  
Marta Pratcorona

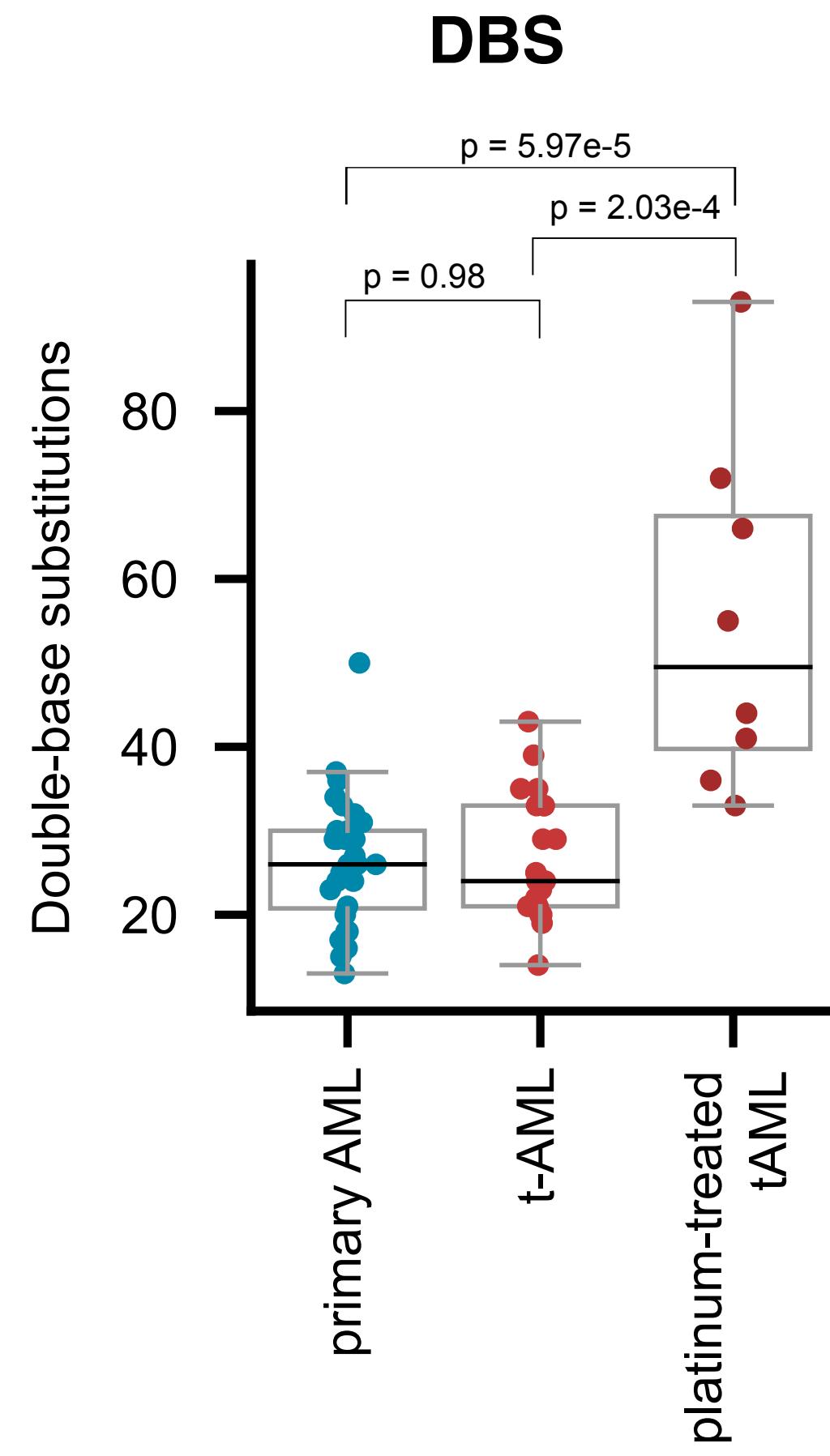
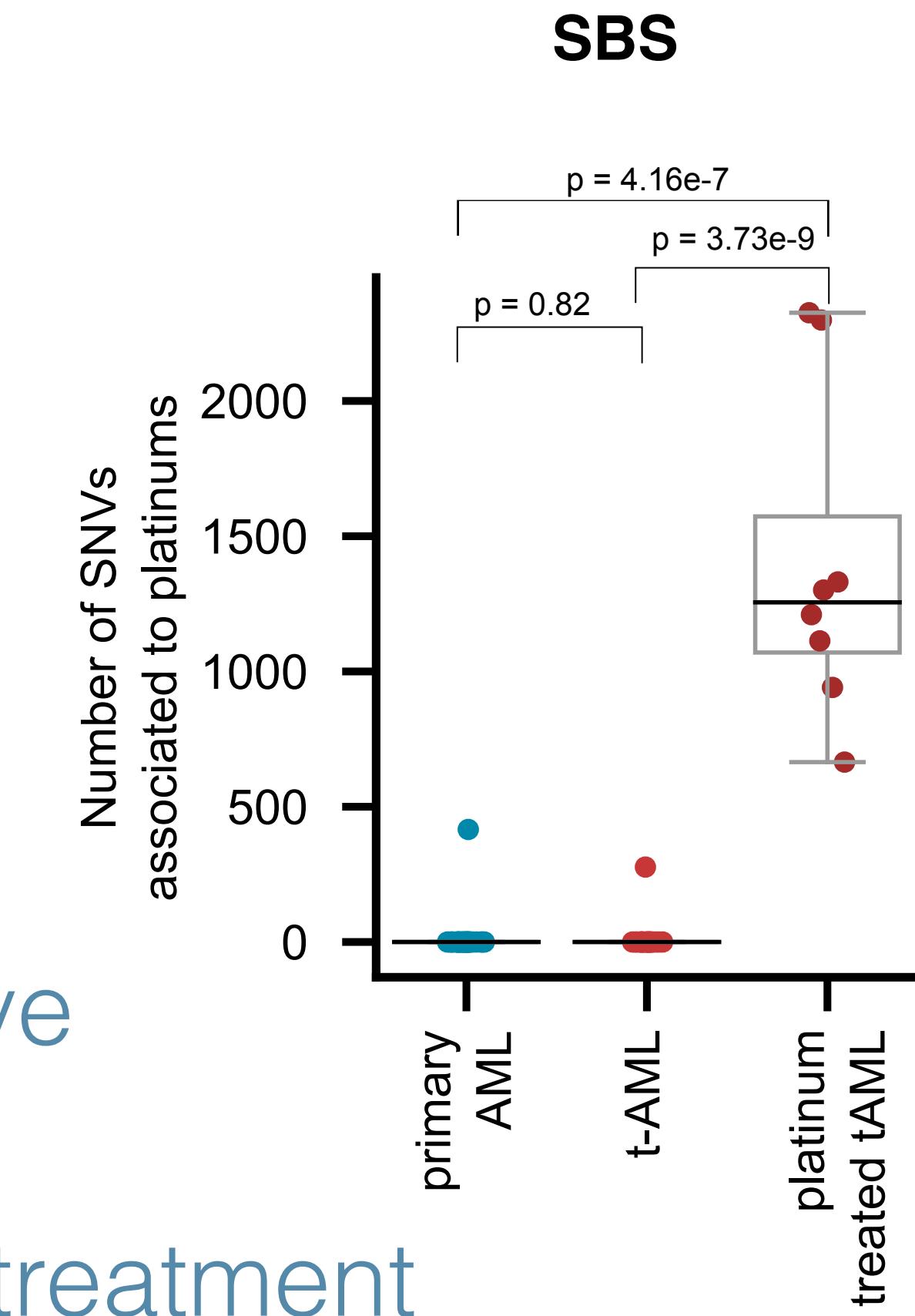
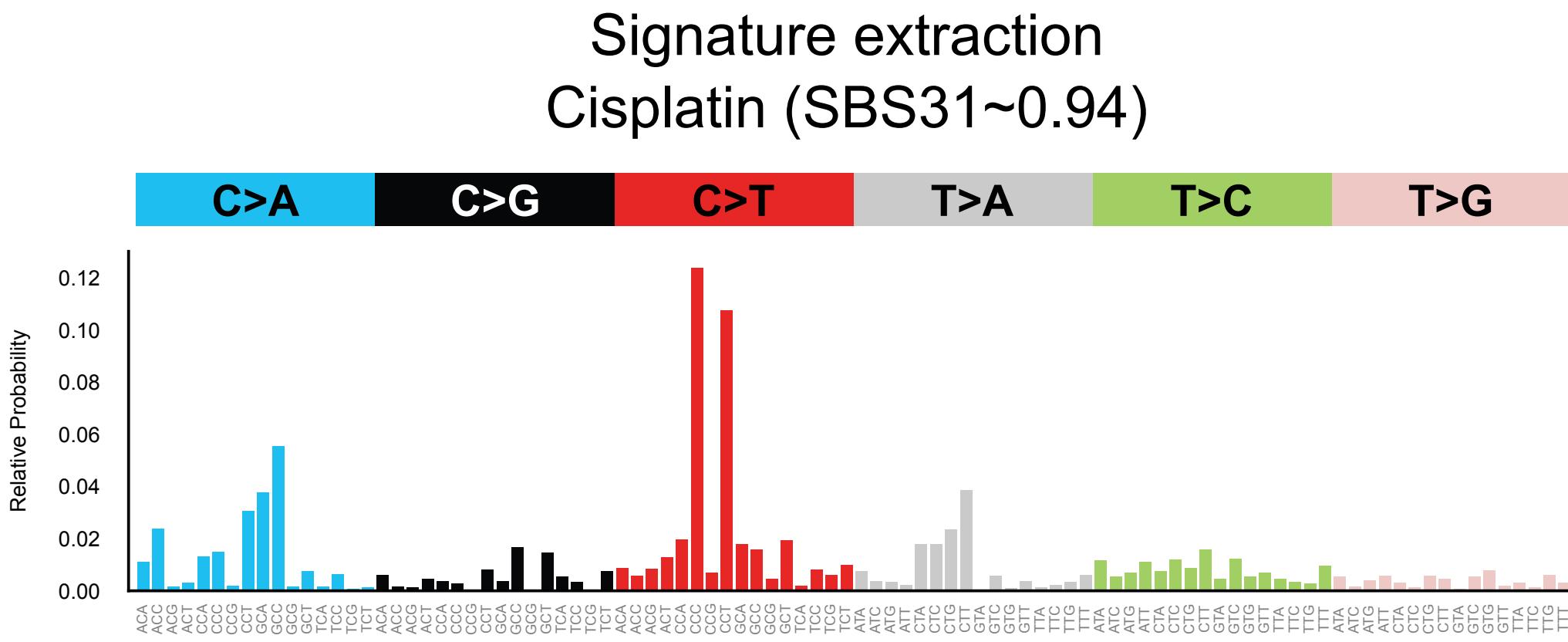


