

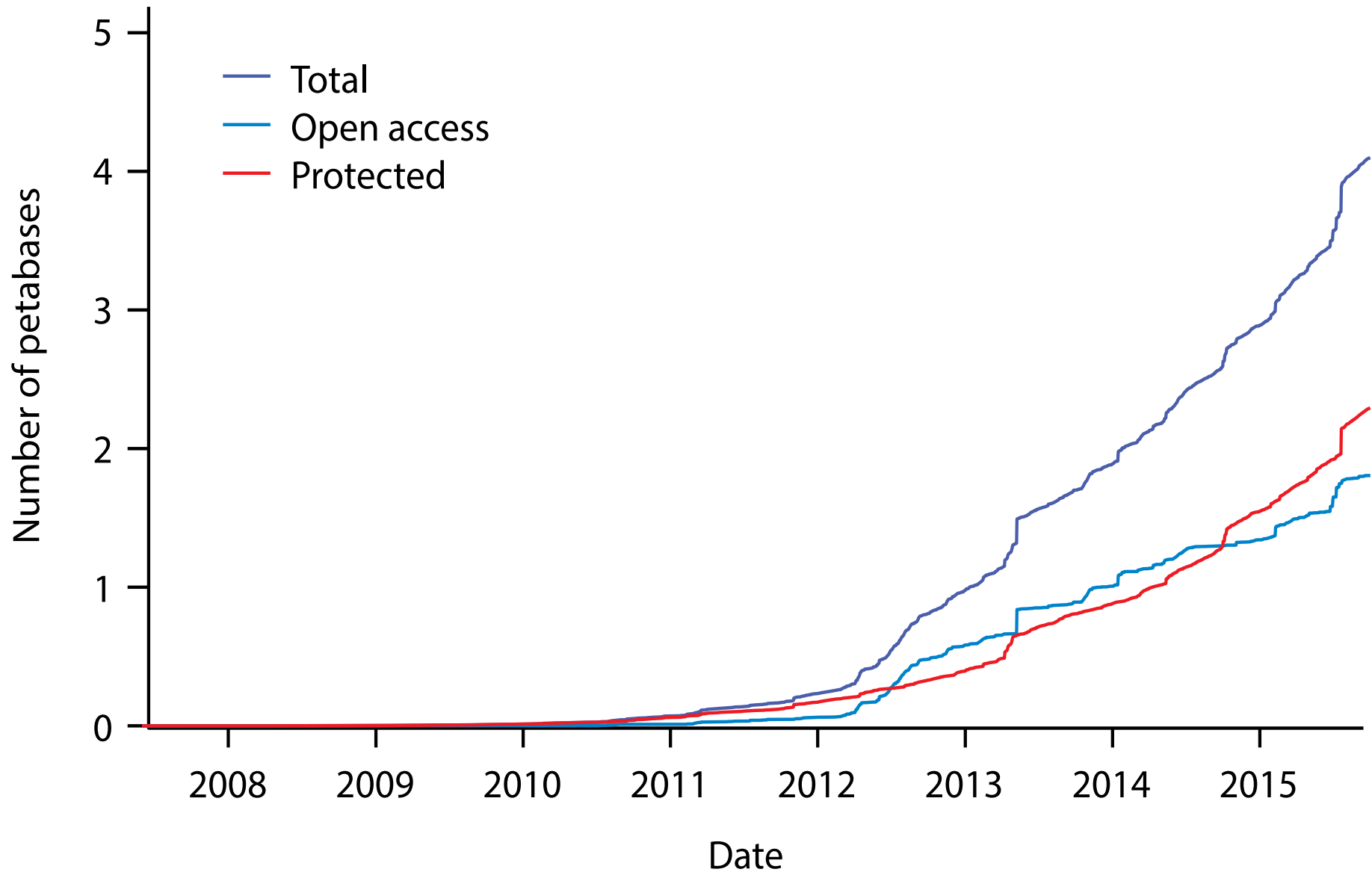
Personal Genomics: Prioritizing High-impact Rare & Somatic Variants



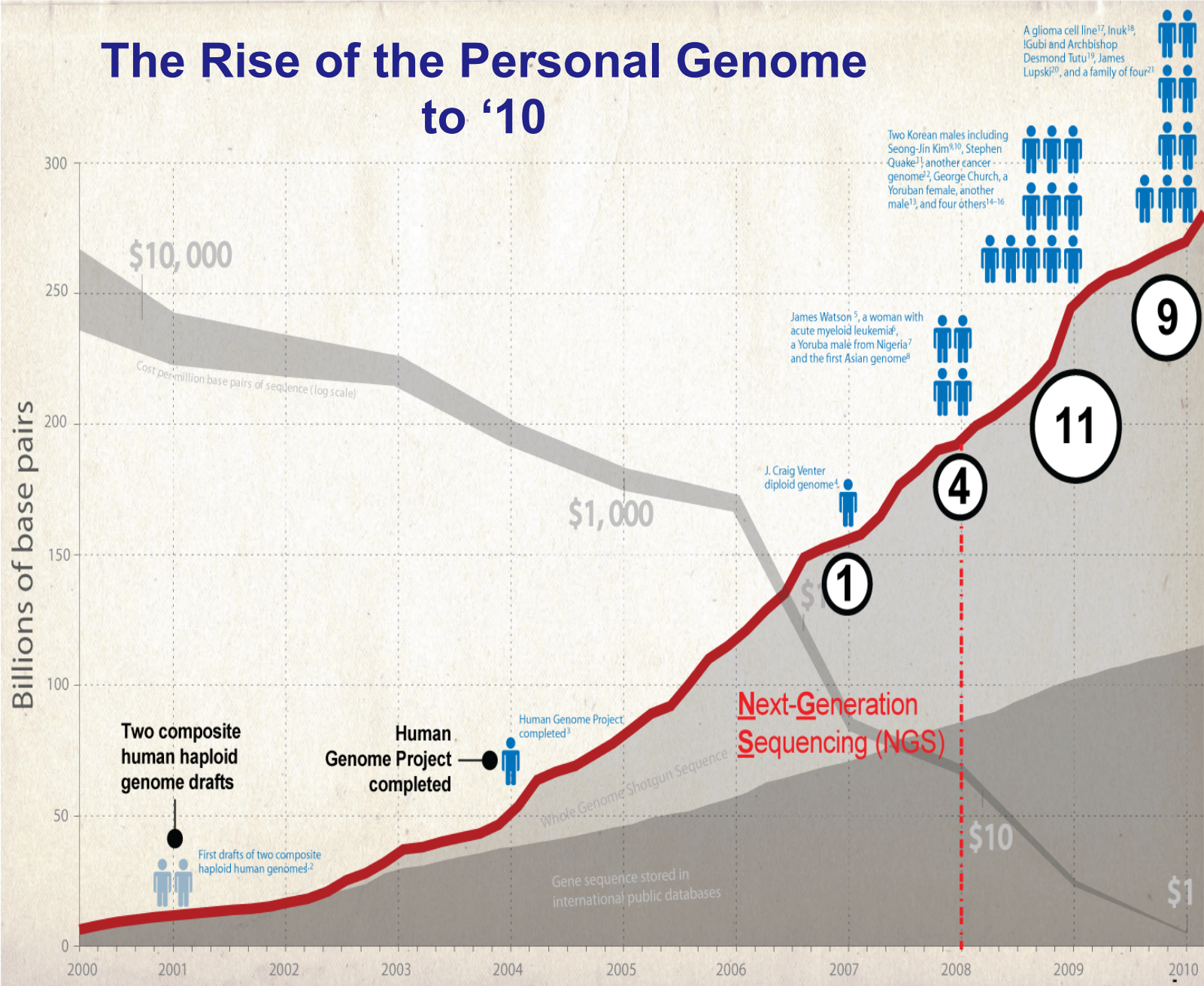
Mark Gerstein, Yale

Slides freely downloadable from Lectures.GersteinLab.org
& “tweetable” (via [@markgerstein](https://twitter.com/markgerstein)). See last slide for more info.

Increase in number of bases in SRA, Peta-scale after '10

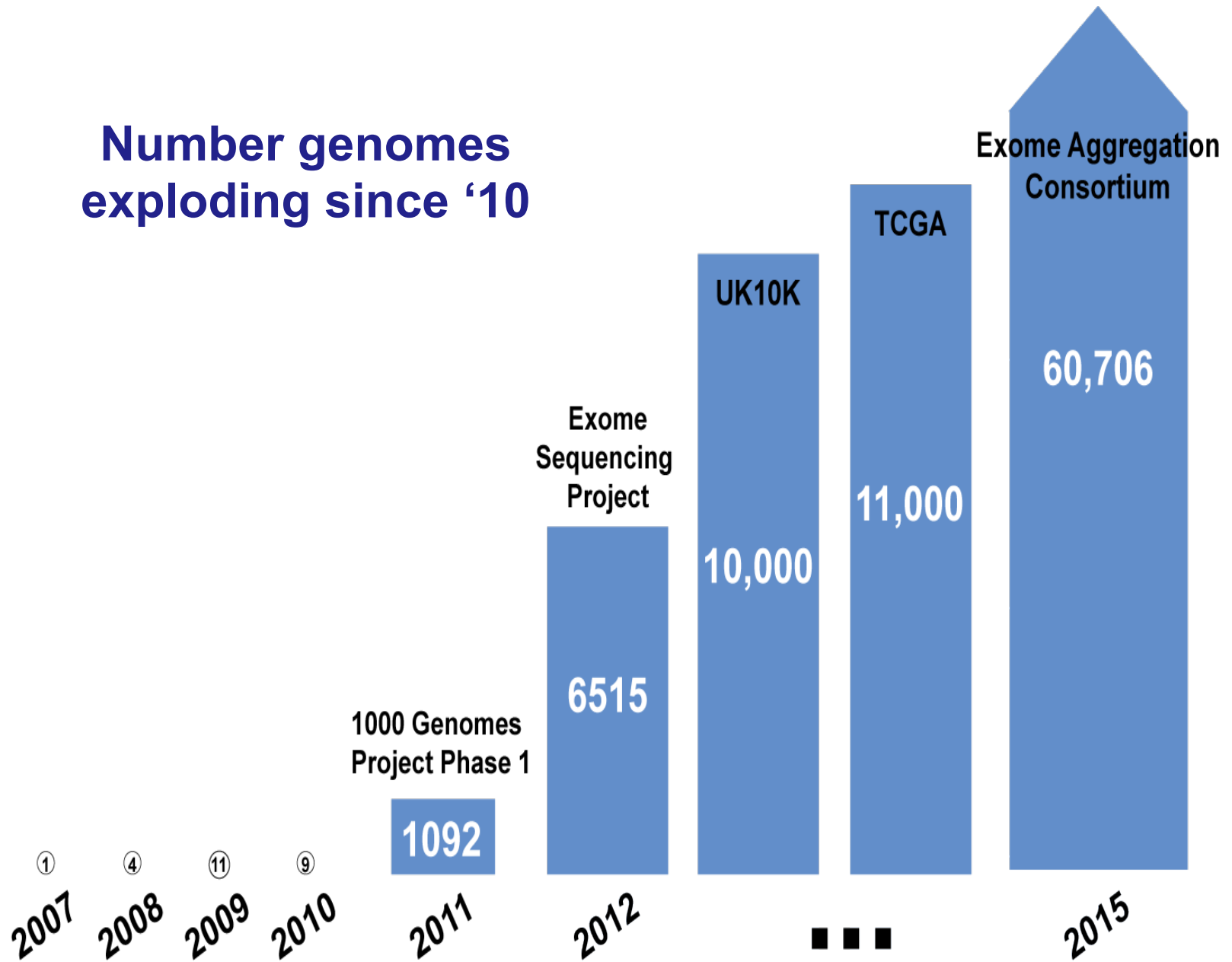


The Rise of the Personal Genome to '10



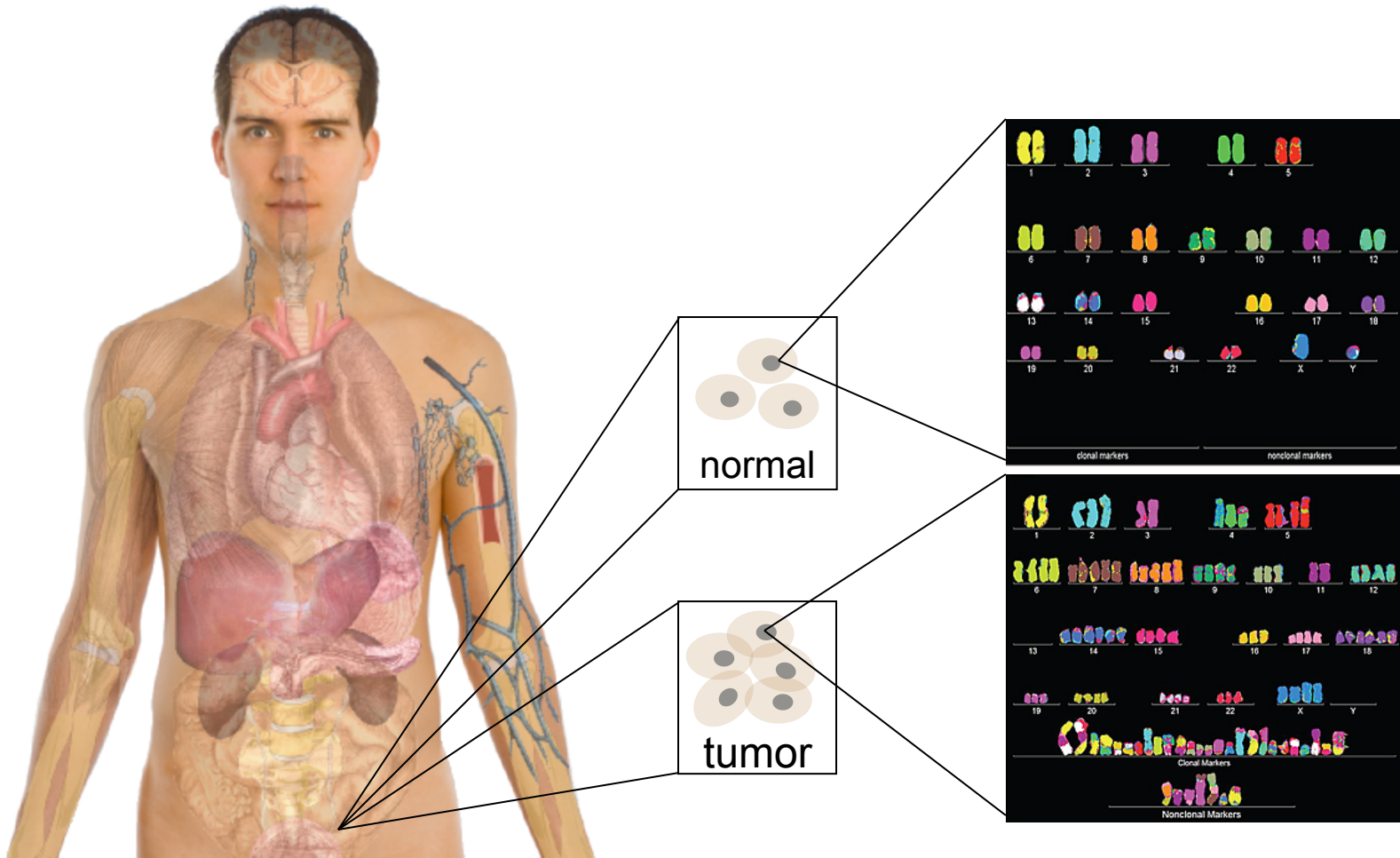
Adapted from *Nature* 2010

Number genomes exploding since '10



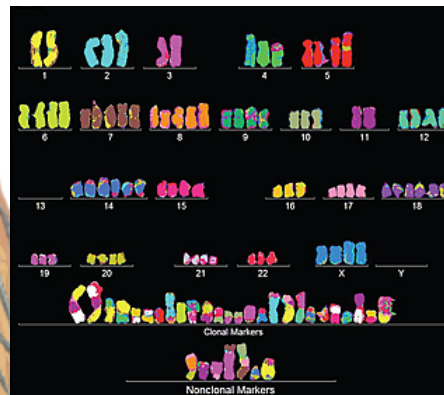
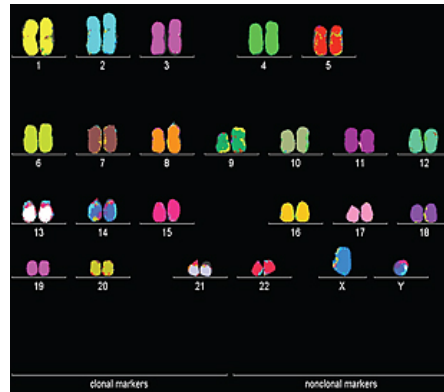
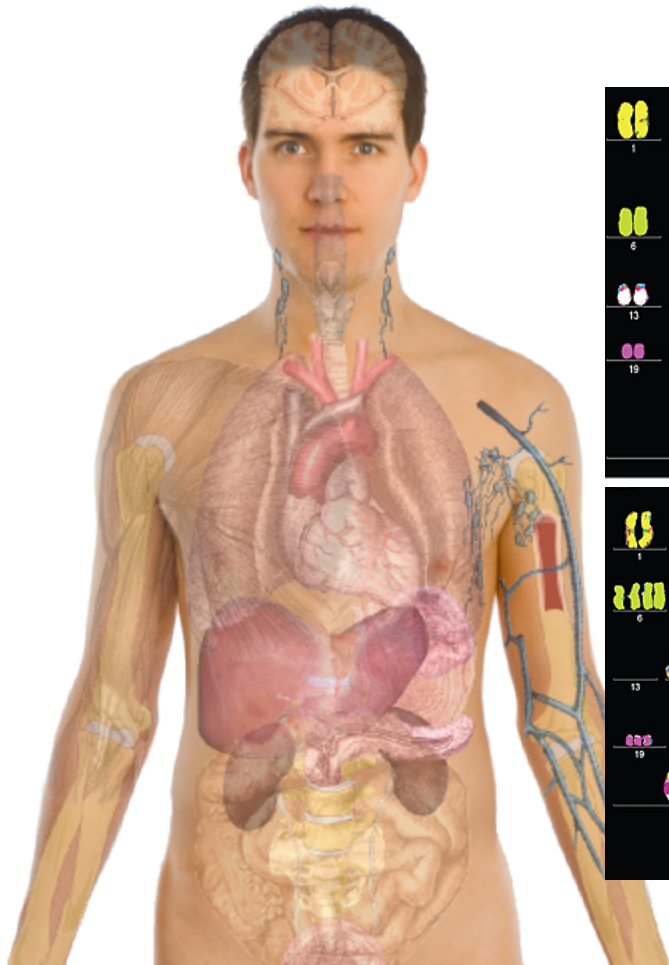
Personal Genomics as a Gateway into Biology