Oriol Pich Abel Gonzalez-Perez

# Platinum mutations detected as clonal in tAML

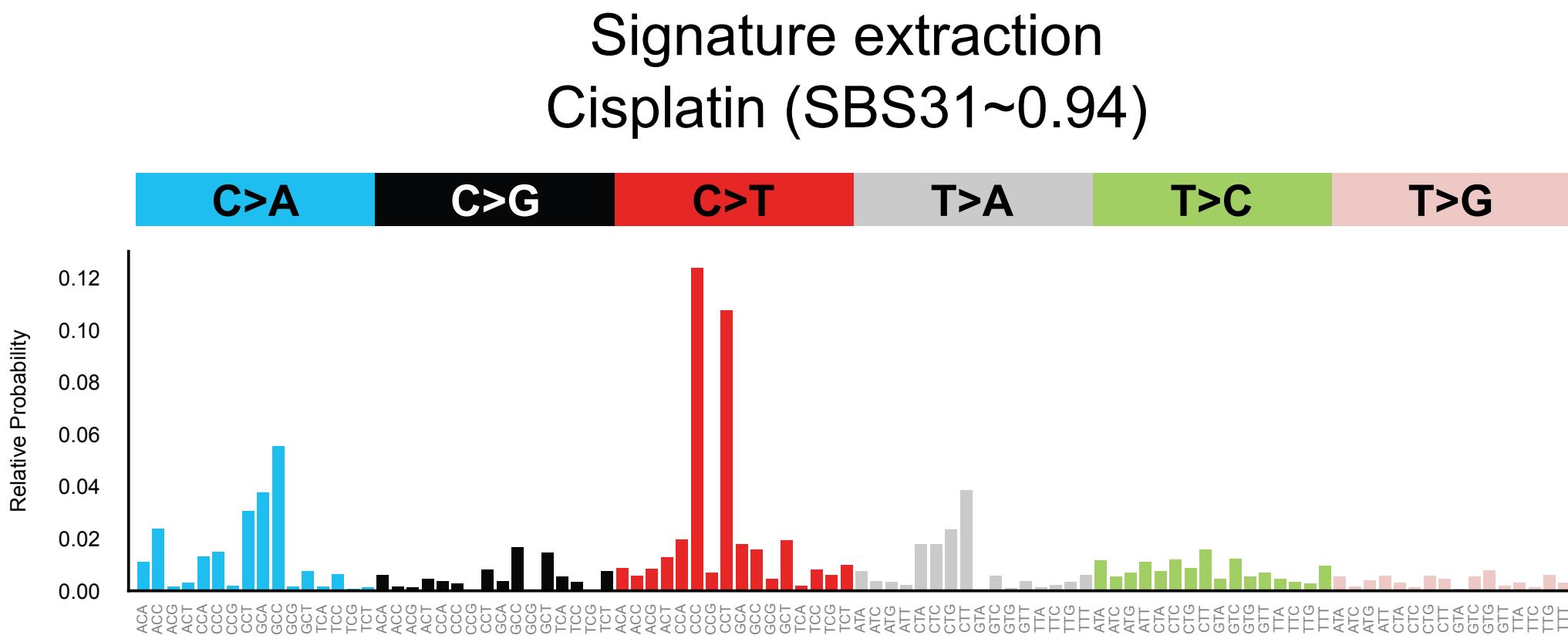


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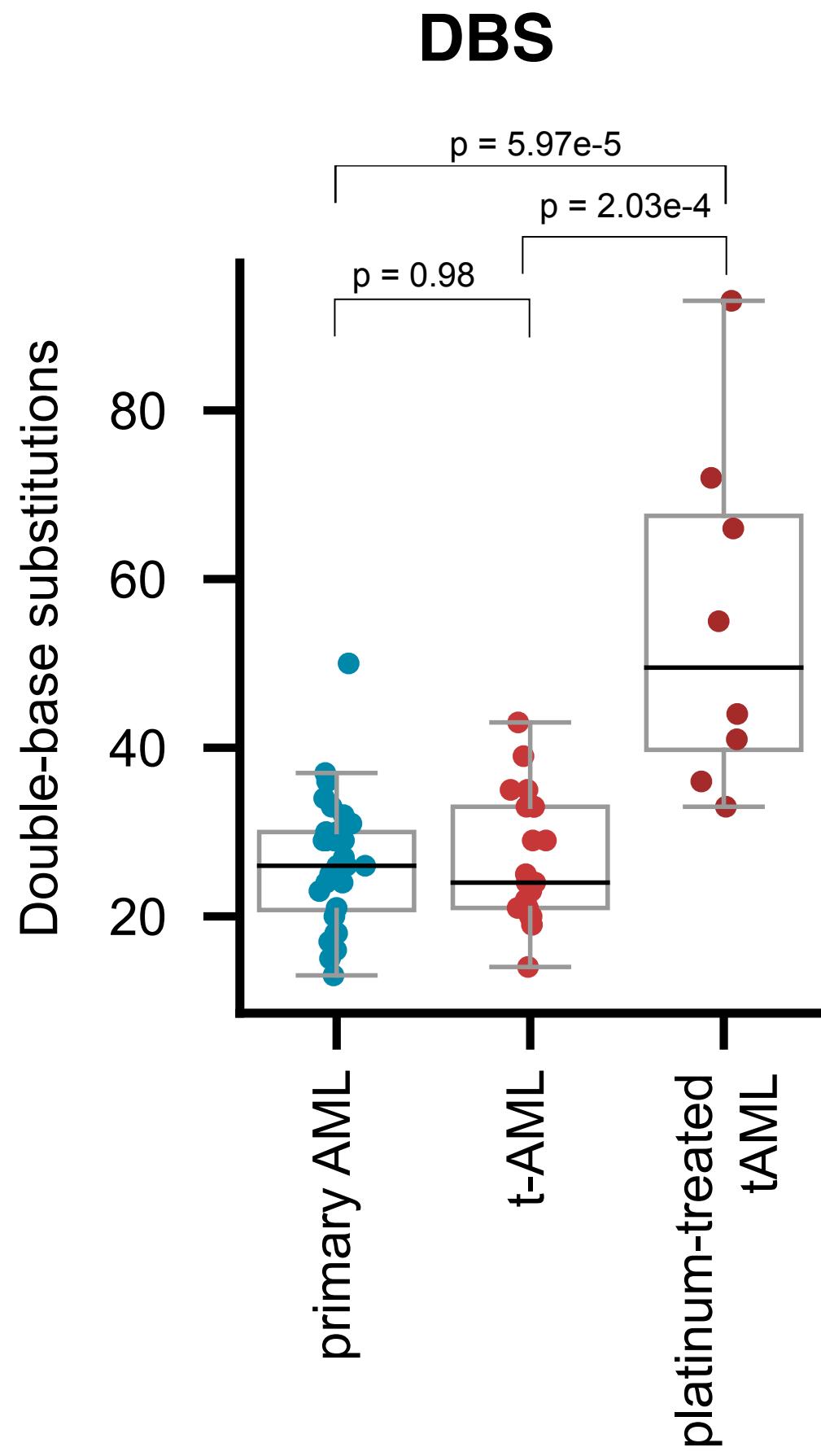
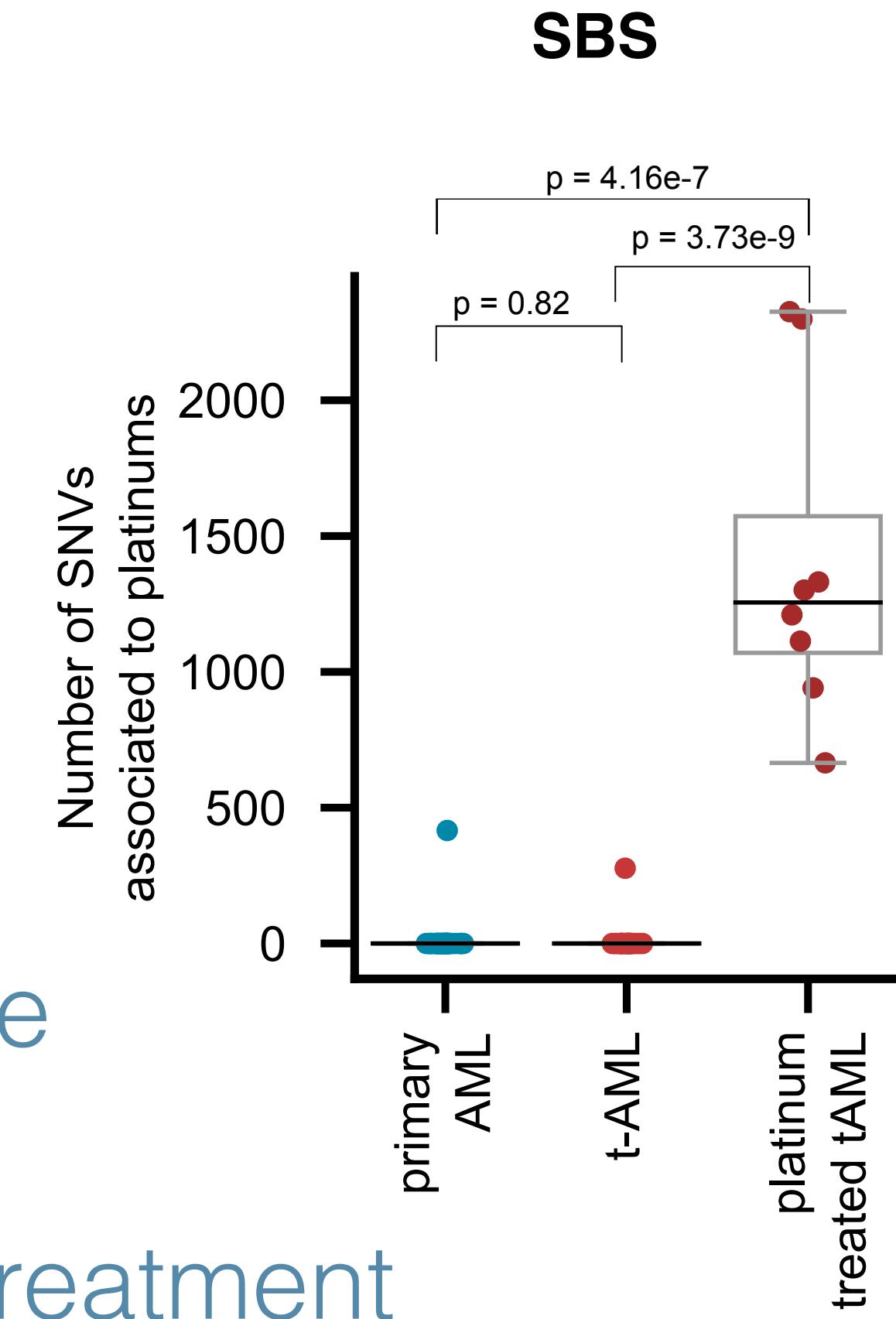


1. Healthy hematopoietic cells receive platinum mutations
2. Full clonal expansion posterior to treatment

# Platinum mutations detected as clonal in tAML

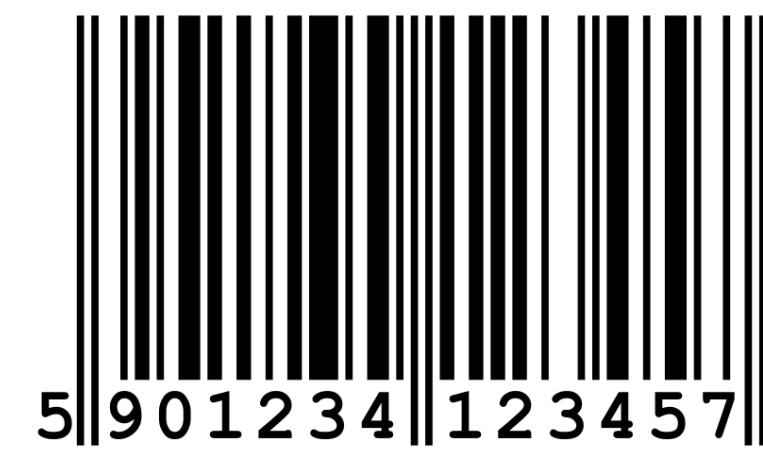


1. Healthy hematopoietic cells receive platinum mutations