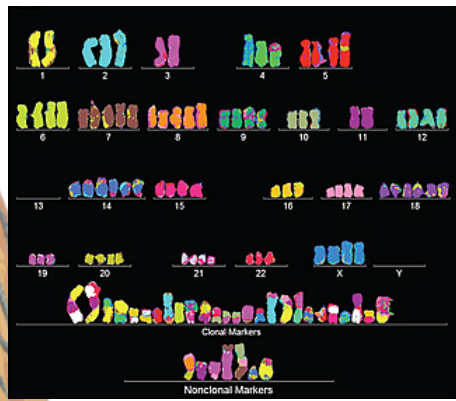
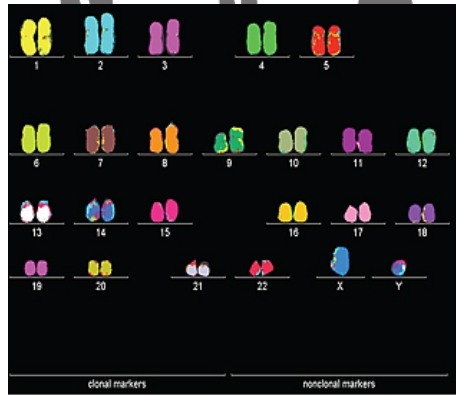
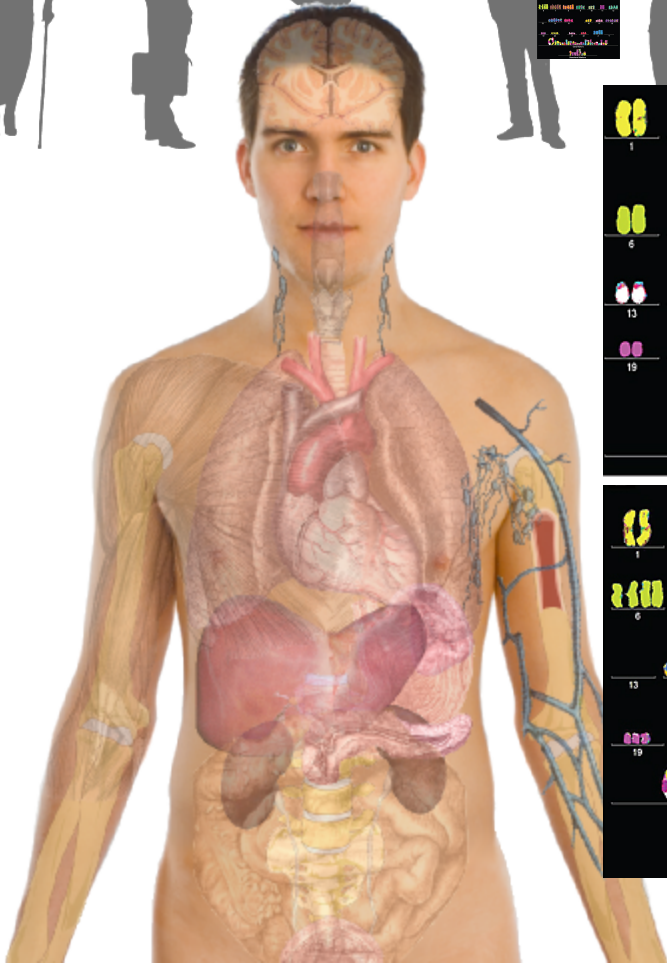
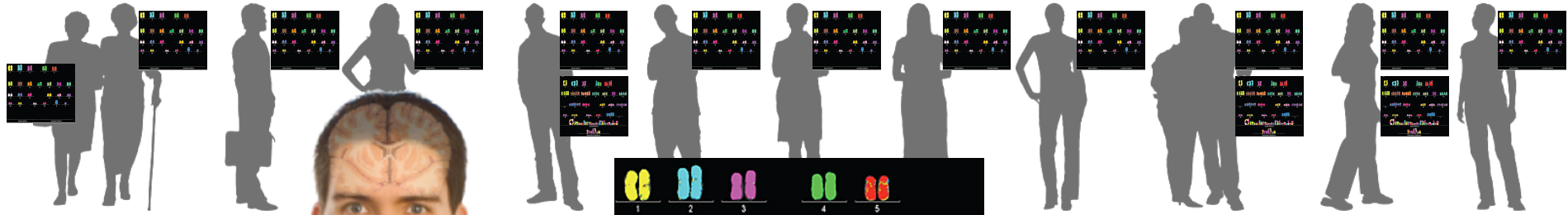
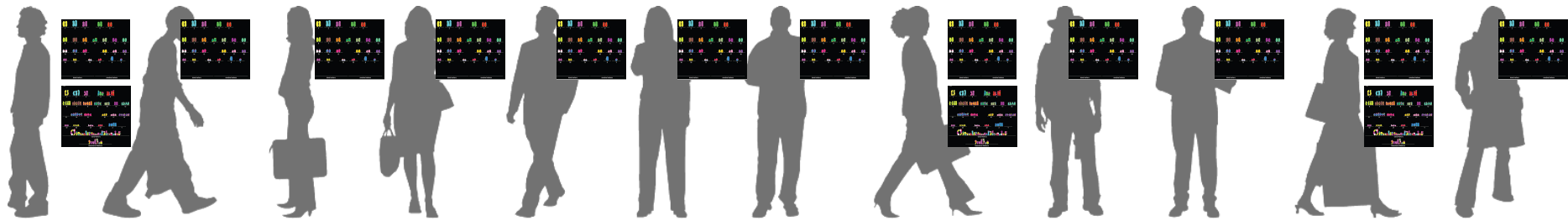
Personal genomes soon will become a commonplace part of medical research & eventually treatment (esp. for cancer). They will provide a primary connection for biological science to the general public.



Personal Genomics as a Gateway into Biology

Personal genomes soon will become a commonplace part of medical research & eventually treatment (esp. for cancer). They will provide a primary connection for biological science to the general public.





Human Genetic Variation

A Cancer Genome



A Typical Genome



Population of 2,504 people



Origin of Variants

| | Coding | Non-coding |
|-----------|--------|------------|
| Germ-line | 22K | 4.1 – 5M |
| Somatic | ~50 | 5K |

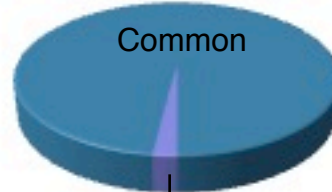


Driver (~0.1%)

Class of Variants

| | |
|-------|-------------------|
| SNP | 3.5 – 4.3M |
| Indel | 550 – 625K |
| SV | 2.1 – 2.5K (20Mb) |
| Total | 4.1 – 5M |

Prevalence of Variants



Rare* (1-4%)

| | |
|-------|-------|
| SNP | 84.7M |
| Indel | 3.6M |
| SV | 60K |
| Total | 88.3M |



Rare (~75%)

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

CAN YOU FIND THE PANDA?

Finding Key Variants

Germline



- **Common variants**

- Can be associated with phenotype (ie disease) via a Genome-wide Association Study (GWAS), which tests whether the frequency of alleles differs between cases & controls.
- Usually their functional effect is weaker.
- Many are non-coding
- Issue of LD in identifying the actual causal variant.

- **Rare variants**

- Associations are usually underpowered due to low frequencies.
- They often have larger functional impact
- Can be collapsed in the same element to gain statistical power (burden tests).
- In some cases, causal variants can be identified through tracing inheritance of Mendelian subtypes of diseases in large families.

CAN YOU FIND THE PANDA?



Finding Key Variants

Somatic

• Overall

- Often these can be conceptualized as very rare variants
- A challenge to identify somatic mutations contributing to cancer is to find driver mutations & distinguish them from passengers.

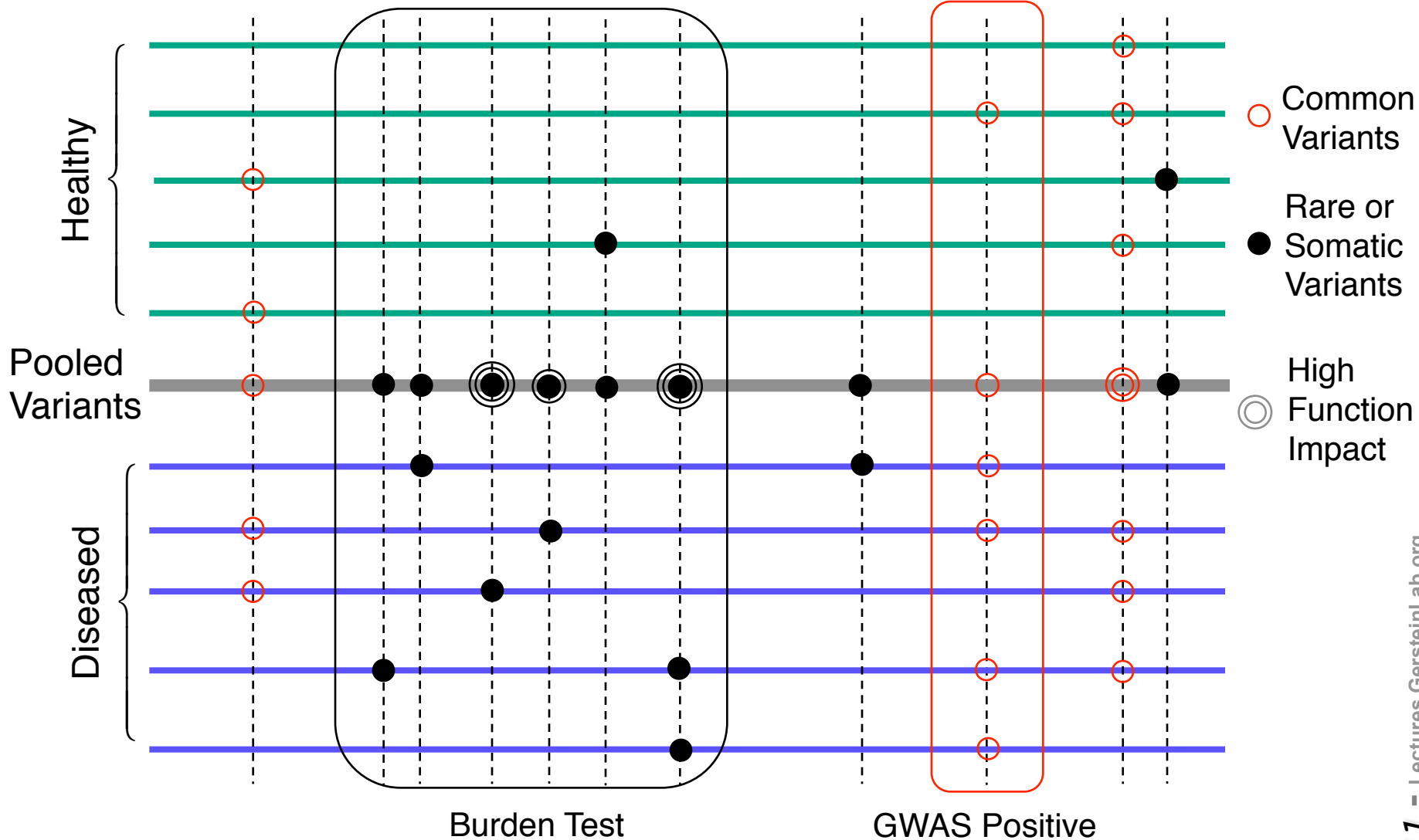
• Drivers

- Driver mutation is a mutation that directly or indirectly confers a selective growth advantage to the cell in which it occurs.
- A typical tumor contains 2-8 drivers; the remaining mutations are passengers.

• Passengers

- Conceptually, a passenger mutation has no direct or indirect effect on the selective growth advantage of the cell in which it occurred.

Association of Variants with Diseases



Personal Genomics: Prioritizing High-impact Rare & Somatic Variants

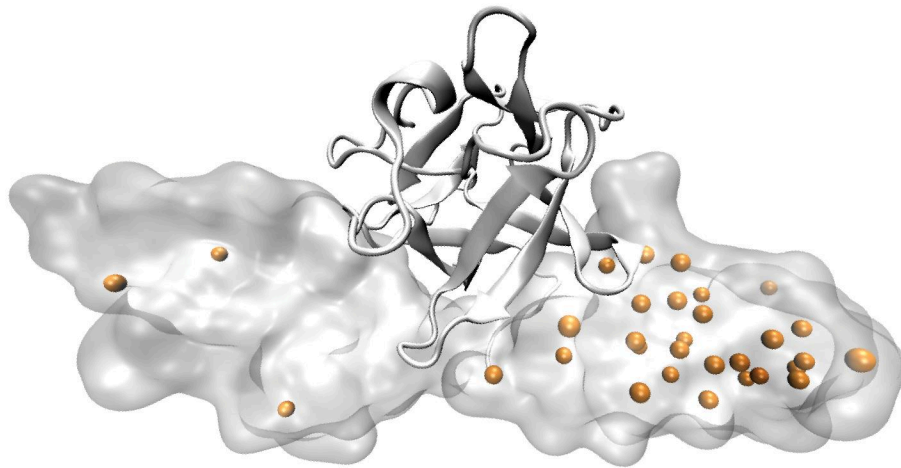
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 - Having observed difference in molecular activity in many contexts
 - **Key technical Issue: Need to build personal genomes**
 - Assessing their quality via read mapping
- Putting it together in workflows
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 - Systematically weighting all the features
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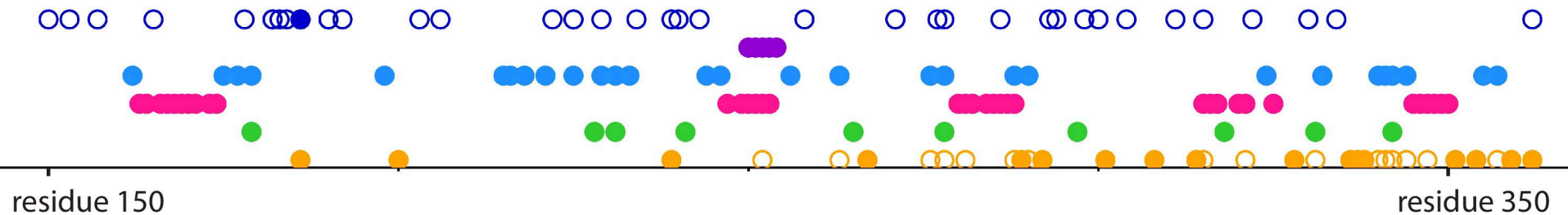
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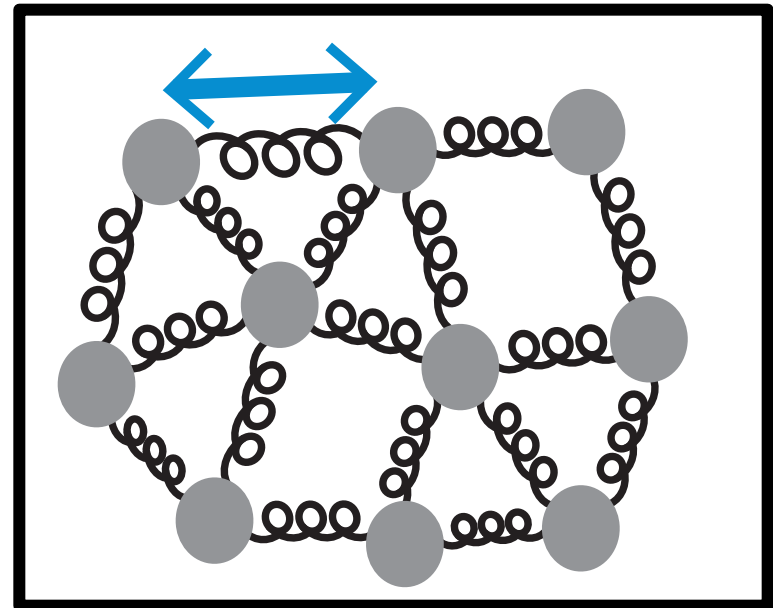
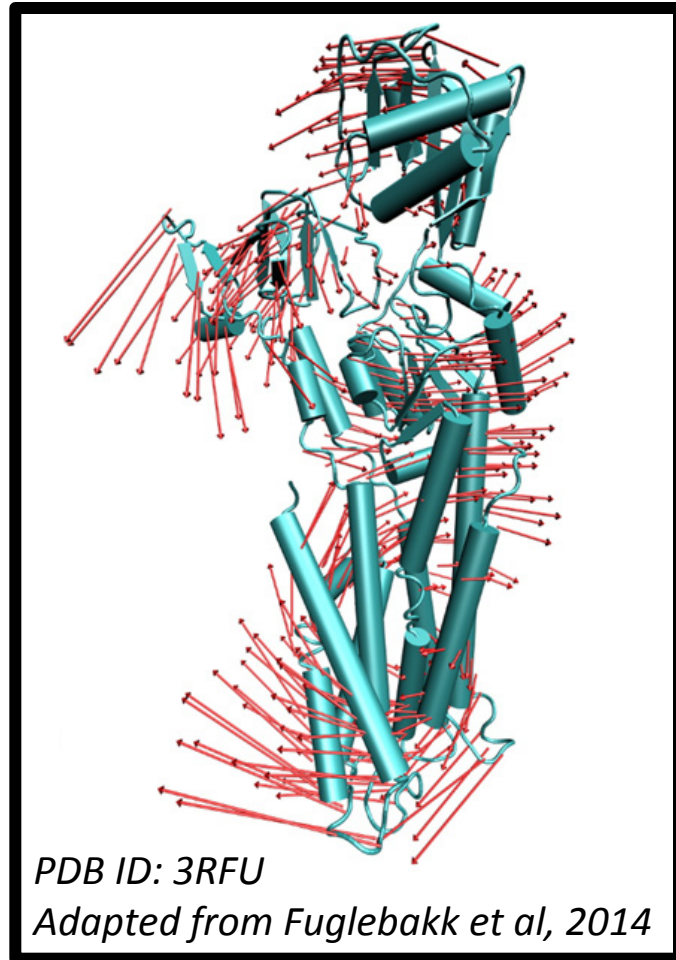
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Fibroblast growth factor receptor 2 (pdb: 1IIL)