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**Mutational signature of treatment as a barcode of clonal expansion**



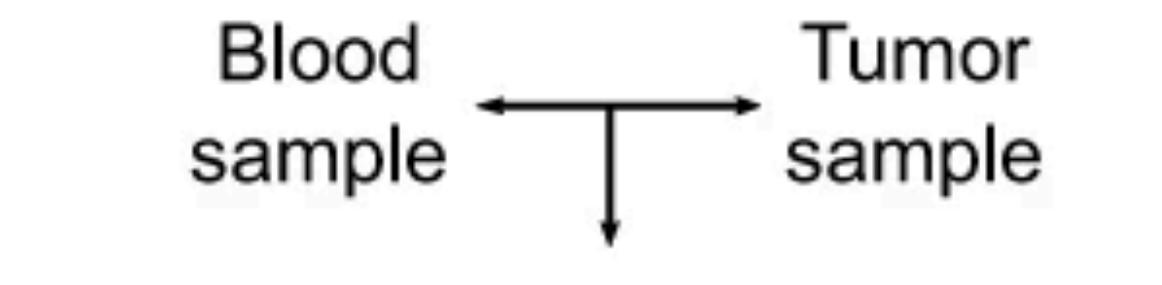


Chemotherapy mutational signatures as  
barcode to time clonal expansion before  
or after treatment

# Identifying blood somatic mutations by Reverse Mutation Calling

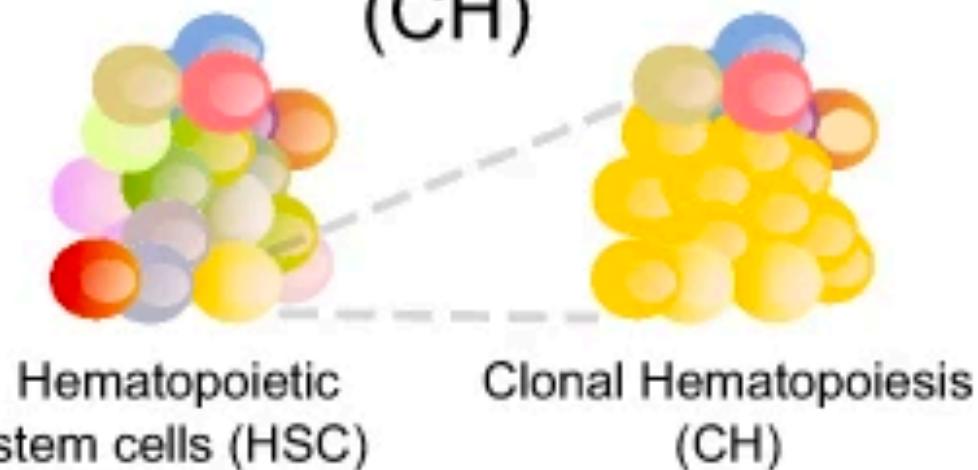


3,785 patients (metastasis cohort)  
(1,766 treated with cytotoxic therapies)



1,429,110 blood somatic mutations

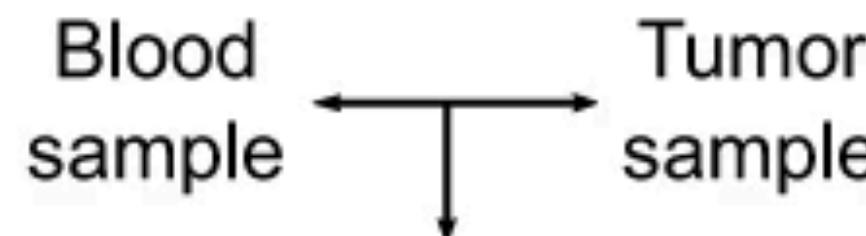
Clonal Hematopoiesis  
(CH)



# Identifying blood somatic mutations by Reverse Mutation Calling

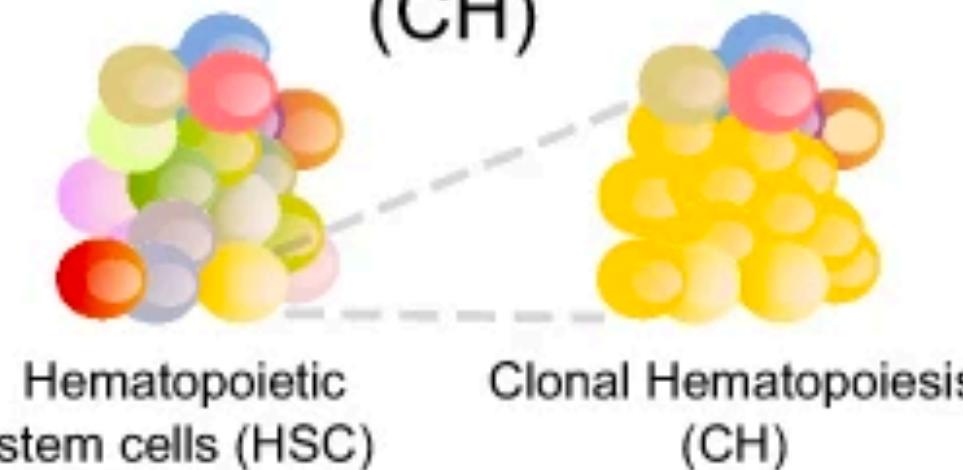


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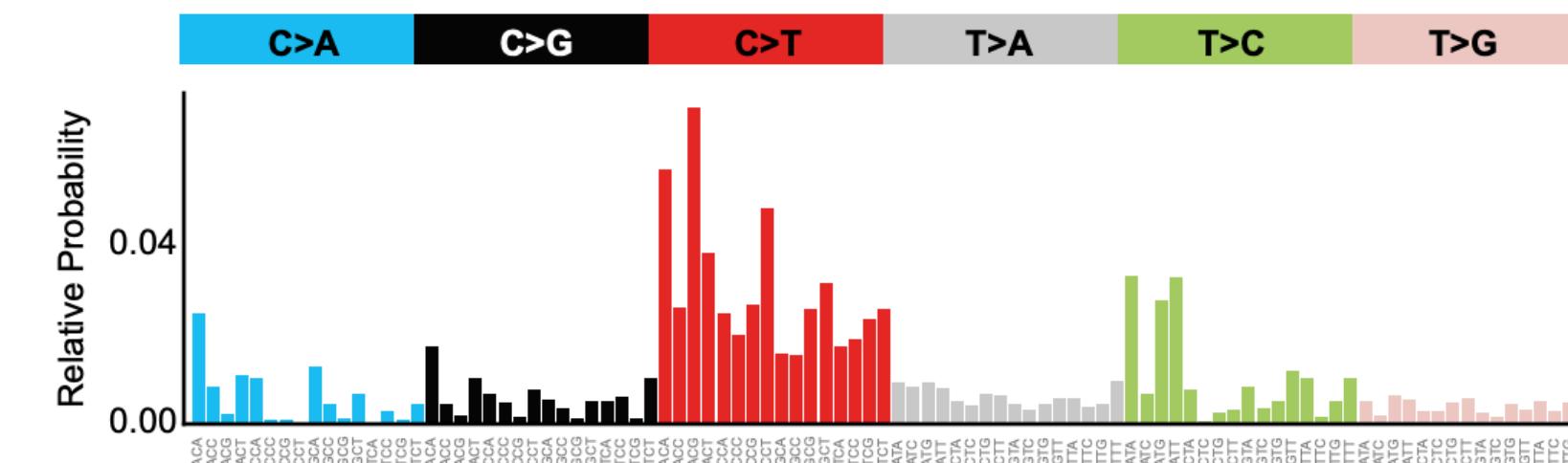
1,429,110 blood somatic mutations

↓  
Clonal Hematopoiesis (CH)



## We find HSC signature

Hematopoietic stem cell (HSC) signature  
in healthy blood (cos similarity = 0.96)



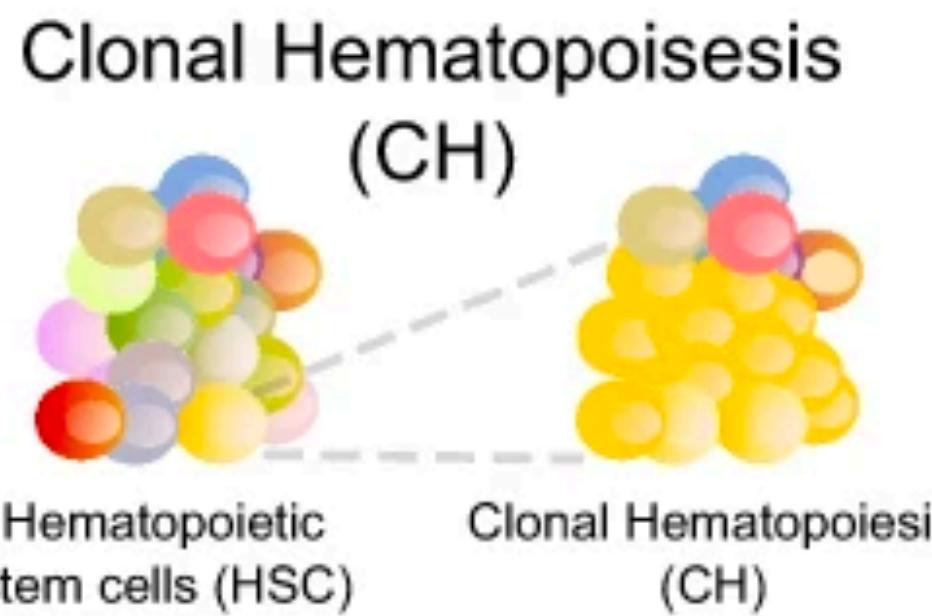
# Identifying blood somatic mutations by Reverse Mutation Calling



3,785 patients (metastasis cohort)  
(1,766 treated with cytotoxic therapies)