Models of Protein Conformational Change

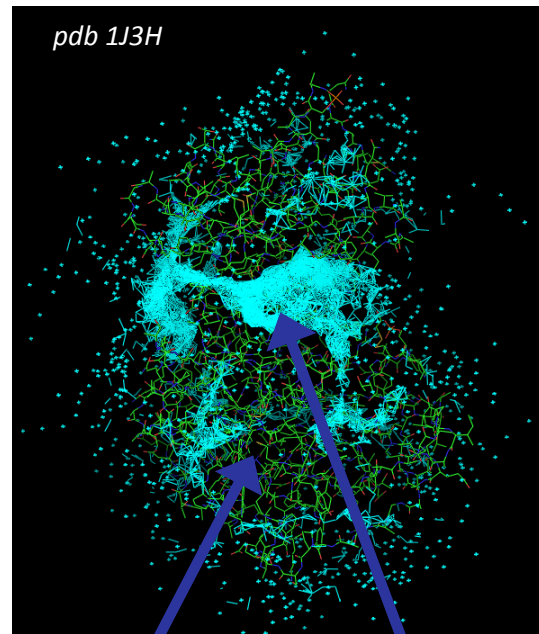
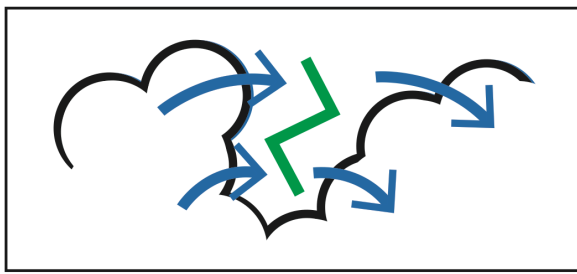
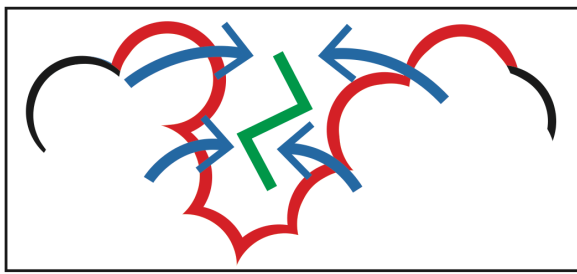
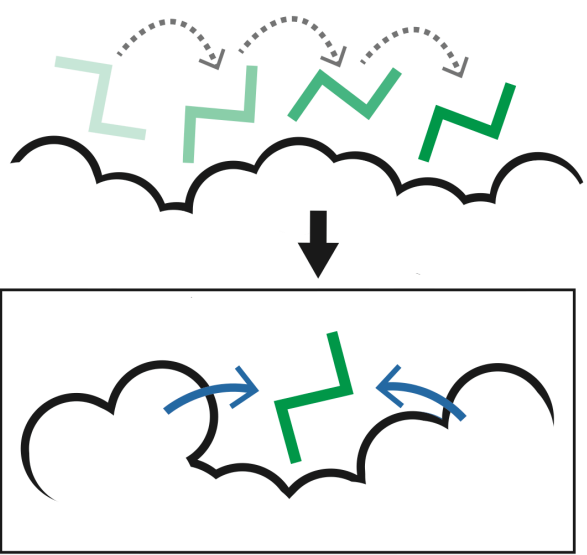
Motion Vectors from Normal Modes (ANMs)



Characterizing uncharacterized variants
<= Finding Allosteric sites
<= Modeling motion

Predicting Allosterically-Important Residues at the Surface

1. MC simulations generate a large number of candidate sites
2. Score each candidate site by the degree to which it perturbs large-scale motions
3. Prioritize & threshold the list to identify the set of high confidence-sites



Surface region with high density of candidate sites

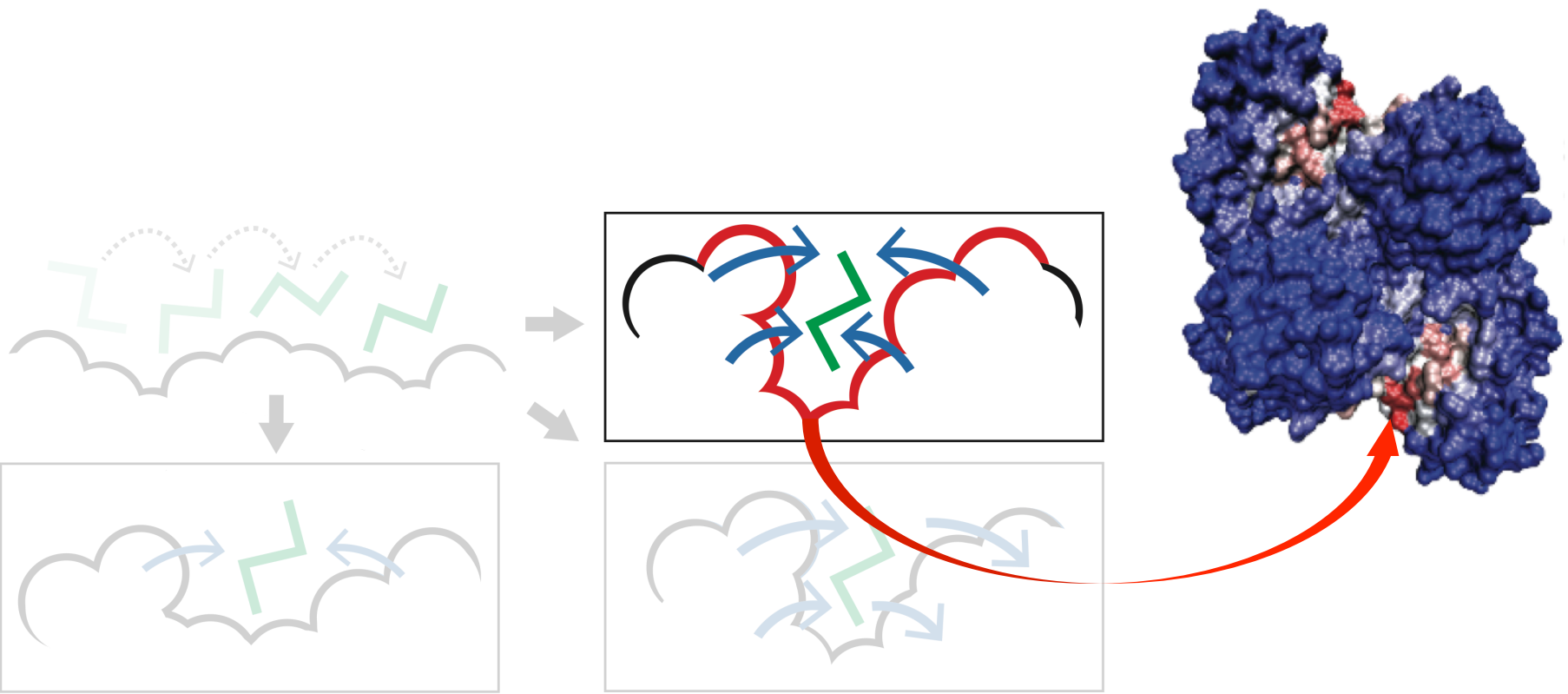
Surface region with low density of candidate sites

$$\text{binding leverage} = \sum_{m=1}^{10} (\sum_i \sum_j \Delta d_{ij(m)}^2)$$

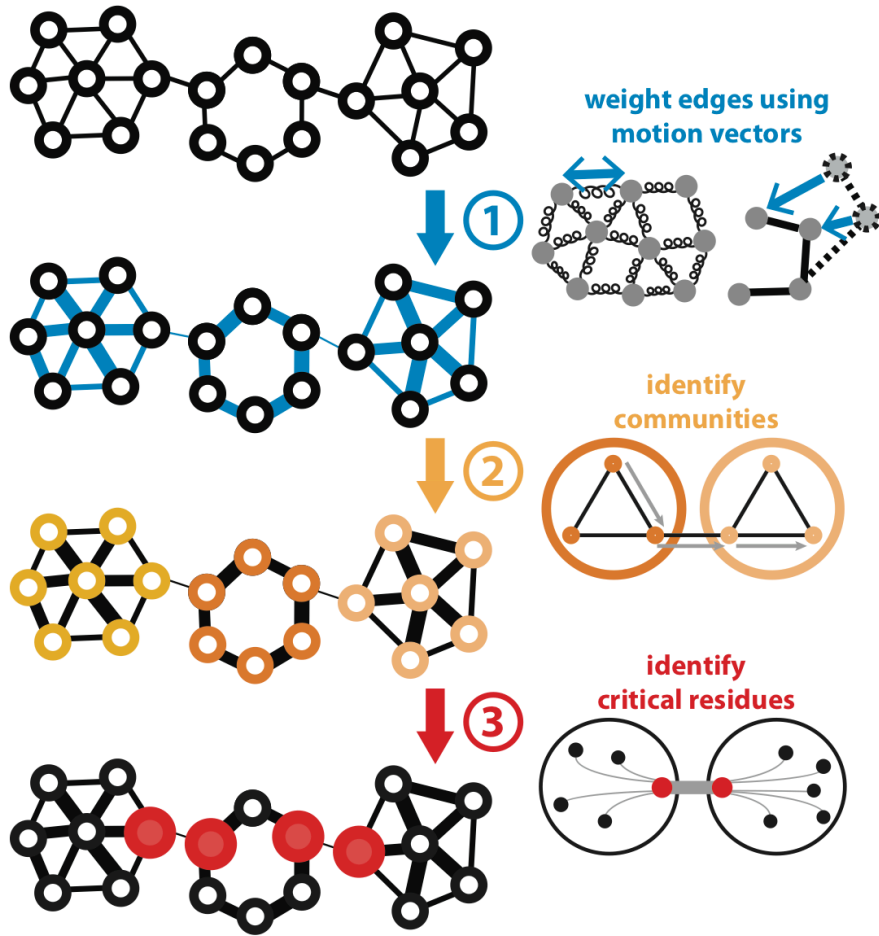
Adapted from Clarke*, Sethi*, et al (in press)

Predicting Allosterically-Important Residues at the Surface

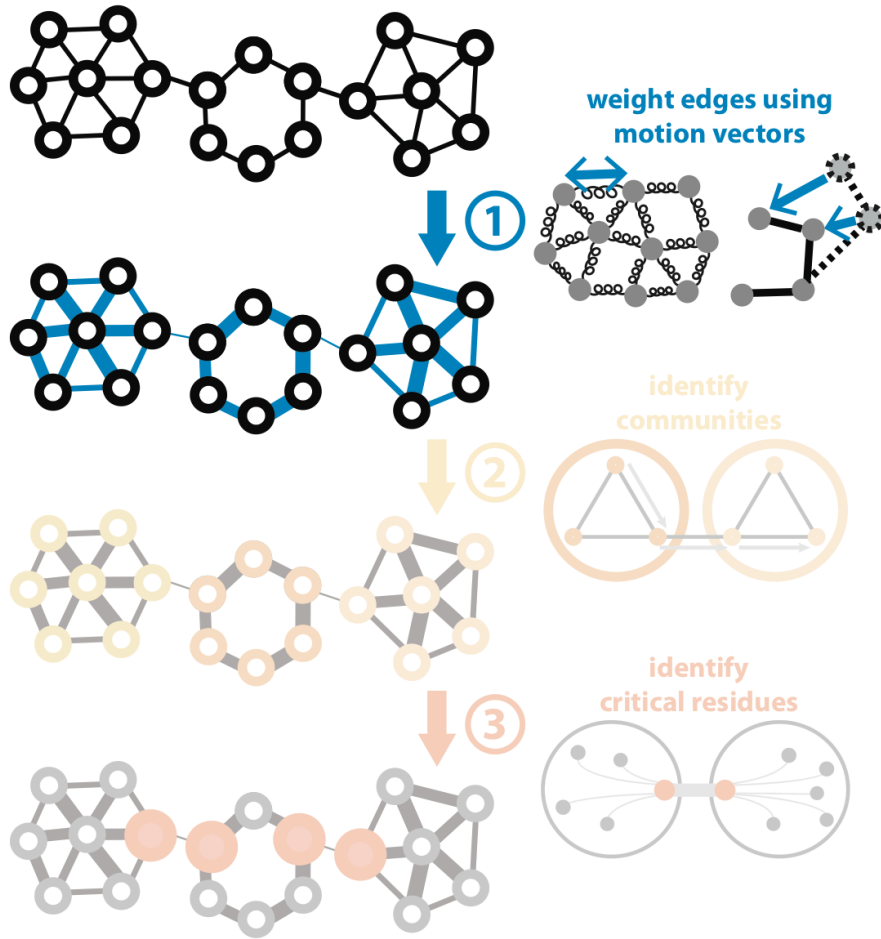
PDB: 3PFK



Predicting Allosterically-Important Residues within the Interior



Predicting Allosterically-Important Residues within the Interior

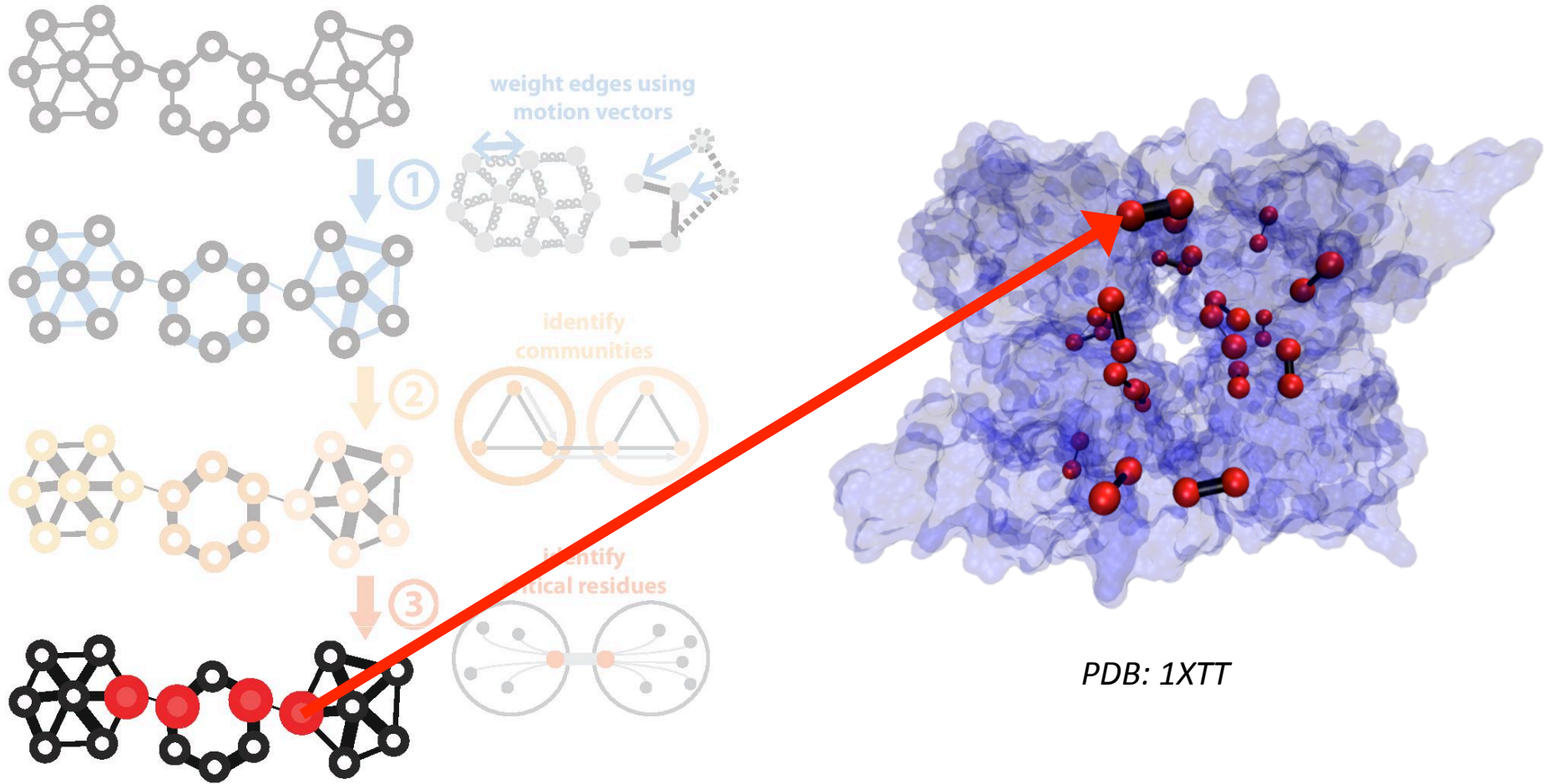


$$Cov_{ij} = \langle \mathbf{r}_i \cdot \mathbf{r}_j \rangle$$

$$C_{ij} = Cov_{ij} / \sqrt{(\langle \mathbf{r}_i^2 \rangle \langle \mathbf{r}_j^2 \rangle)}$$

$$D_{ij} = -\log(|C_{ij}|)$$

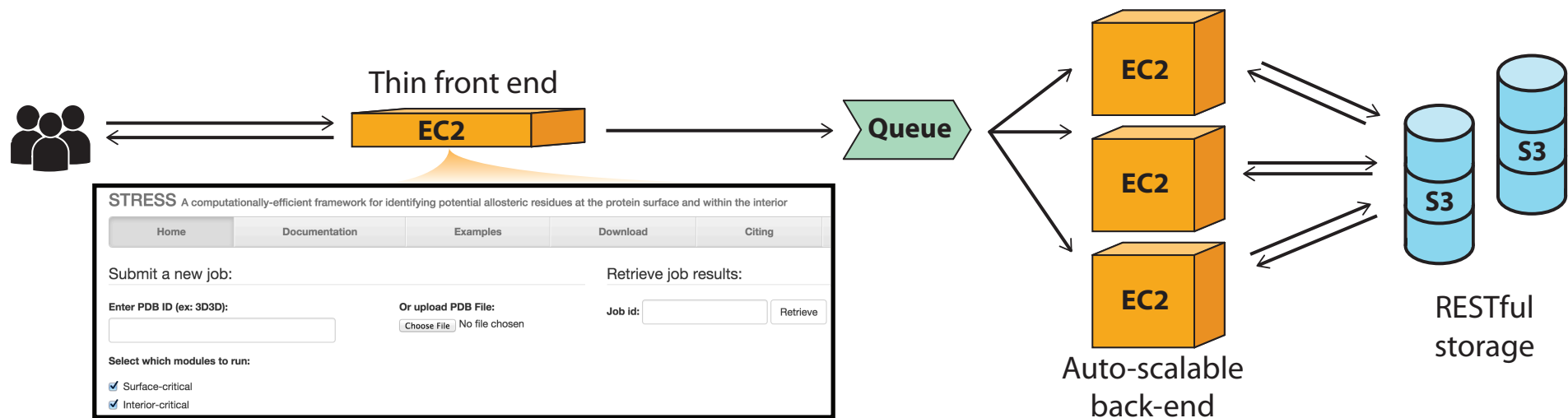
Predicting Allosterically-Important Residues within the Interior



PDB: 1XTT

STRESS Server Architecture: Highlights

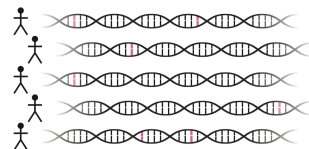
stress.molmovdb.org



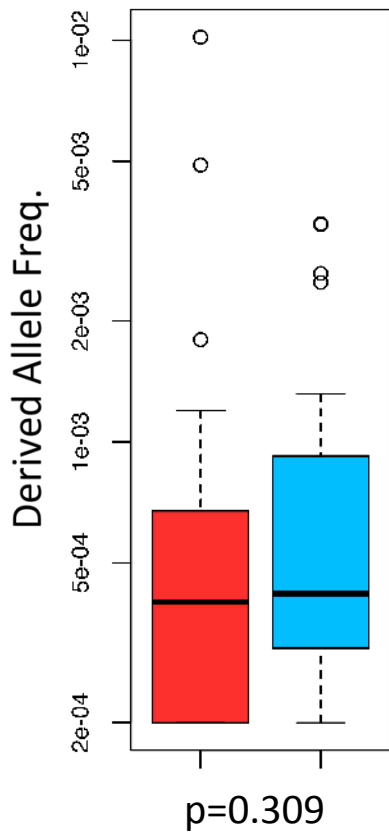
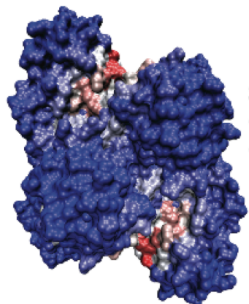
- A light front-end server handles incoming requests, and powerful back-end servers perform calculations.
- Auto Scaling adjusts the number of back-end servers as needed.
- A typical structure takes ~30 minutes on a E5-2660 v3 (2.60GHz) core.
- Input & output (i.e., predicted allosteric residues) are stored in S3 buckets.