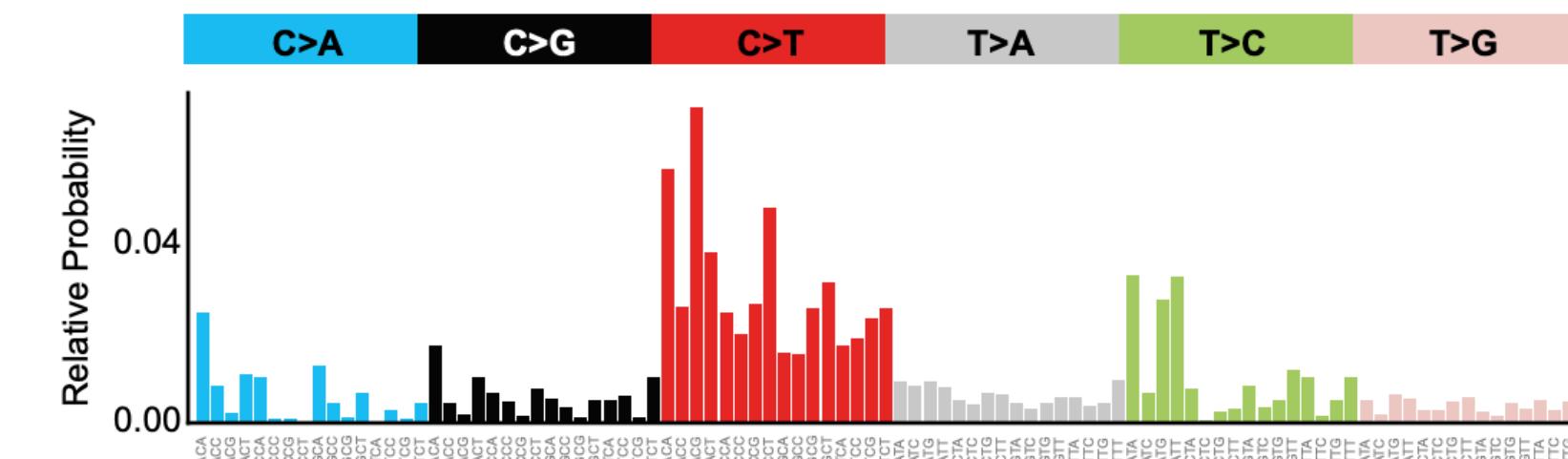


1,429,110 blood somatic mutations



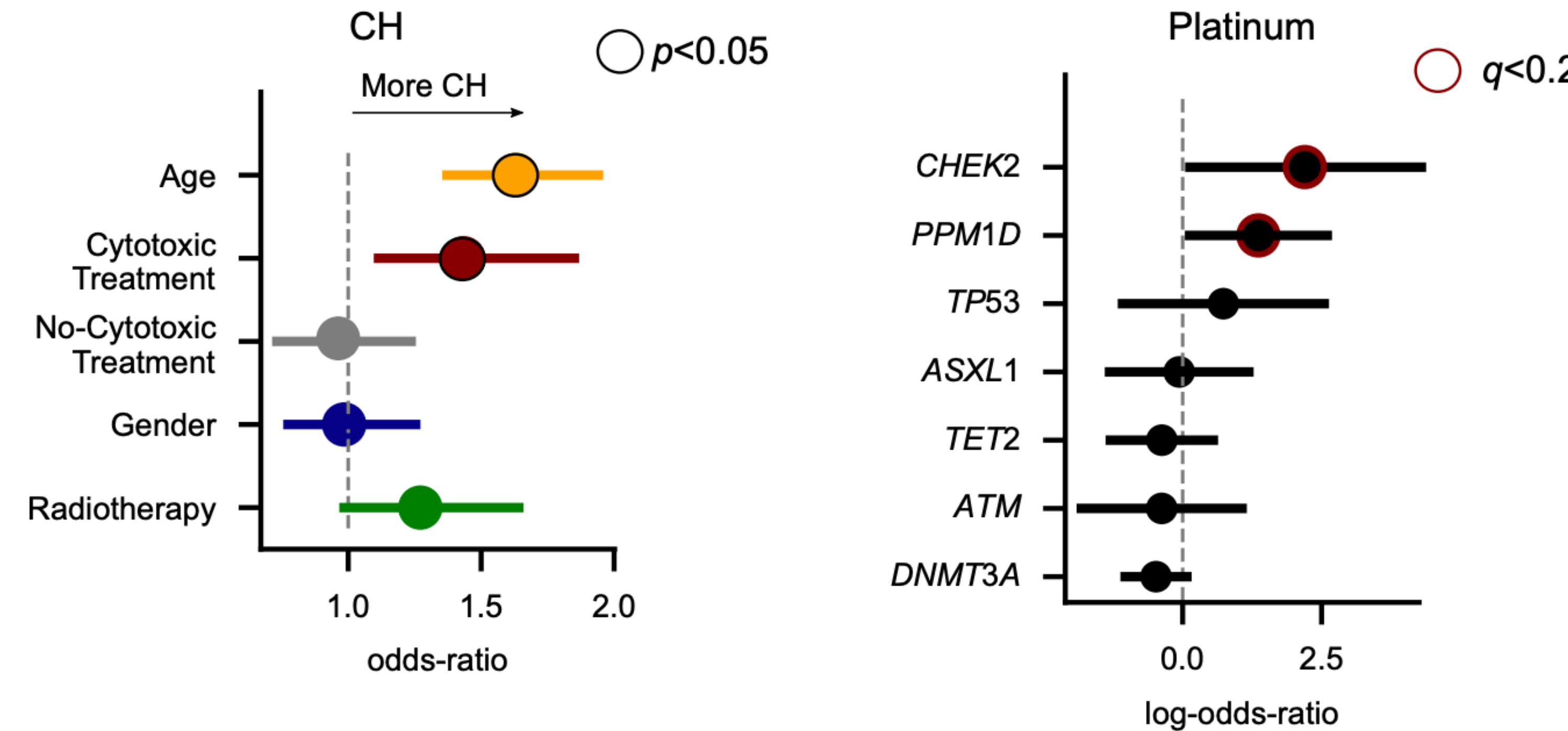
## We find HSC signature

Hematopoietic stem cell (HSC) signature  
in healthy blood (cos similarity = 0.96)