Intra-species conservation of predicted allosteric residues

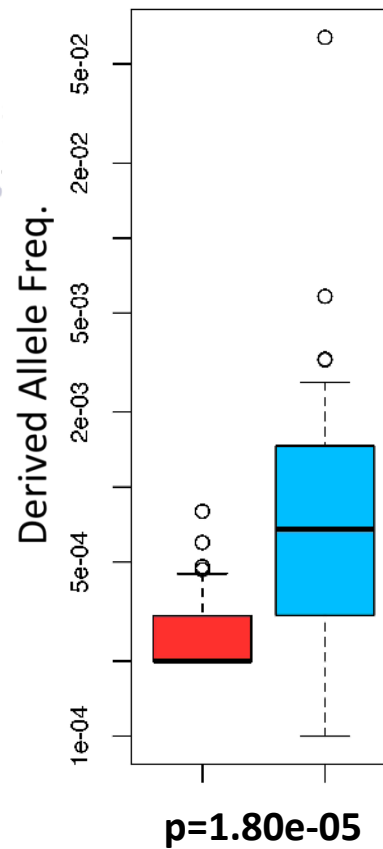
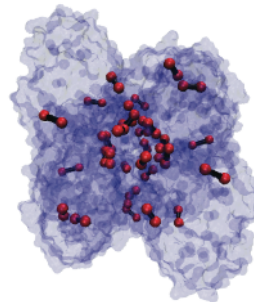
1000 Genomes



Surface



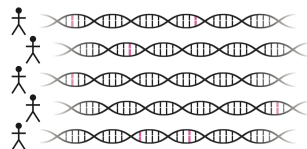
Interior



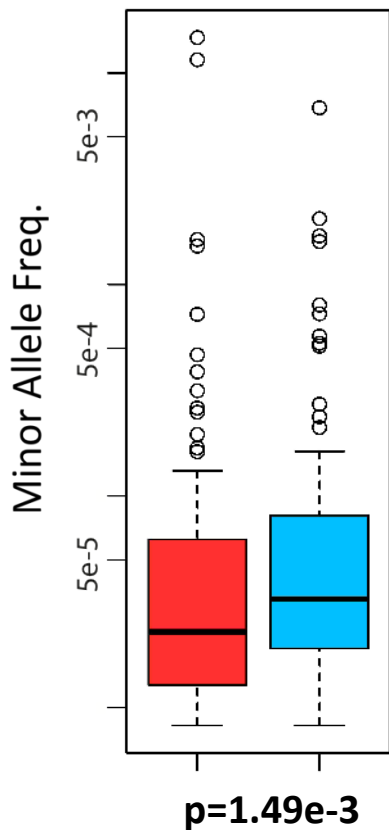
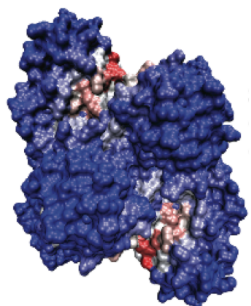
 critical
 non-critical

Intra-species conservation of predicted allosteric residues

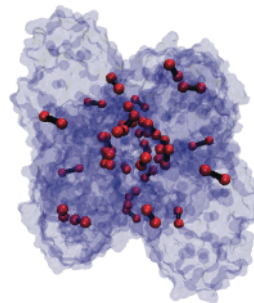
ExAC



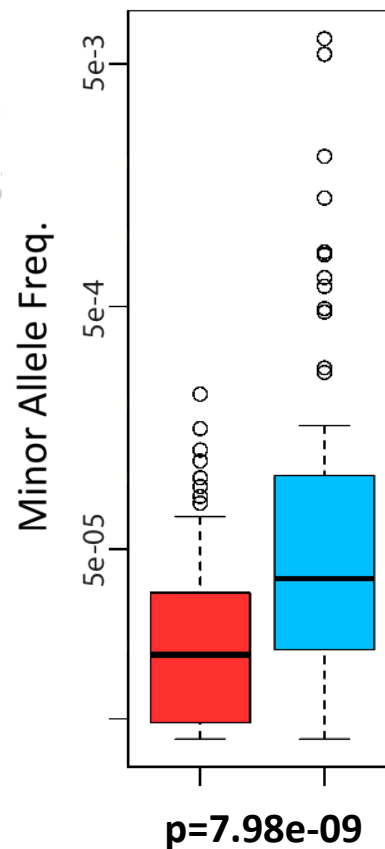
Surface



Interior

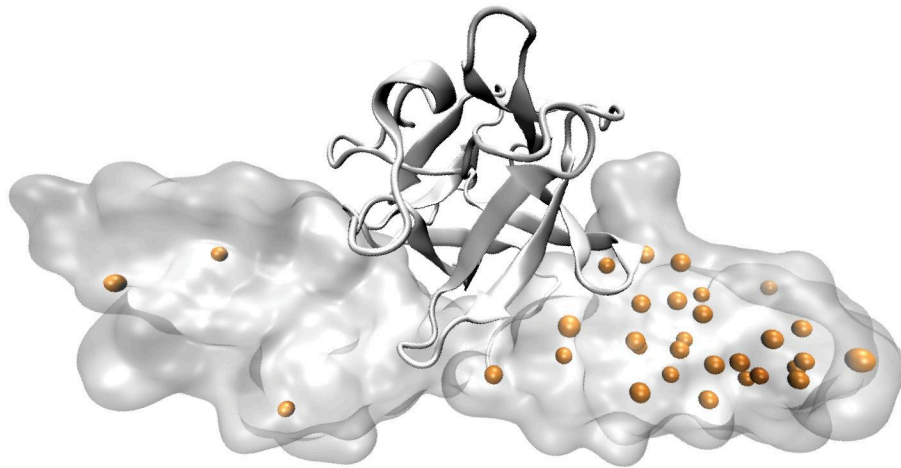


■ critical
■ non-critical



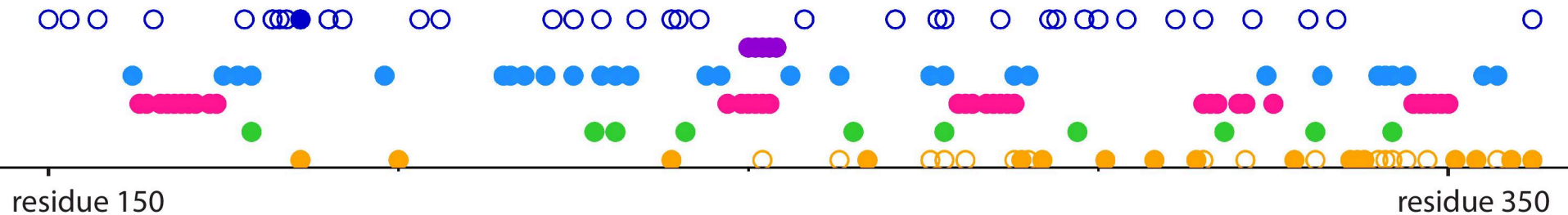
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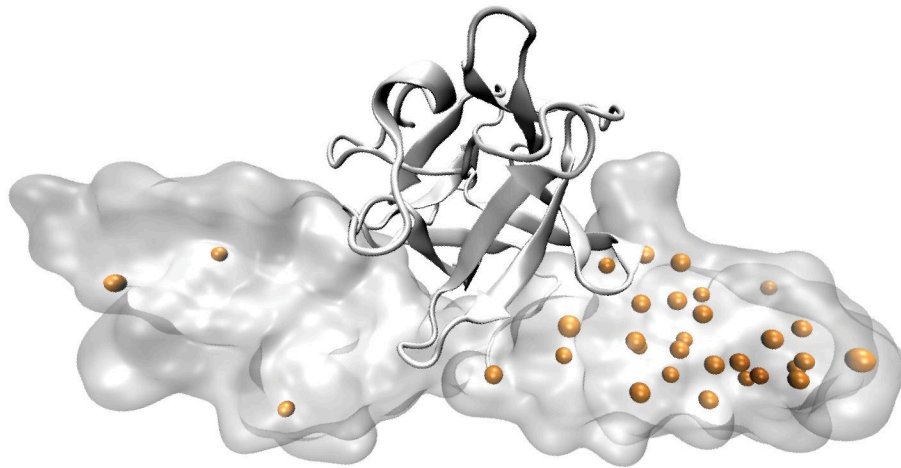
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Fibroblast growth factor receptor 2 (pdb: 1IIL)



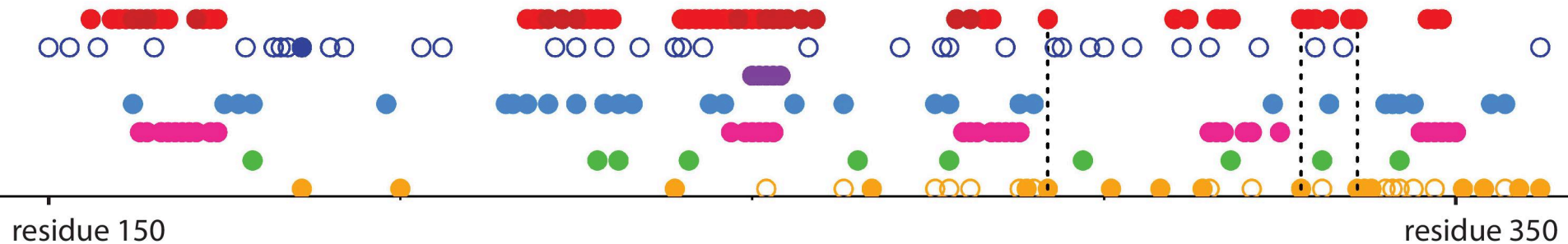
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Rationalizing disease variants in the context of allosteric behavior with allostery as an added annotation



- Predicted allosteric (surface | interior)
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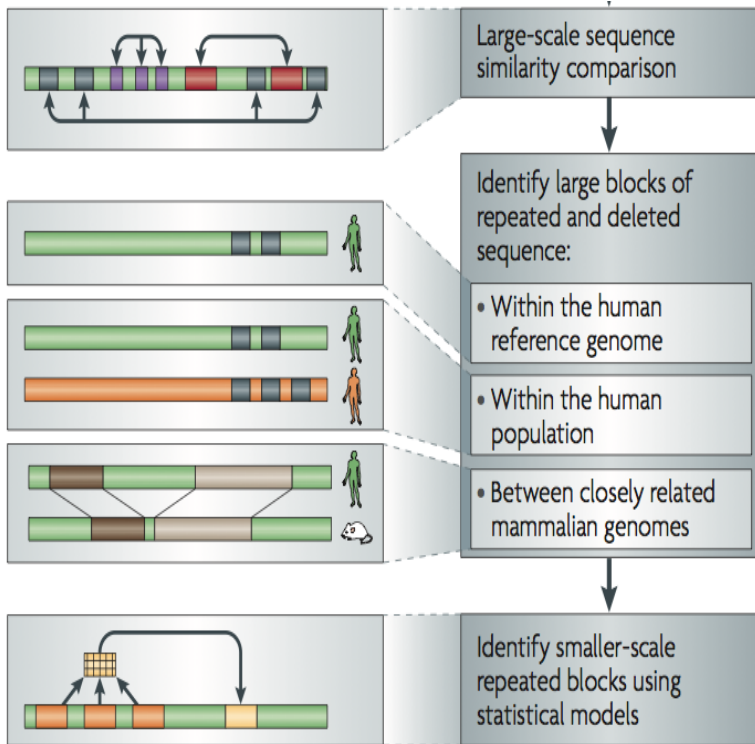


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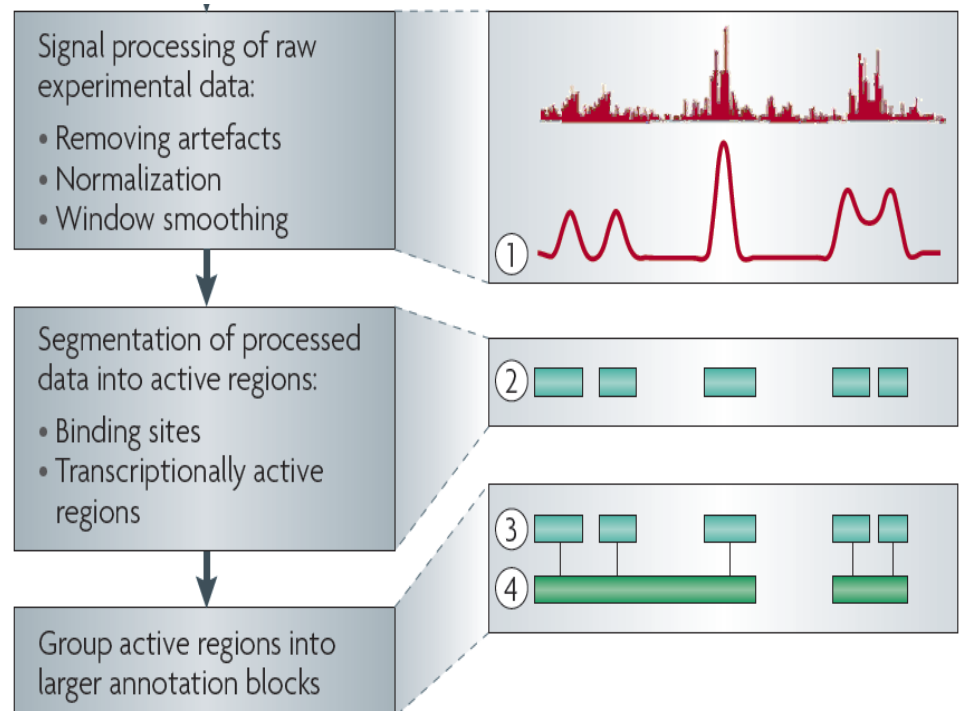
Non-coding Annotations: Overview

Sequence features, incl. Conservation



Functional Genomics

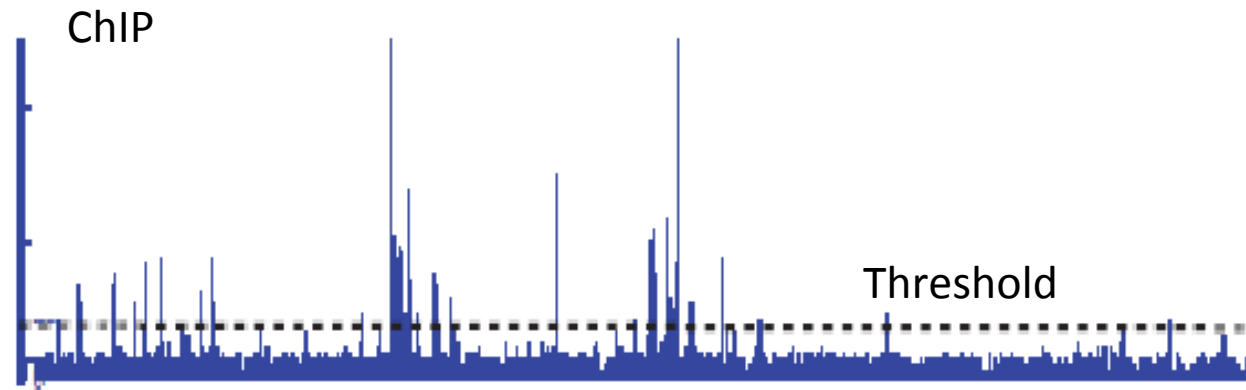
Chip-seq (Epigenome & seq. specific TF) and ncRNA & un-annotated transcription



[Alexander et al., *Nat. Rev. Genet.* ('10)]

Summarizing the Signal: "Traditional" ChIPSeq Peak Calling

- Generate & threshold the signal profile to identify candidate target regions
 - Simulation (PeakSeq),
 - Local window based Poisson (MACS),
 - Fold change statistics (SPP)