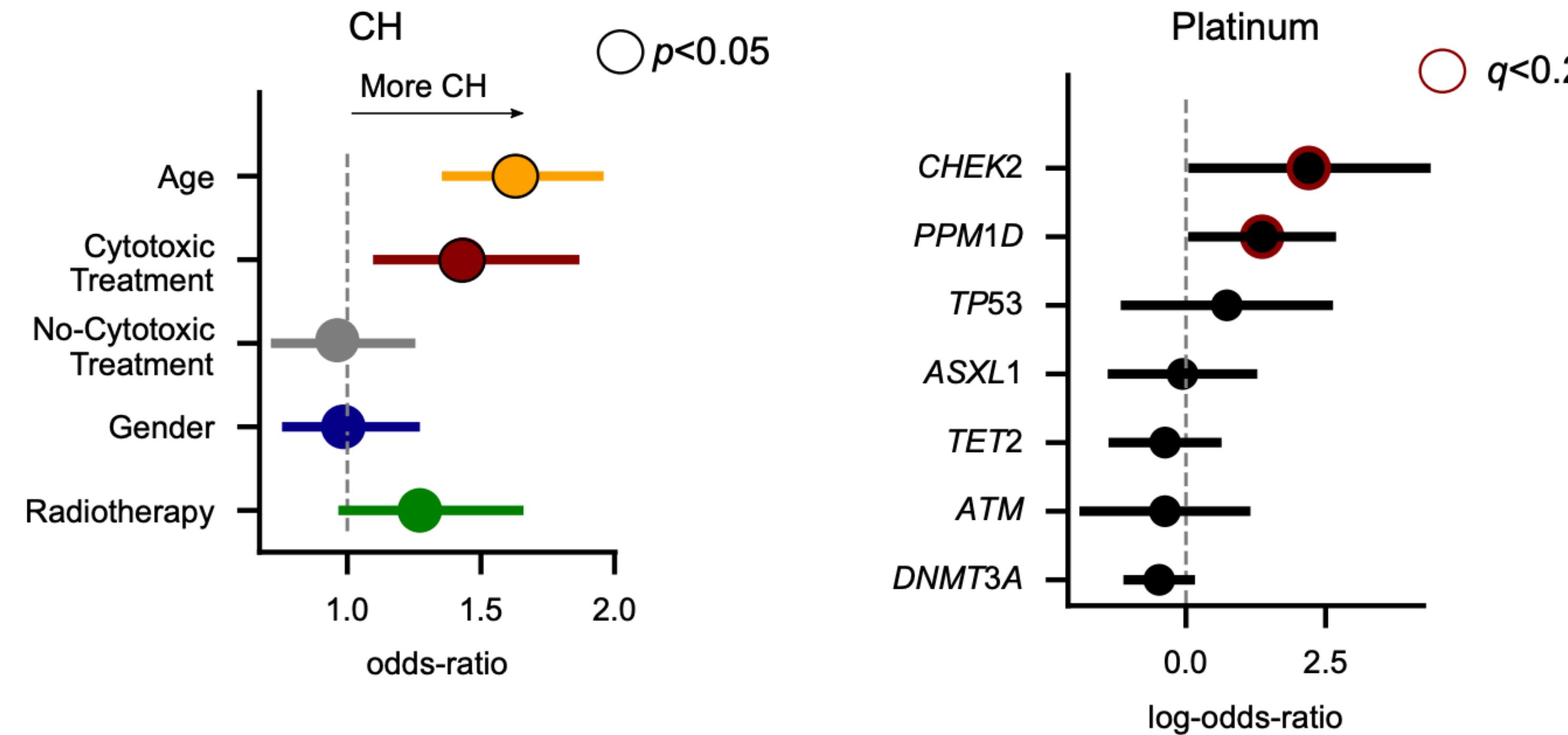


## In contrast we do not find the chemotherapy mutational signatures

# Chemotherapy is associated with clonal hematopoiesis with preference for mutations in certain genes

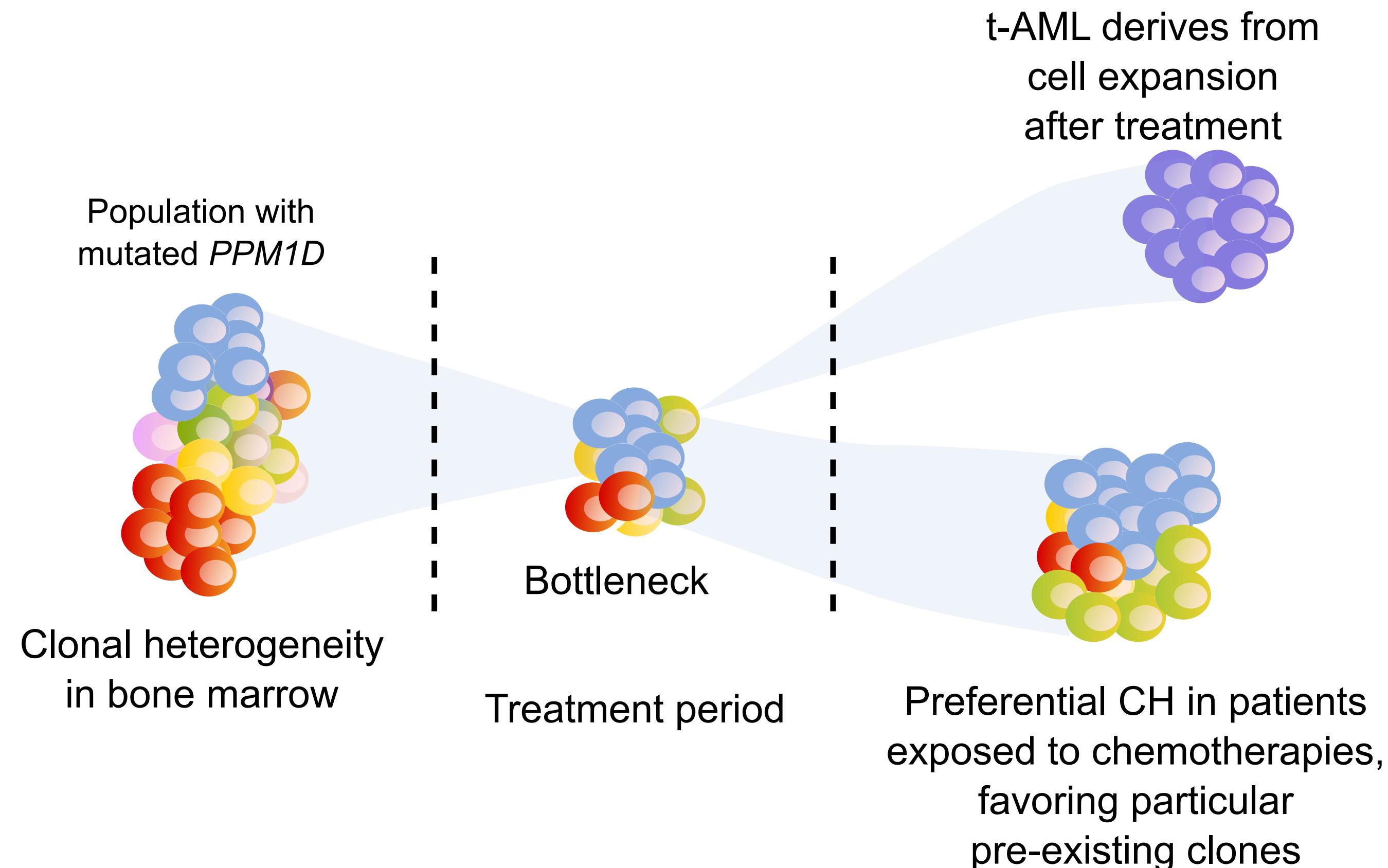


# Chemotherapy is associated with clonal hematopoiesis with preference for mutations in certain genes



Chemotherapy selects preexisting clones with specific mutations

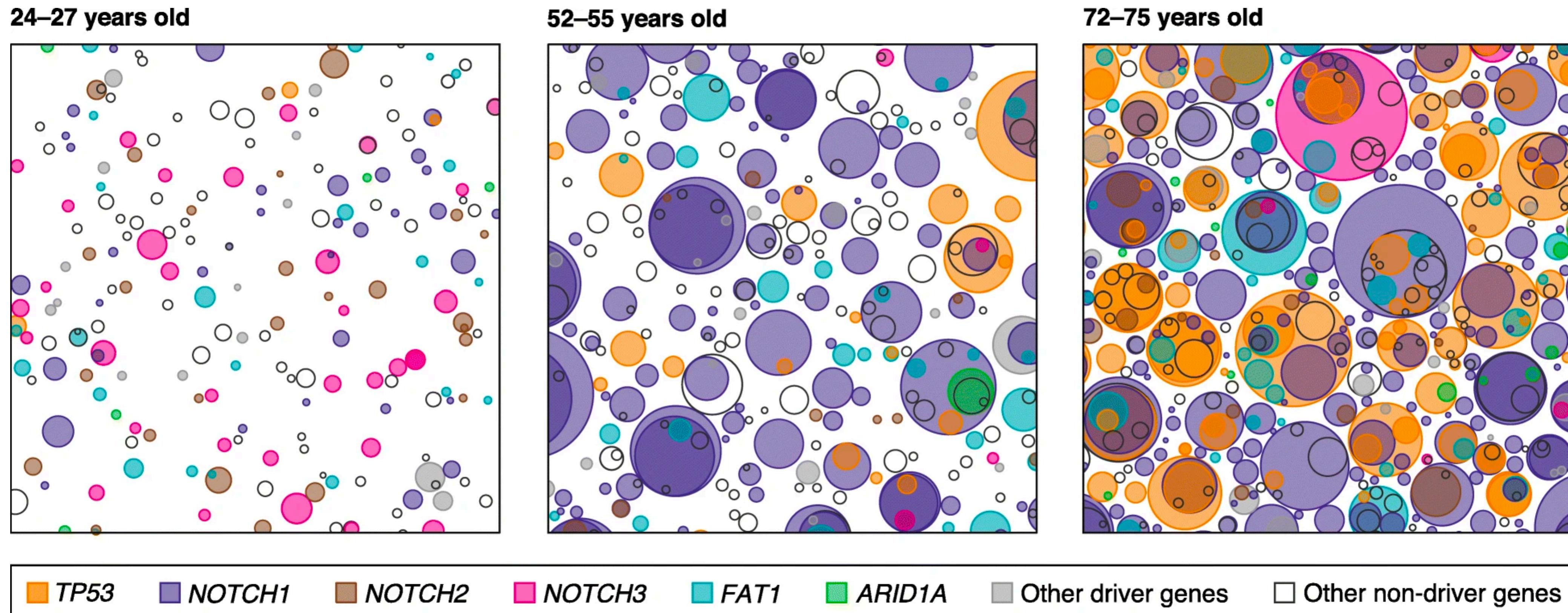
# Evolution of hematopoietic cells under cancer therapy



- Identifying Cancer Drivers
- Understanding Neutral Mutagenesis
- Identifying Clonal Hematopoiesis Drivers
- Chemotherapy effect in hematopoiesis
- Cancer Promotion

# Driver mutations are necessary

# Driver mutations are necessary but not sufficient



Mutant cell colonization of healthy esophageal epithelium with age

Martincorena Genome Biology 2019  
Martincorena et al., Science 2015  
Martincorena et al., Science 2018