Potential Targets



- Score against the control



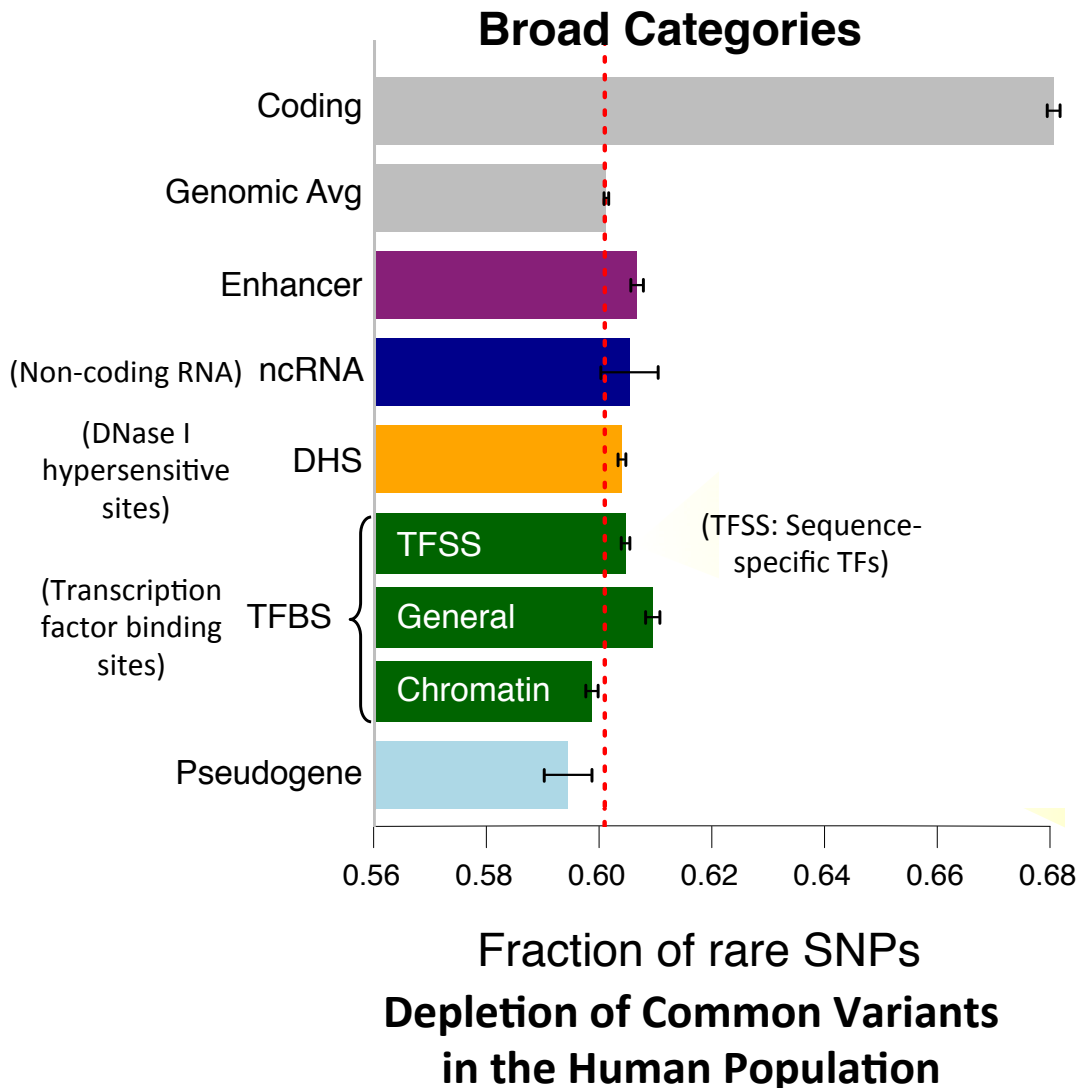
Significantly Enriched targets



Now an update: "PeakSeq 2" => MUSIC

Finding "Conserved" Sites in the Human Population:

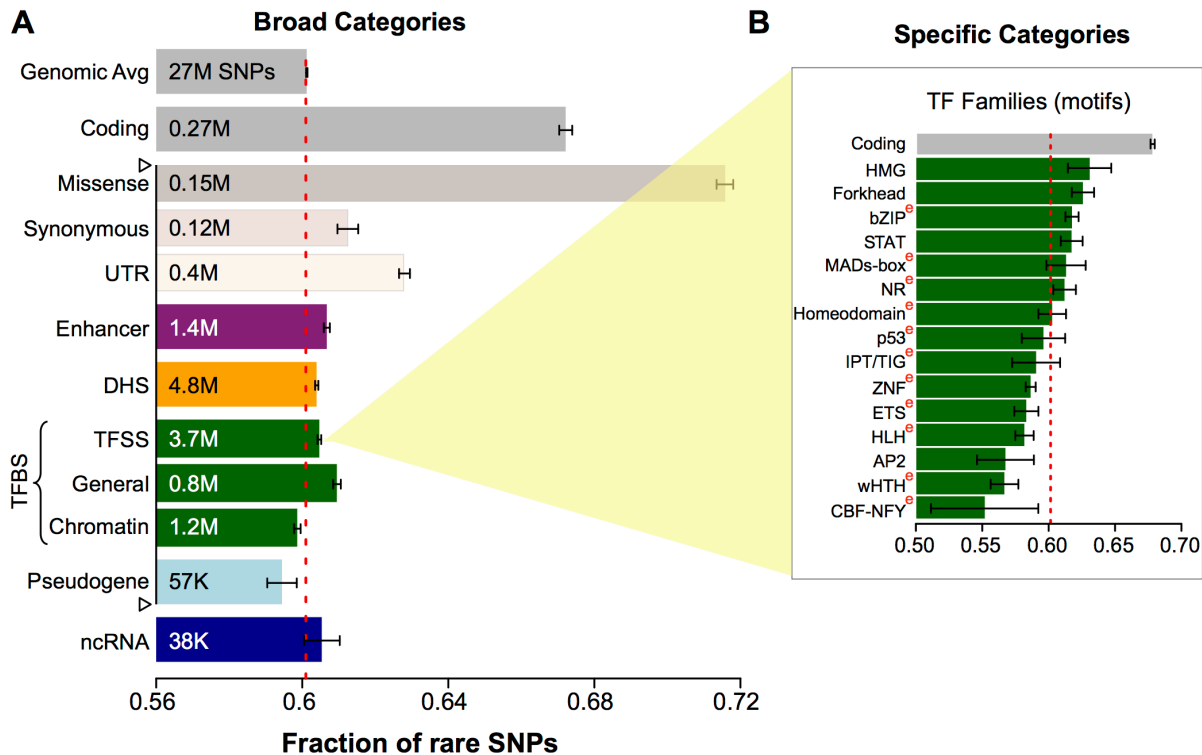
Negative selection in non-coding elements based on
Production ENCODE & 1000G Phase 1



- Broad categories of regulatory regions under negative selection
 - Related to:

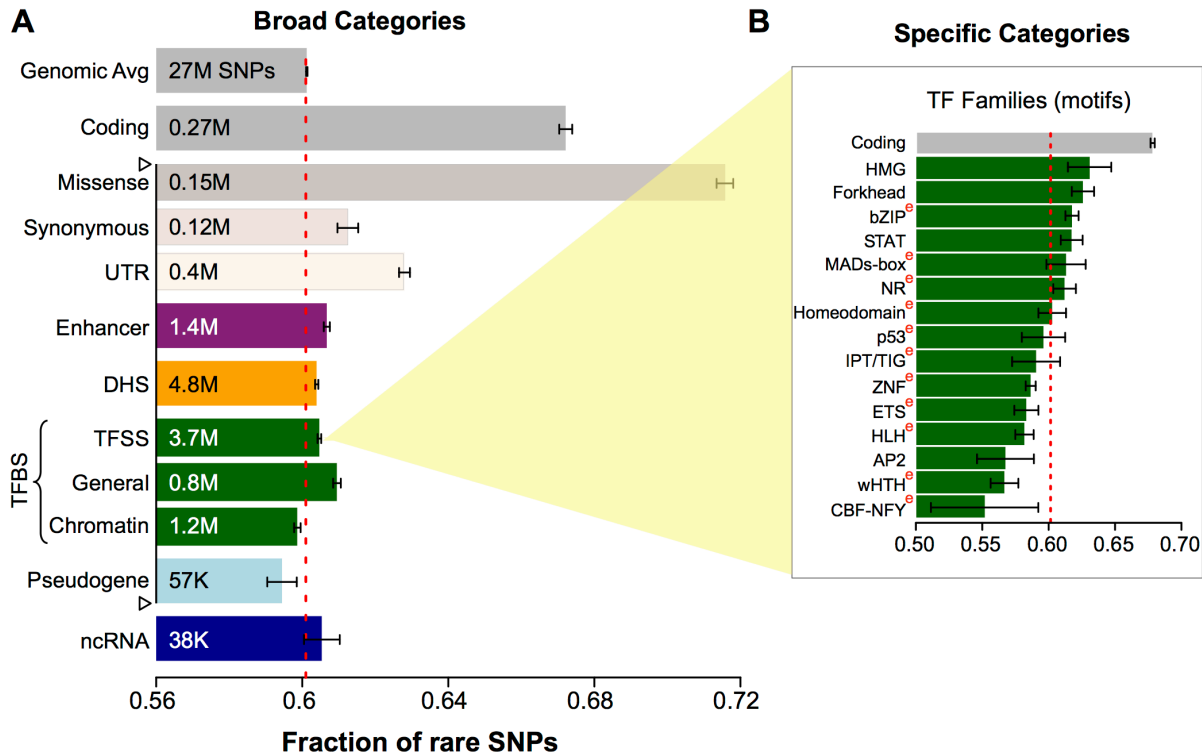
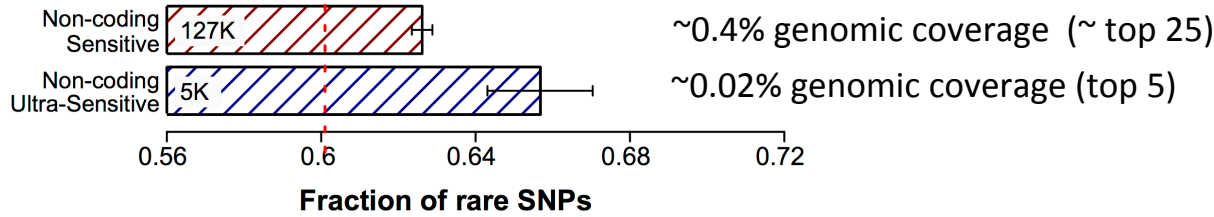
ENCODE, *Nature*, 2012
Ward & Kellis, *Science*, 2012
Mu et al, *NAR*, 2011

Differential selective constraints among specific sub-categories



Sub-categorization possible because of better statistics from 1000G phase 1 v pilot

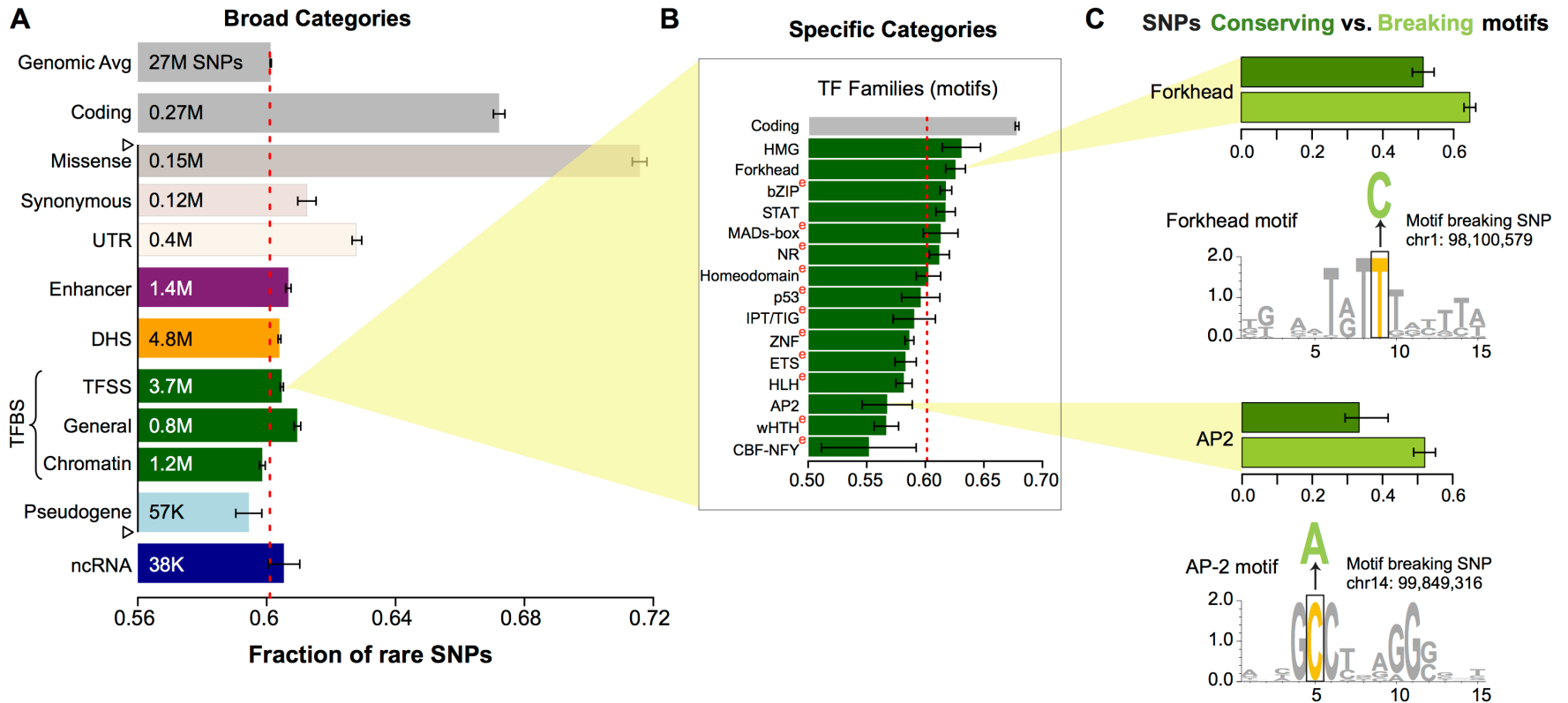
Defining Sensitive non-coding Regions



Start **677** high-resolution non-coding categories; Rank & find those under strongest selection

Sub-categorization possible because of better statistics from 1000G phase 1 v pilot

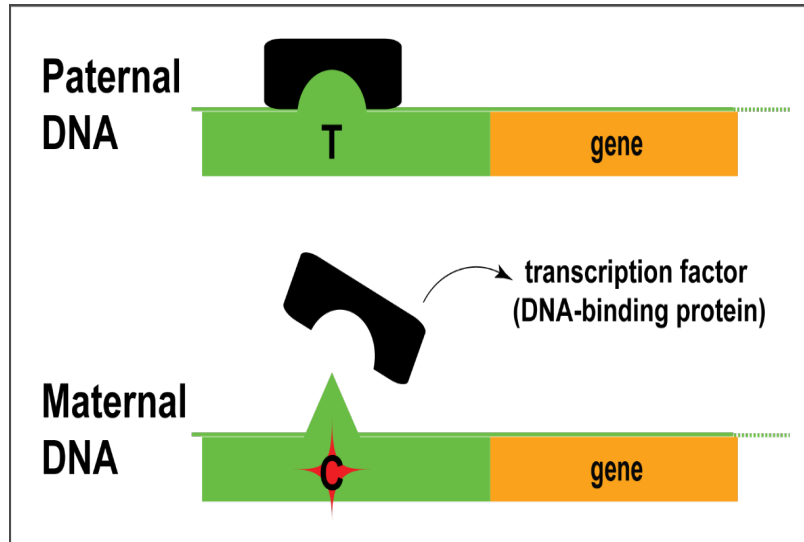
SNPs which break TF motifs are under stronger selection



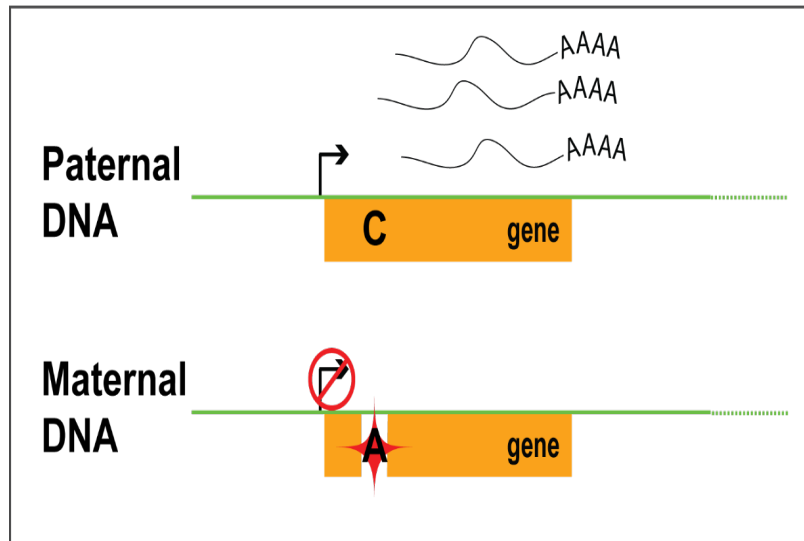
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Allele-specific binding and expression



Genomic variants affecting allele-specific behavior e.g. allele-specific binding (ASB)



e.g. allele-specific expression (ASE)

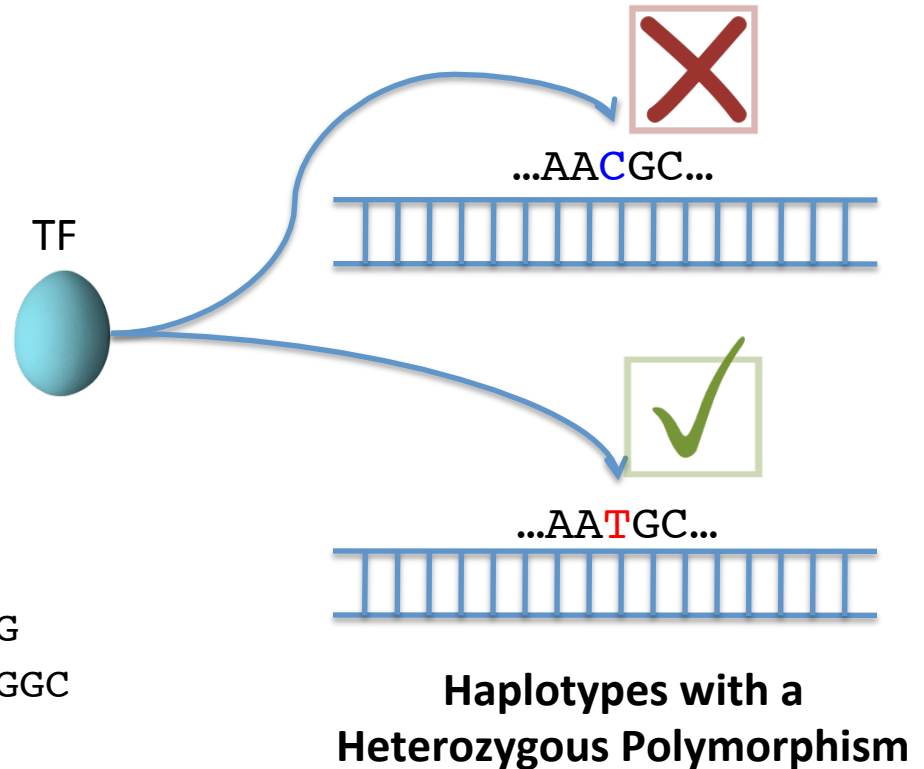
Inferring Allele Specific Binding/Expression using Sequence Reads