Driver mutations and clonal expansions in normal tissue

# Many carcinogens are not mutagens

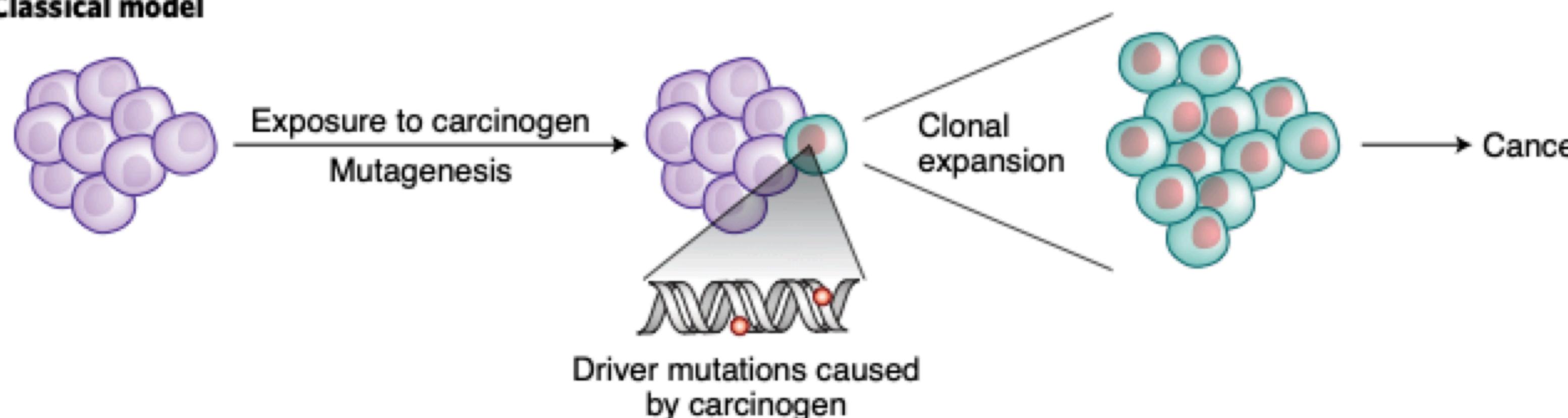


## The mutational signature profile of known and suspected human carcinogens in mice

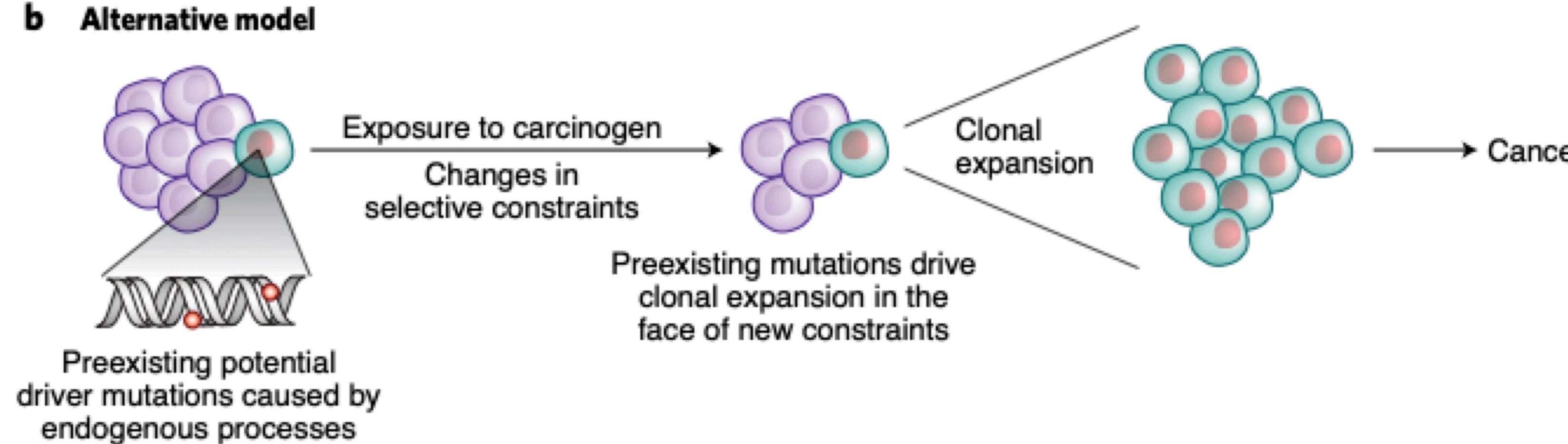
Laura Riva<sup>1,5</sup>, Arun R. Pandiri<sup>2,5</sup>, Yun Rose Li<sup>3,5</sup>, Alastair Droop<sup>1</sup>, James Hewinson<sup>1</sup>, Michael A. Quail<sup>1</sup>, Vivek Iyer<sup>1</sup>, Rebecca Shepherd<sup>1</sup>, Ronald A. Herbert<sup>2</sup>, Peter J. Campbell<sup>1,5</sup>, Robert C. Sills<sup>2</sup>, Ludmil B. Alexandrov<sup>3,4</sup>, Allan Balmain<sup>3,6</sup>✉ and David J. Adams<sup>1,6</sup>✉

# Many carcinogens are not mutagens

## a Classical model



## b Alternative model



Abel Gonzalez-Perez



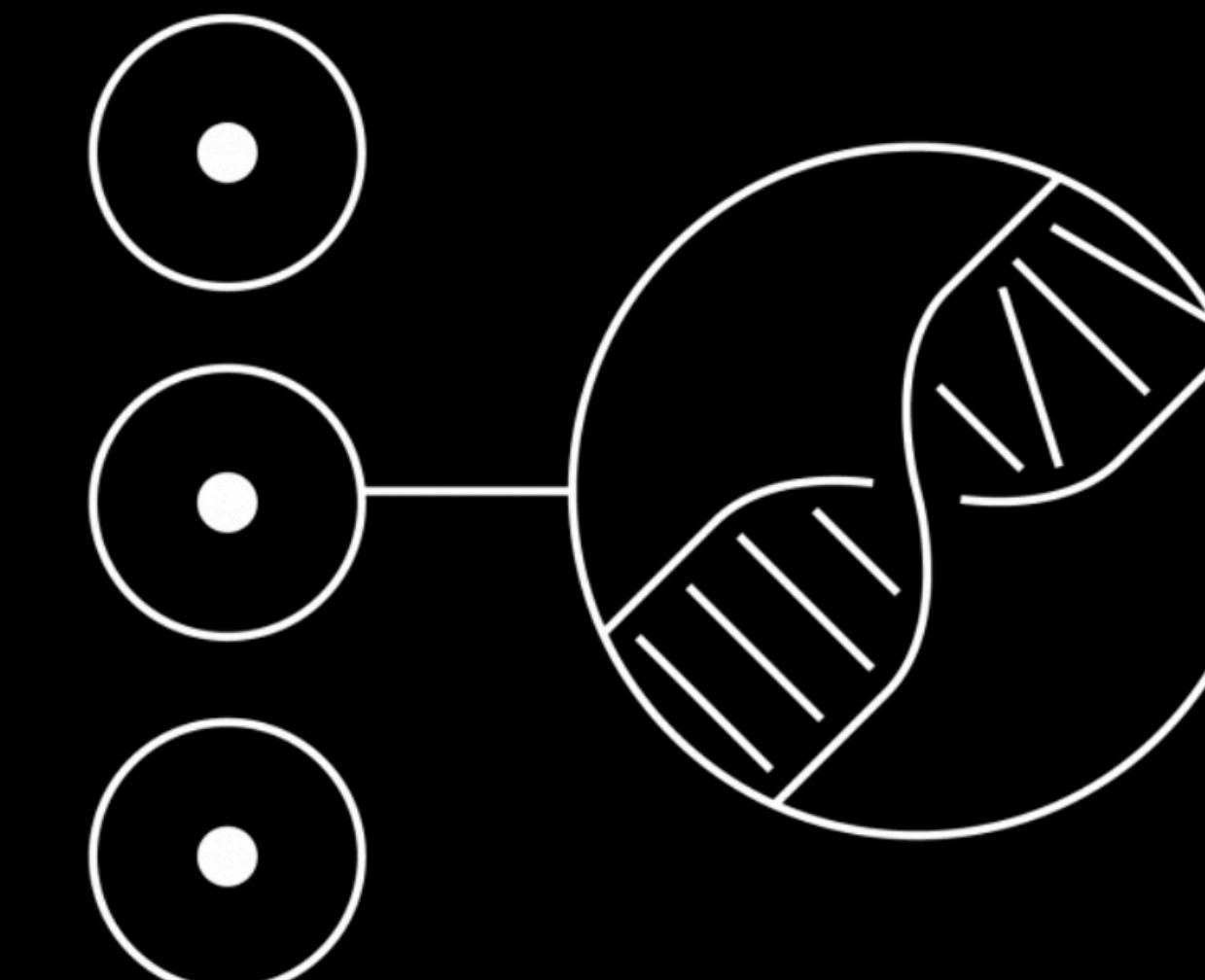
## Driving progress through unprecedented collaboration

Cancer Grand Challenges is a global funding initiative founded by Cancer Research UK and the National Cancer Institute. We set ambitious challenges, providing diverse, global teams with £20m to come together, think differently, with the aim to make the progress against cancer the world urgently needs.

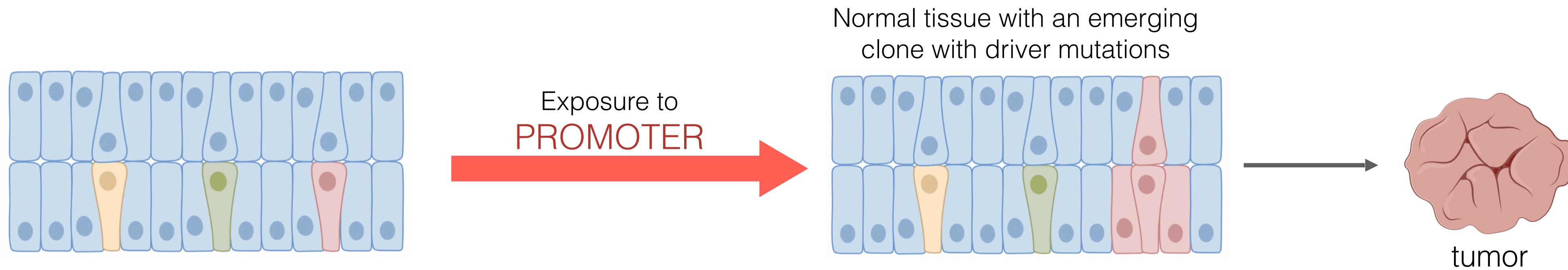
### Normal phenotypes

#### CHALLENGE:

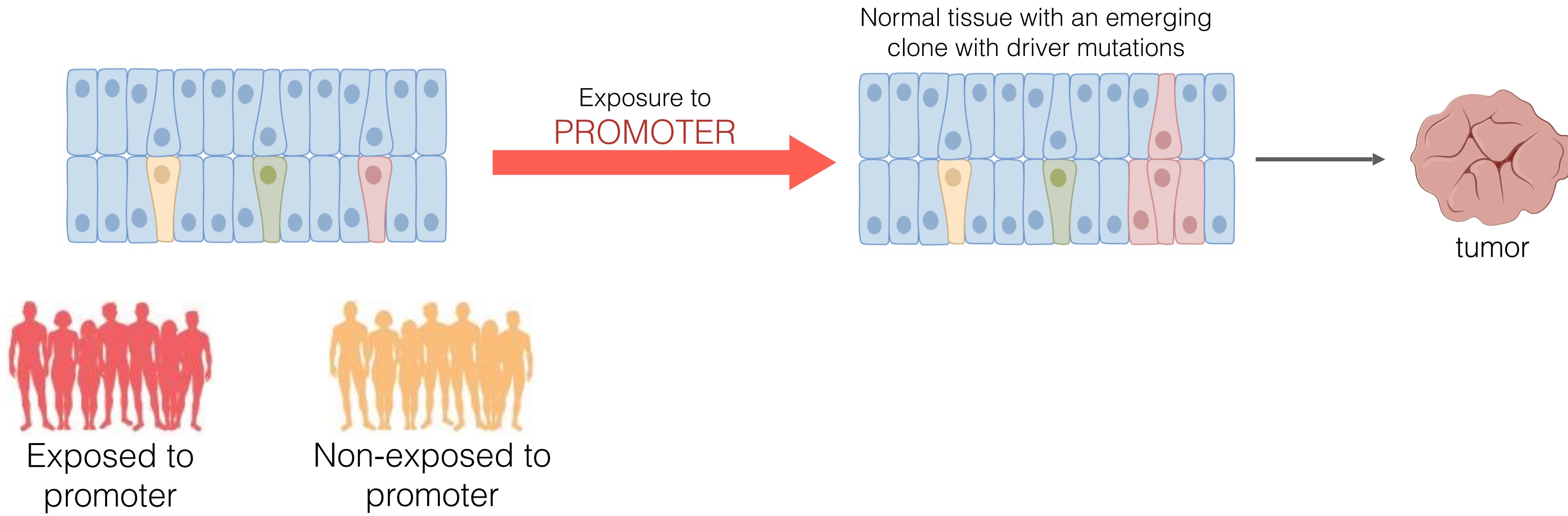
**Understand how cells and tissues maintain “normal” phenotypes whilst harbouring oncogenic mutations and how they transition to become a tumour**



# How does exposure to promoters change the normal tissue to eventually lead to cancer?

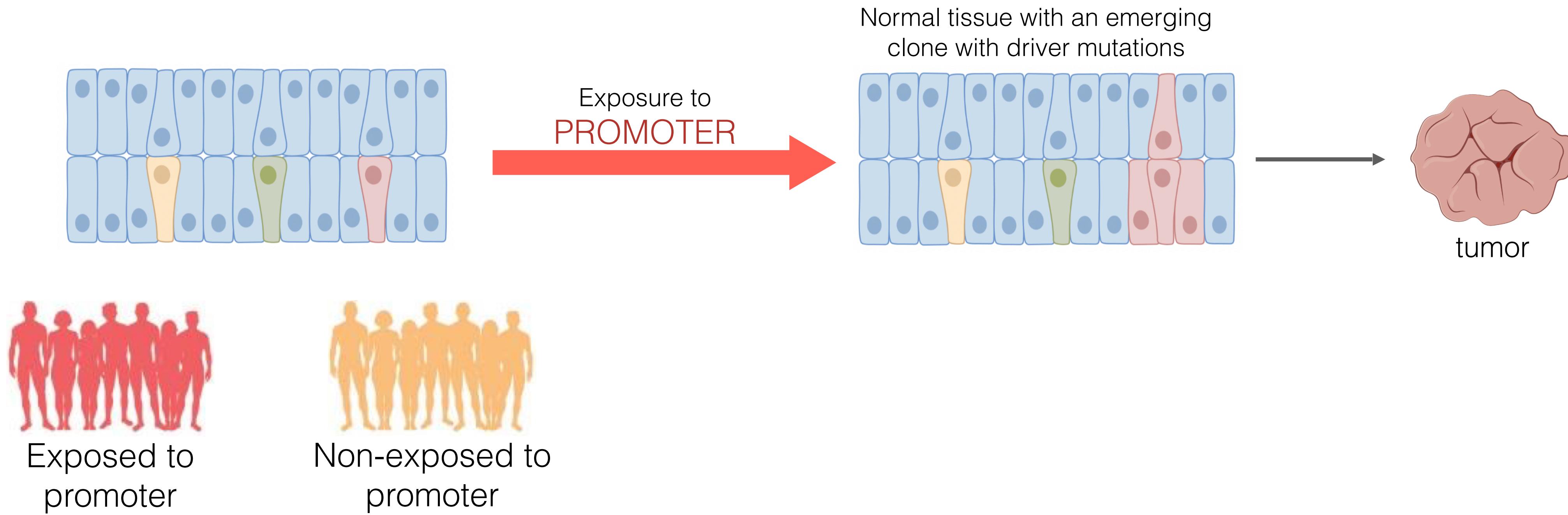


# How does exposure to promoters change the normal tissue to eventually lead to cancer?



Detect emerging clones with driver mutations in normal tissue of individuals exposed and non-exposed to a promoter

# How does exposure to promoters change the normal tissue to eventually lead to cancer?



Detect emerging clones with driver mutations in normal tissue of individuals exposed and non-exposed to a promoter

- Deep mutagenesis to identify emerging clones
- Single cell profiling with clone genotyping
- Spatial proteomics/transcriptomics with in situ mutation detection



## Two stage model of carcinogenesis Initiation + Promotion

Berenblum and Shubik, 1947

*“...the initiating process represents a sudden and irreversible change in a small minority of the cells of the treated area, giving rise to isolated “latent tumour cells” ....*

*“The presence of these latent tumour cells is only demonstrable by subsequent promoting action, which converts them into morphological tumours.”*



# PROMINENT TEAM

## Co-Leaders:



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**Emma LUNDBERG**



**Chris COUNTER**



# Thanks to:

Those who did the work



Those who generate and share data



And many others

Funding agencies