RNA/ChIP-Seq Reads

ACTTTGATAGCGTCAATG
 CTTTGATAGCGTCAATGC
 CTTTGATAGCGTCAACGC
 TTGACAGCGTCAATGCAC
 TGATAGCGTCAATGCACG
 ATAGCGTCAATGCACGTC
 TAGCGTCAATGCACGTCG
 CGTCAACGCACGTCGGGA
 GTCAATGCACGTCGAGAG
 CAATGCACGTCGGGAGTT
 AATGCACGTCGGGAGTTG
 TGCACGTTGGGAGTTGGC

10 x T

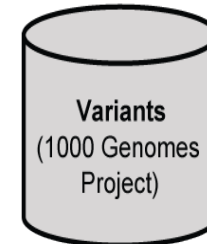
2 x C



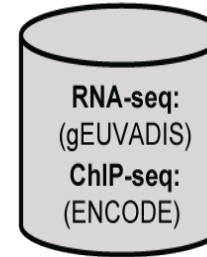
Interplay of the annotation and individual sequence variants

AlleleDB: Building 382 personal genomes to detect allele-specific variants on a large-scale

1. Build personal genomes

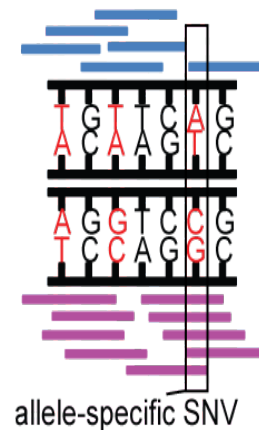


2. Align ChIP-seq & RNA-seq reads

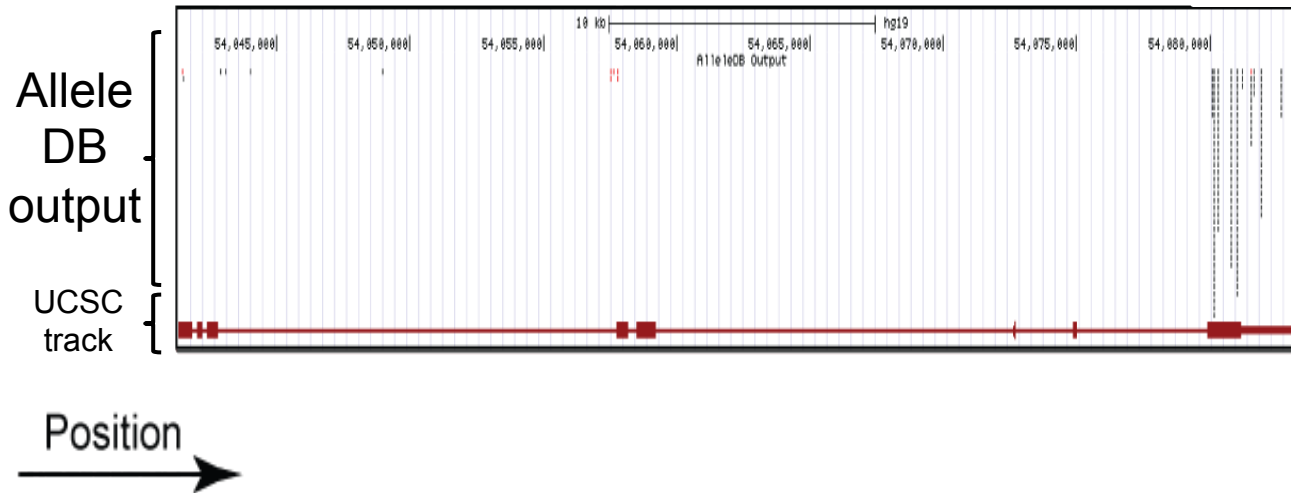


3. Detect allele-specific variants via a series of filters and tests

**Many Technical Issues:
Reference bias, Ambiguous
mapping bias, Over-dispersed
(non binomial null)**

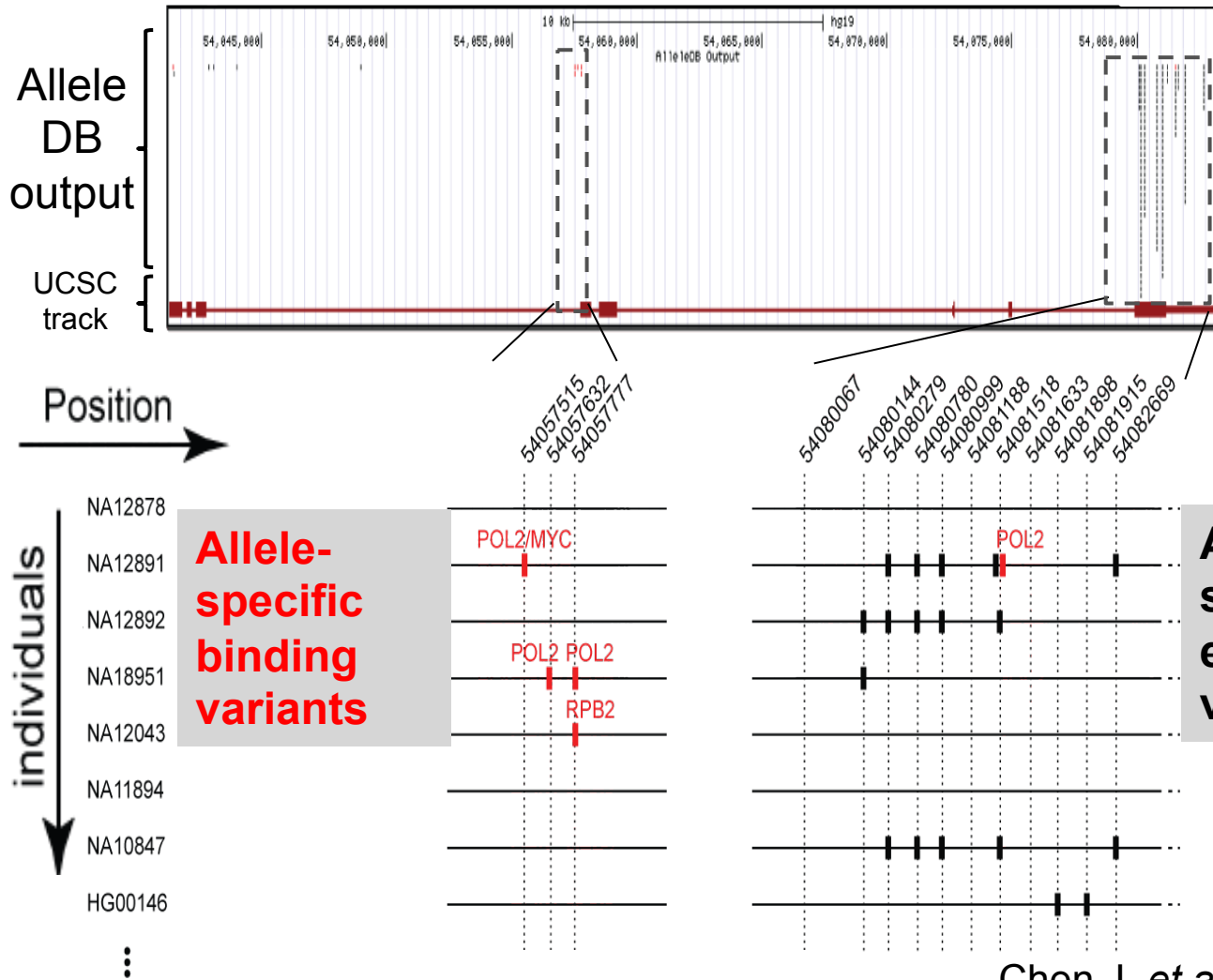


AlleleDB: Annotating rare & common allele-specific variants over a population



- Interfaces with UCSC genome browser
- Showing ZNF331 gene structure

AlleleDB: Annotating rare & common allele-specific variants over a population



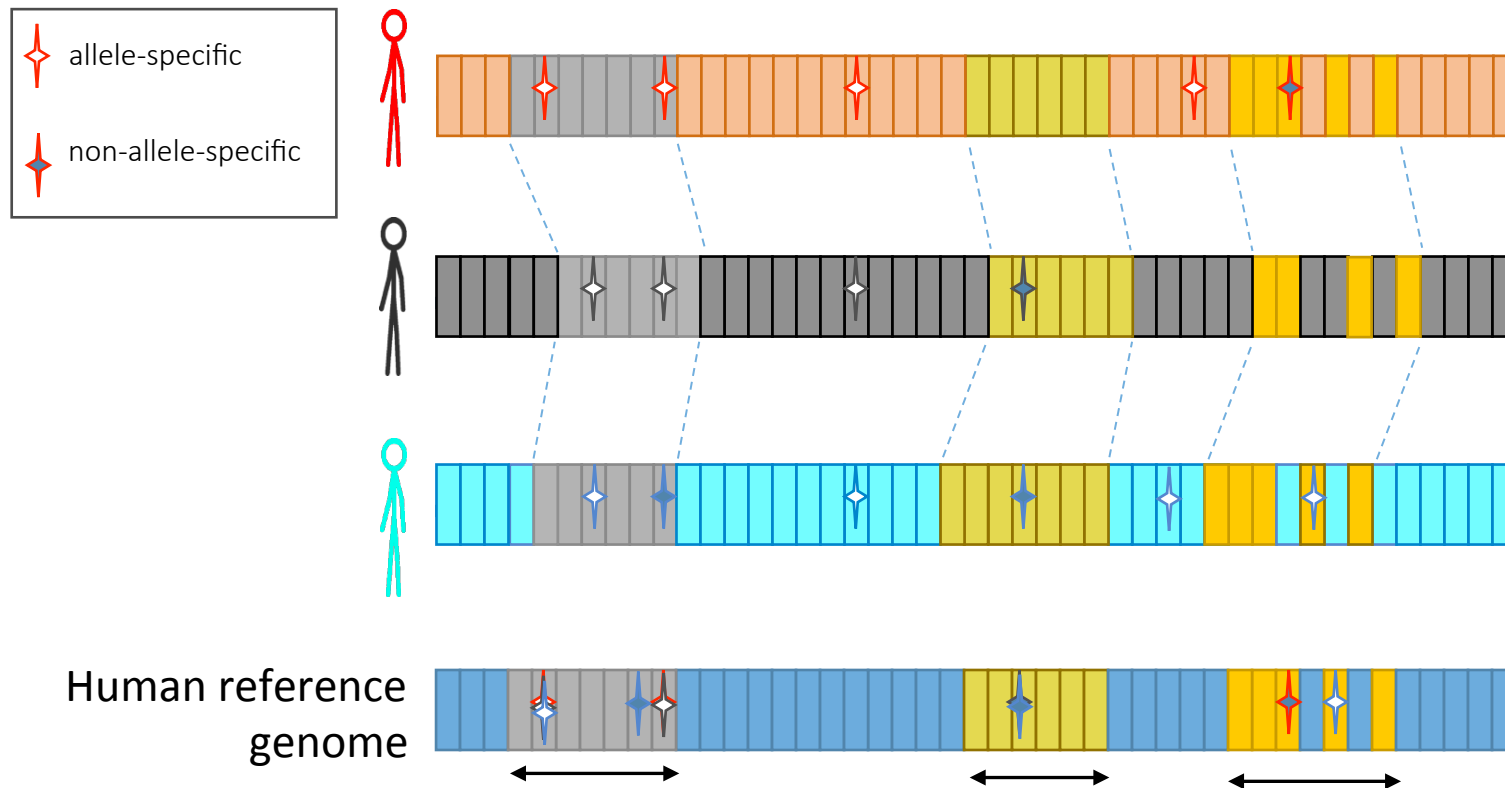
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- Showing ZNF331 gene structure

Chen J. et al. (*Nature Commun*, in press)

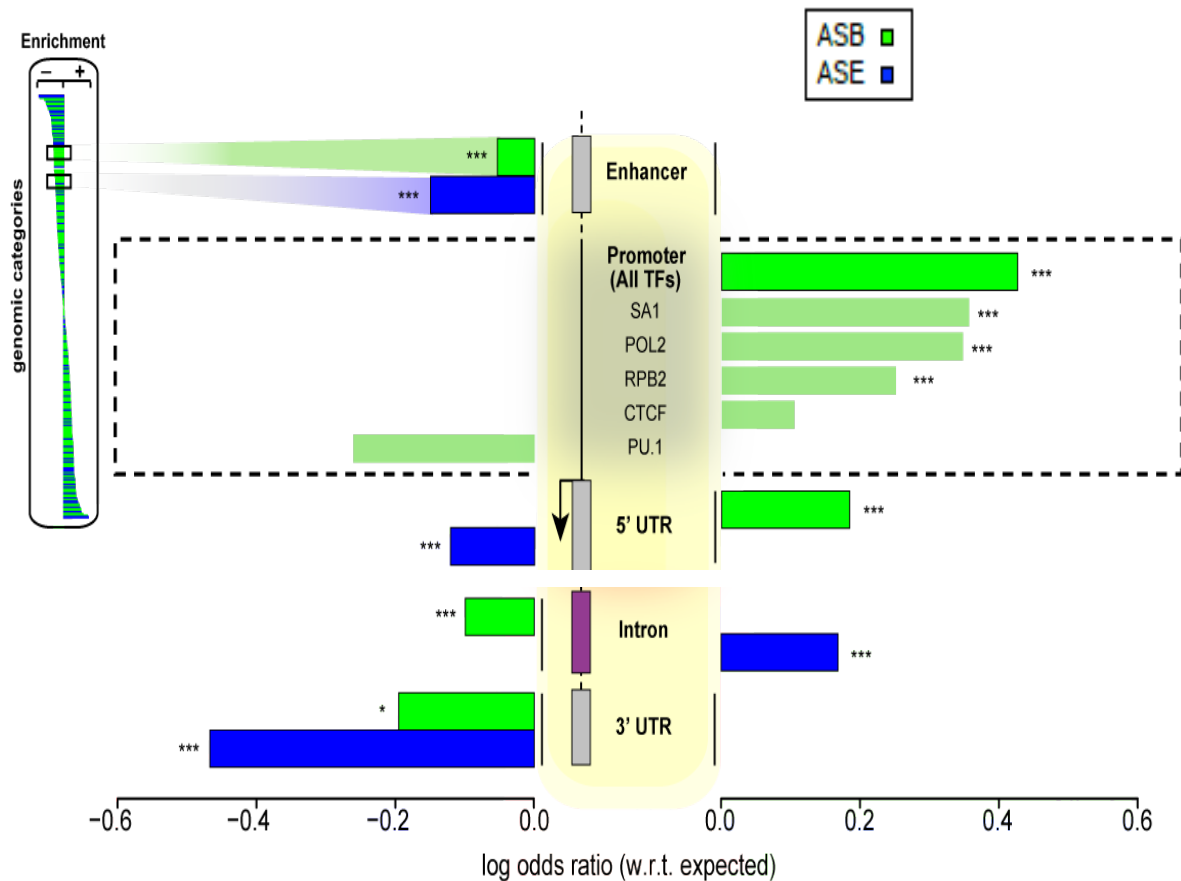
Collecting ASE/ASB variants into allele-specific genomic regions

Does a particular genomic element have a higher tendency to be allele-specific?

Fisher's exact test, for the **enrichment** of allele-specific variants in the element (with respect to non-allele-specific variants that could potentially be called as allelic)



Groups of elements that are enriched or depleted in allelic activity

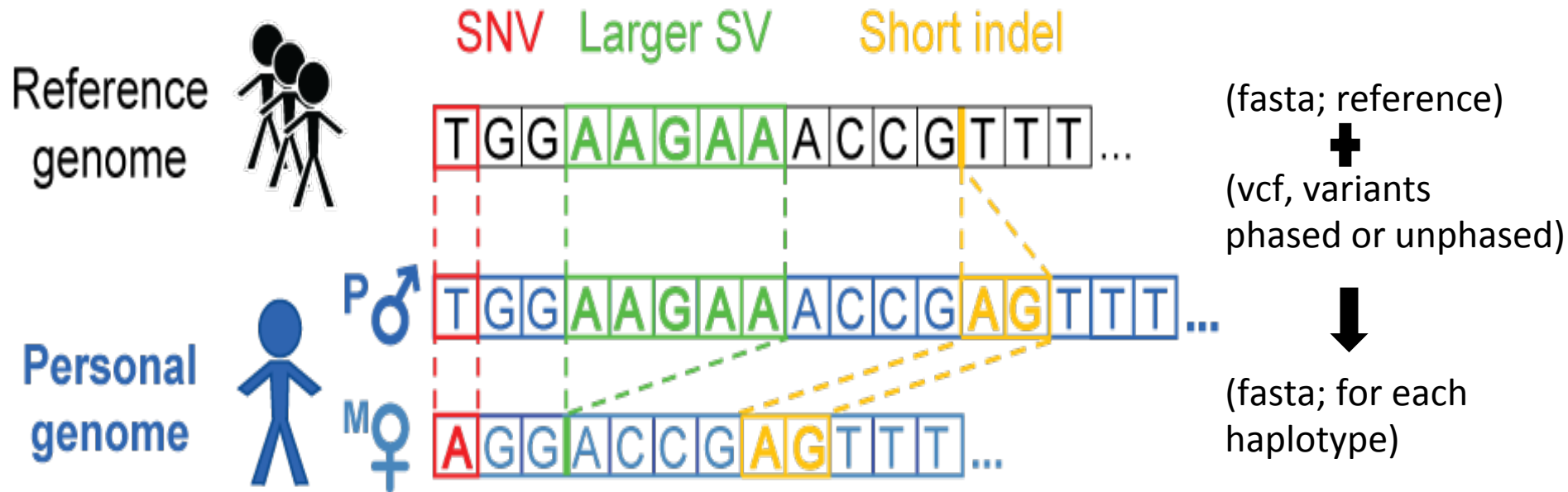


Chen J. *et al.* (*Nature Commun*, in press)

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- Introduction: the landscape of variants in personal genomes
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How to build a personal genome



Why the personal genome (PG) should be the platform for functional genomics

- 1. Diploid**
 - Ability to incorporate private variants of any size
 - exhibit phase information
- 2. Scale easily with more samples (v graph genome) and improving sequencing technologies: longer reads and more accurate phase information**
- 3. Very useful in functional genomic assay analyses**
 - a) read alignment
 - b) RNA-seq quantification
 - c) allele-specific analyses

Some construction considerations

1. Choice of call set(s)

-- e.g. different versions of 1000GP call sets

2. Choice of variants

-- e.g. SVs or indels or SNVs only

3. Choice of reference

-- choose the reference genome in which the call set is derived from


4. Assessment of call set quality

-- e.g. analysis of Mendelian inconsistency in family data

NA12878 family of PGs we already have

| | Source | Refgen | Depth | Variants |
|---|--|--------|-------|---|
| 1 | 1000 Genomes Project (1000GP) pilot | hg18 | 60x | SNVs, indels, deletions (including 33 from fosmid sequencing) |
| 2 | GATK Best Practices v3 (UnifiedGenotype) | hg19 | 64x | SNVs, indels |
| 3 | GATK Best Practices v4 (HaplotypeCaller, PCR-free) | hg19 | 64x | SNVs, indels |
| 4 | 1000GP Phase 3 SNVs-only | hg19 | 7.4x | SNVs |
| 5 | 1000GP Phase 3 SNVs-indels | hg19 | 7.4x | SNVs, indels |
| 6 | 1000GP Phase 3 SNVs-indels-SVs | hg19 | 7.4x | SNVs, indels, SVs |


Alignment gets better as variant sets get more complete: NA12878 Pol2 ChIP-seq (ENCODE)

| | Ref genome | Pgenome: SNVs only | Pgenome: SNVs + indels only | Pgenome: SNVs + indels + SVs |
|--------------------------|-------------------------|--|-----------------------------|------------------------------|
| Reads processed | 208,051,087 | | | |
| # reads uniquely aligned | 171,944,588 (82.65%) | 172,591,380 (82.96%) | 172,738,321 (83.03%) | 172,743,175 (83.03%) |
| | |  | | |
| # reads that multimap | 17,826,675 (8.57%) | 17,795,258 (8.55%) | 17,782,167 (8.55%) | 17,779,800 (8.55%) |

Alignment gets better as variant sets get more complete: NA12878 RNA-seq (Kilpinen *et al.* 2013)

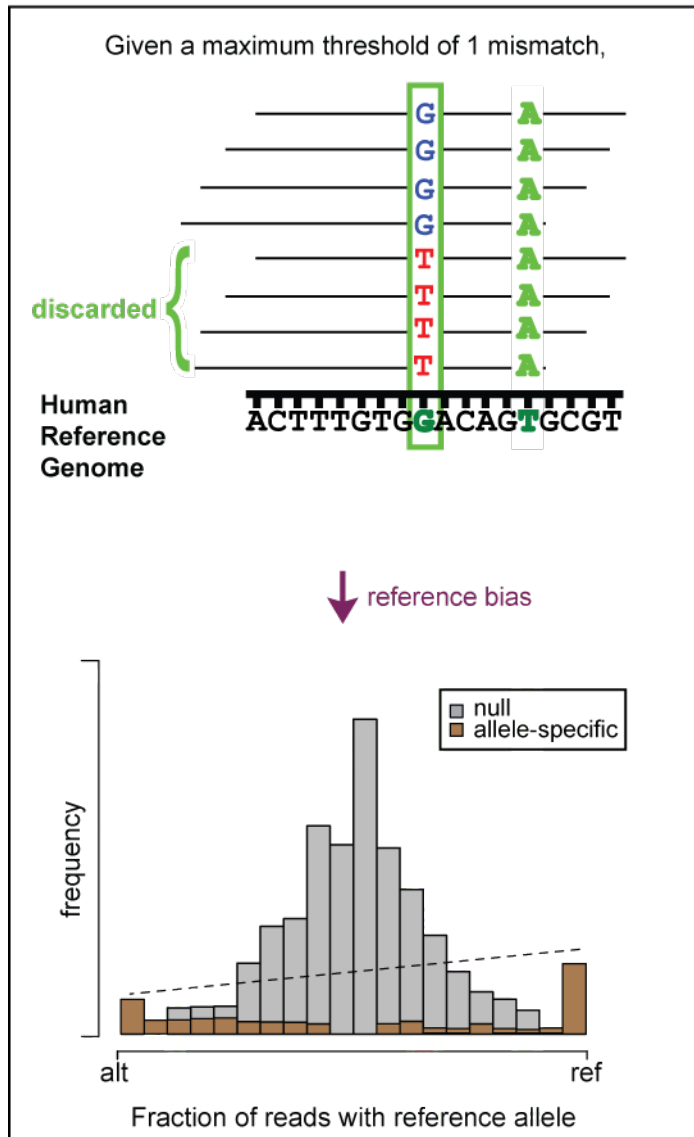
| | Ref genome | Pgenome: snvs only | Pgenome: snvs + indels only | Pgenome: snvs + indels + SVs |
|--------------------------|------------------------|------------------------|-----------------------------|------------------------------|
| Reads processed | 37,558,398 | | | |
| # reads uniquely aligned | 25,303,498 (67.37%) | 25,486,837 (67.86%) | 25,538,449 (68.00%) | 25,568,042 (68.08%) |
| | | | | |
| # reads that multimap | 4,041,495 (10.76%) | 4,010,417 (10.68%) | 4,012,297 (10.68%) | 3,972,990 (10.58%) |

Over 260K increase in reads



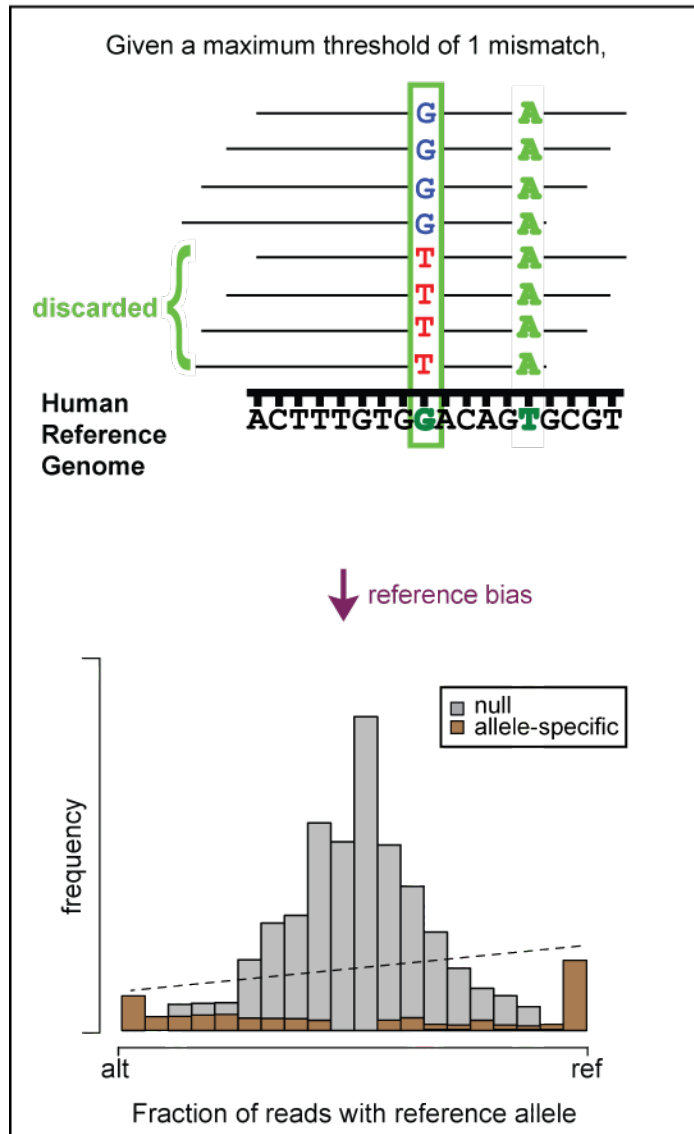
PG alleviates reference bias in alignment

Human reference genome alignment

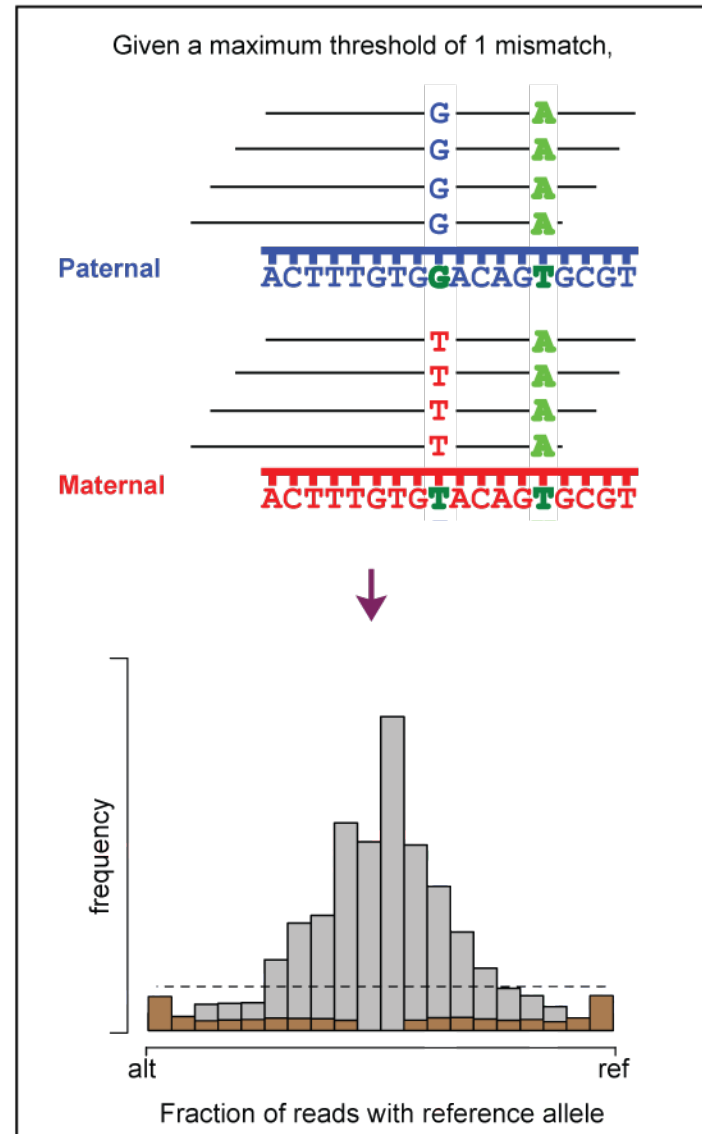


PG alleviates reference bias in alignment

Human reference genome alignment

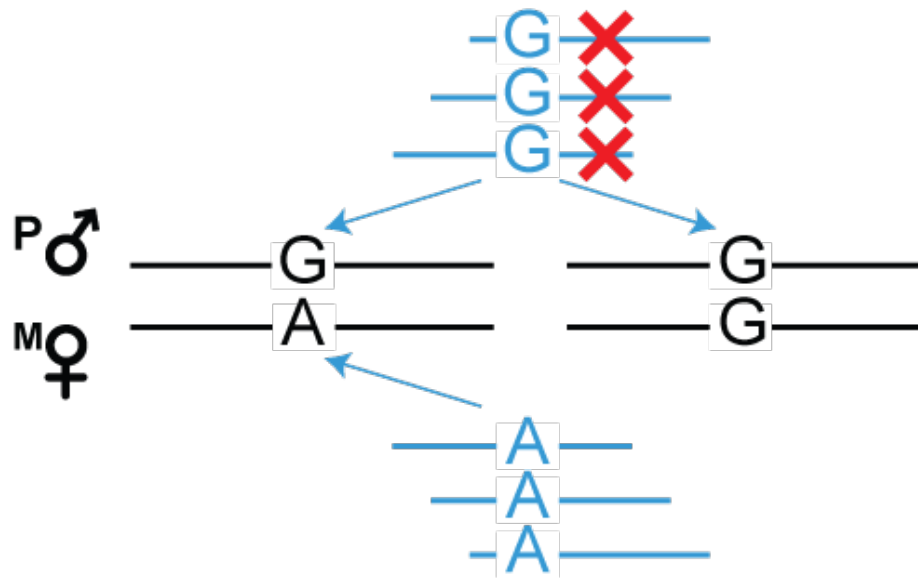


Diploid personal genome alignment



Ambiguous mapping bias due to sequence similarity

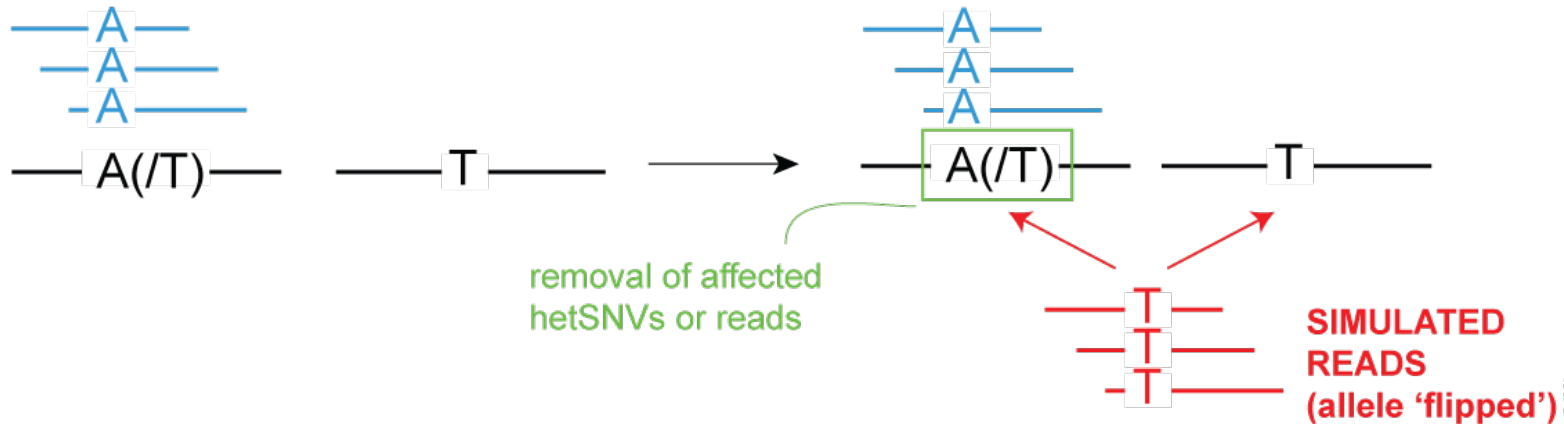
- For AS analyses, discard reads that multi-map



Account for ambiguous mapping bias

- Using the reference genome, new simulated reads are created where alleles of the original reads are flipped (at het SNV positions)

READS
FROM DATA



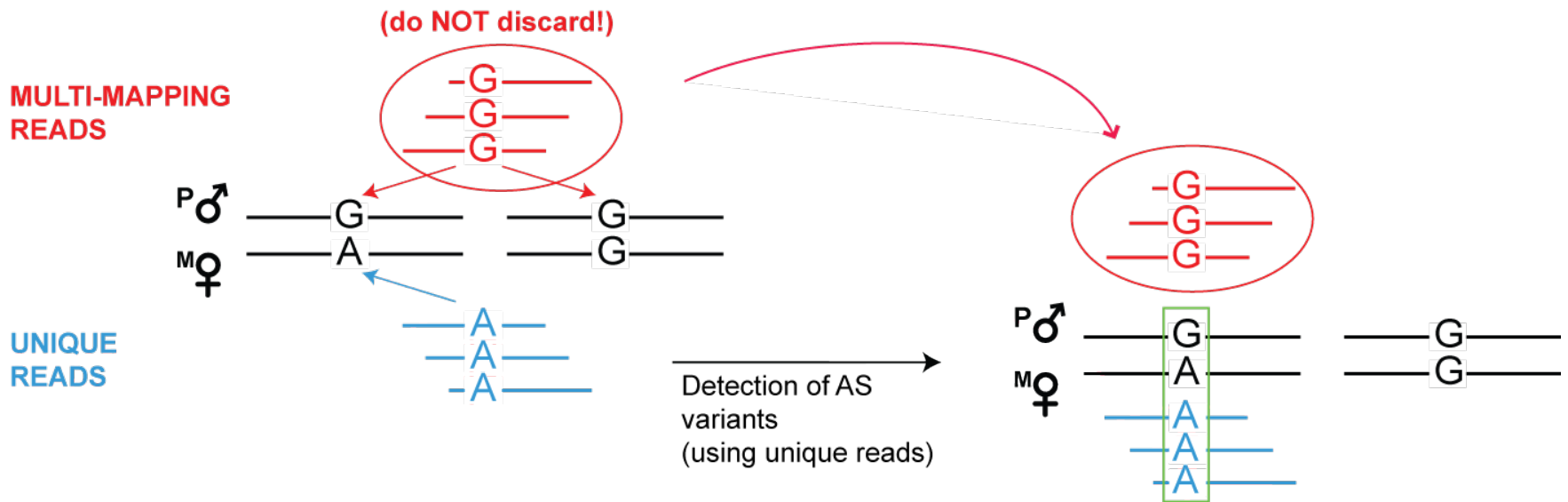
Lappalainen *et al.* (2013)

Panousis *et al.* (2014)

Van de Geijn *et al.* (2015)

PG facilitates the resolution of ambiguous mapping bias

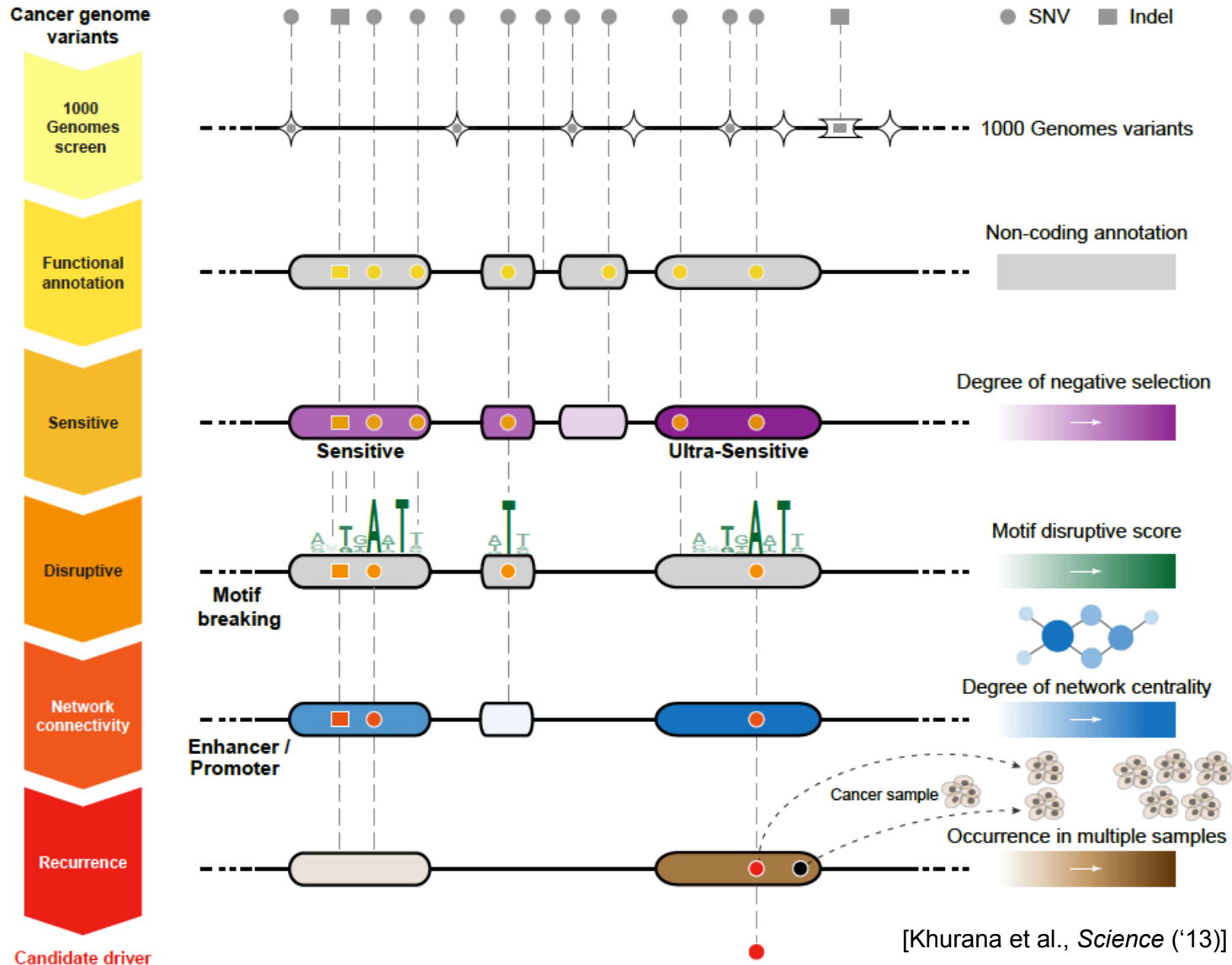
- Using the personal genome, we do not need to simulate reads.
- We can directly test affected sites using multi-mapping read pile



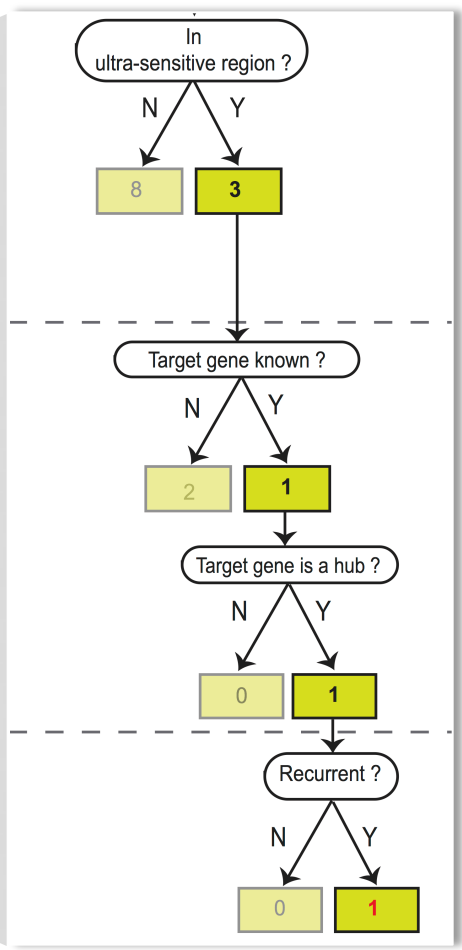
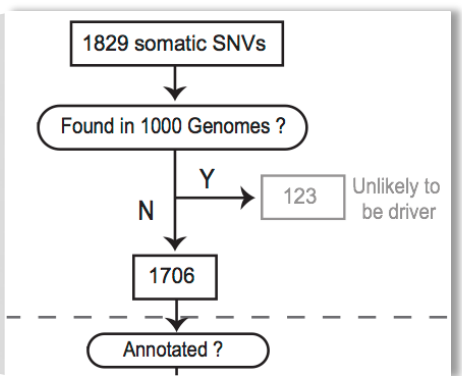
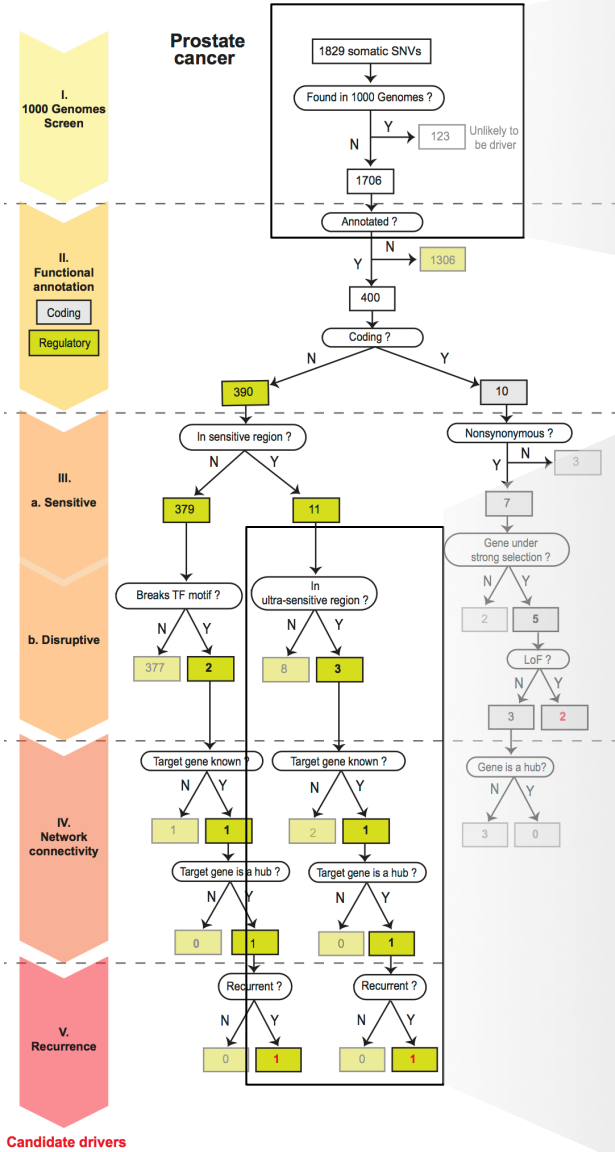
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Identification of non-coding candidate drivers amongst somatic variants: Scheme



Flowchart for 1 Prostate Cancer Genome (from Berger et al. '11)





Overview

This tool is specialized to prioritize somatic variants from cancer whole genome sequencing. It contains two components : 1) building data context from various resources; 2) variants prioritization. We provided downloadable scripts for users to customize the data context (found under 'Downloads'). The variants prioritization step is downloadable, and also implemented as web server (Right Panel), with pre-processed data context.

Instructions

- ♣ Input File - BED or VCF formatted. Click "green" button to add multiple files. With multiple files, the tool will do recurrent analysis. (Note: for BED format, user can put variants from multiple genomes in one file, see [Sample input file](#) .)
- ♣ Recurrence DB - User can choose particular cancer type from the database. The DB will continue be updated with newly available WGS data.
- ♣ Gene List - Option to analyze variants associated with particular set of genes. Note: Please use Gene Symbols, one row per gene.
- ♣ Differential Gene Expression Analysis - Option to detect differentially expressed genes in RNA-Seq data. Two files needed: expression file & class label file. Please refer to [Expression input files](#) for instructions to prepare those files.

♣ Note: In addition to on-site calculation, we also provide scores for all possible noncoding SNVs of GRCh37/hg19 under 'Downloads' (without annotation and recurrence analysis).

Input File: (only for hg19 SNVs)

Choose File No file chosen

BED or VCF files as input. [Sample input file](#)

Output Format:

bed

MAF:

0

Minor allele frequency threshold to filter polymorphisms from 1KG (value 0~1)

Cancer Type from Recurrence DB: [Summary table](#)

All Cancer Types

[Add a gene list](#) (Optional)

[Add differential gene expression analysis](#) (Optional)

Upload

Site integrates user variants with large-scale context

Data Context

Variant Prioritization

Weighted scoring scheme

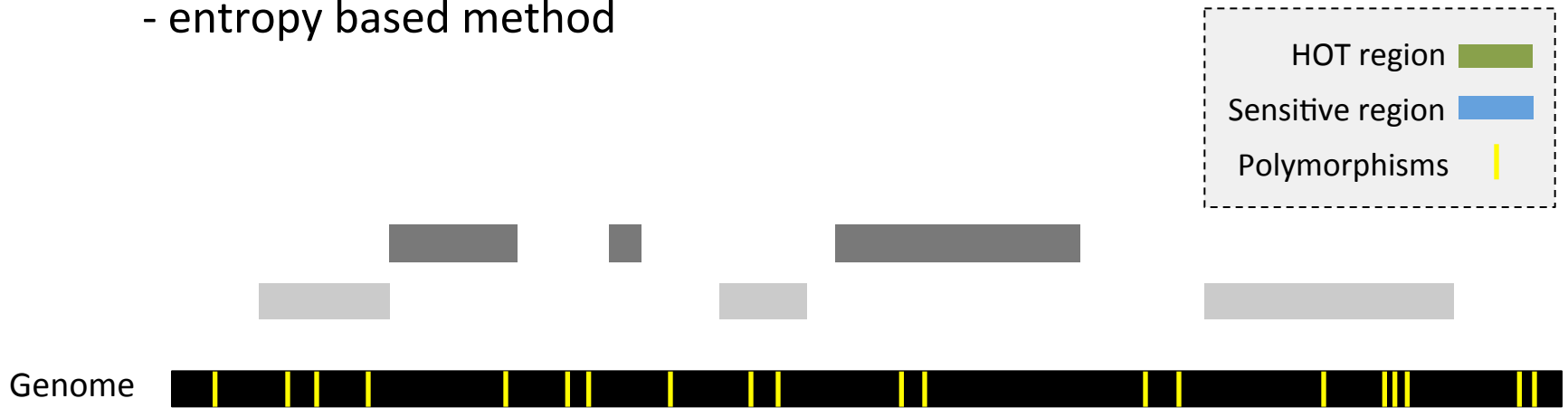
Highlighting variants

User Variants

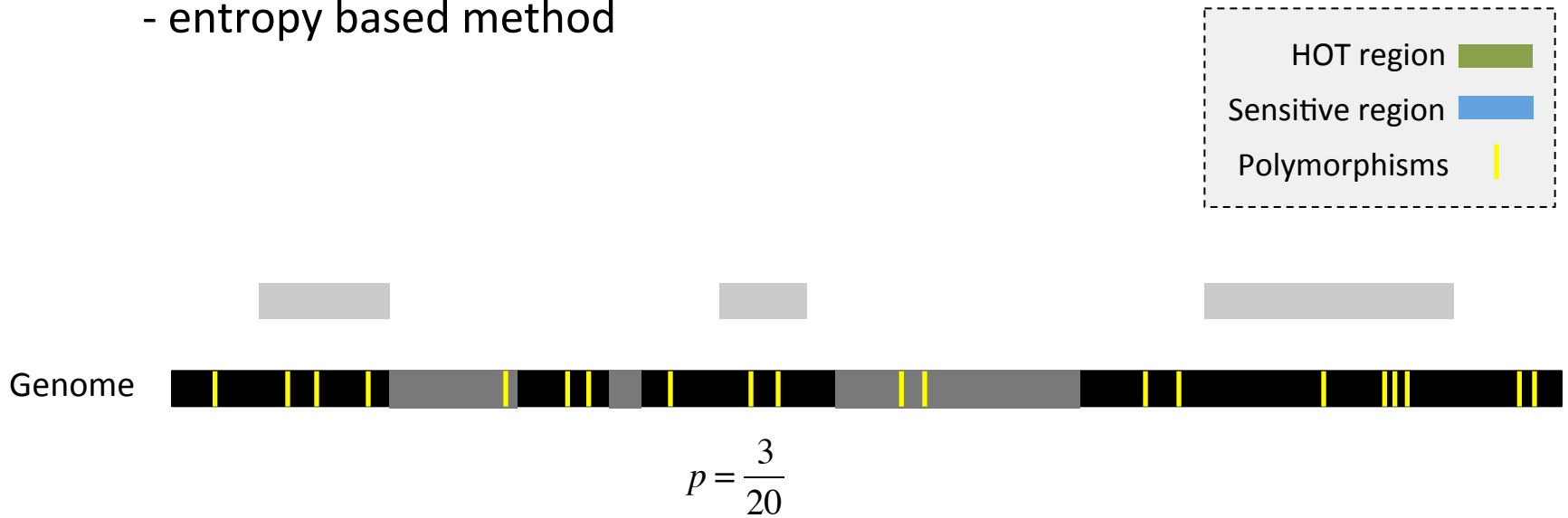
Variant Reports

FunSeq.gersteinlab.org

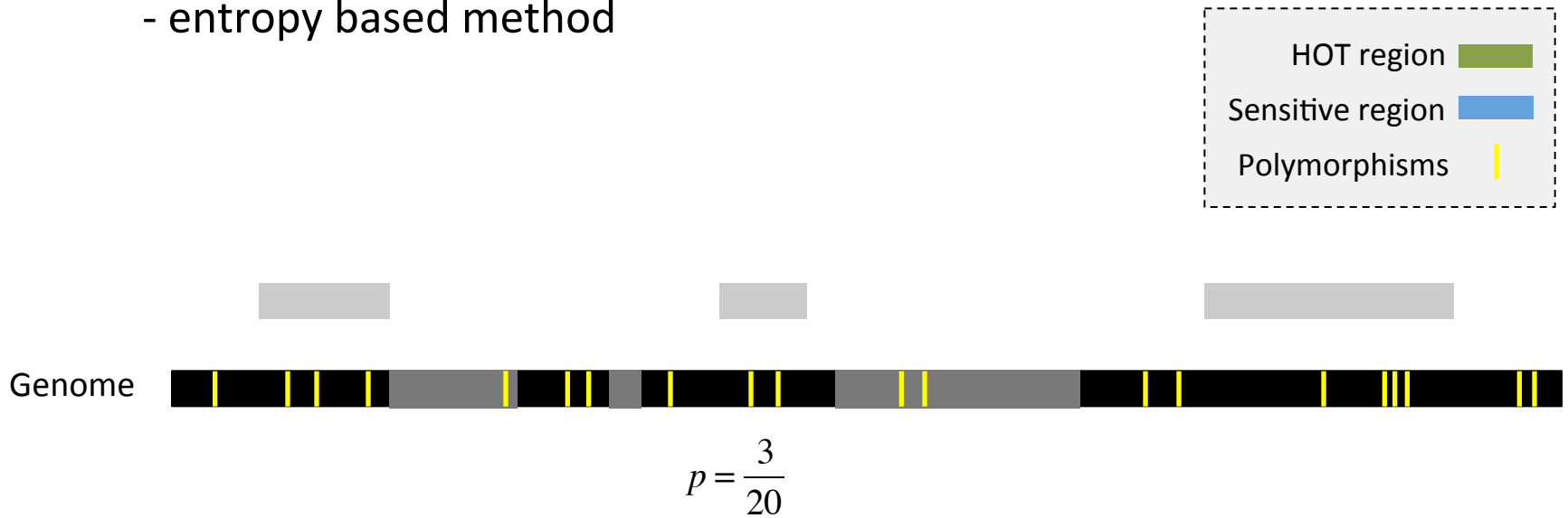
- Feature weight
 - Weighted with mutation patterns in natural polymorphisms
(features frequently observed weight less)
 - entropy based method



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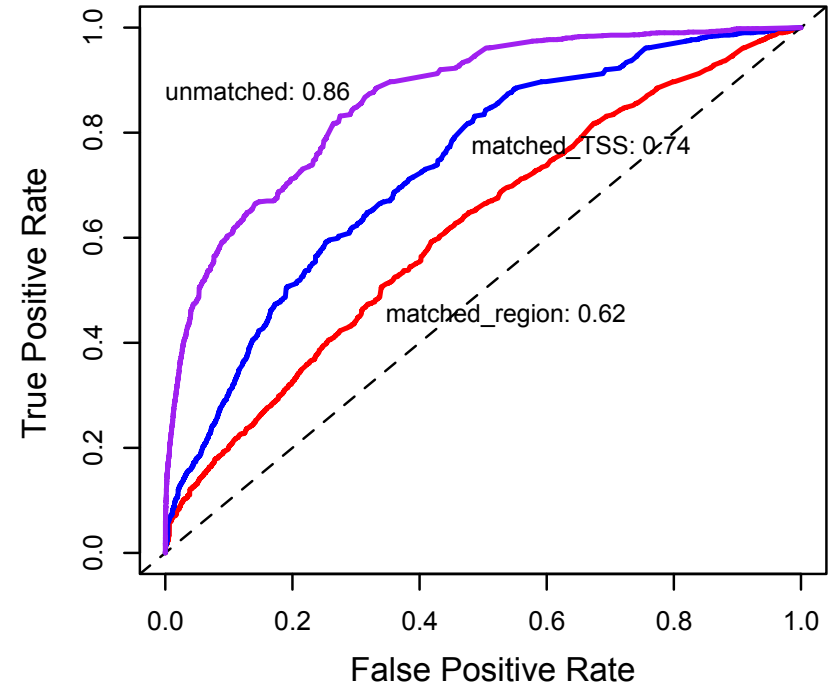
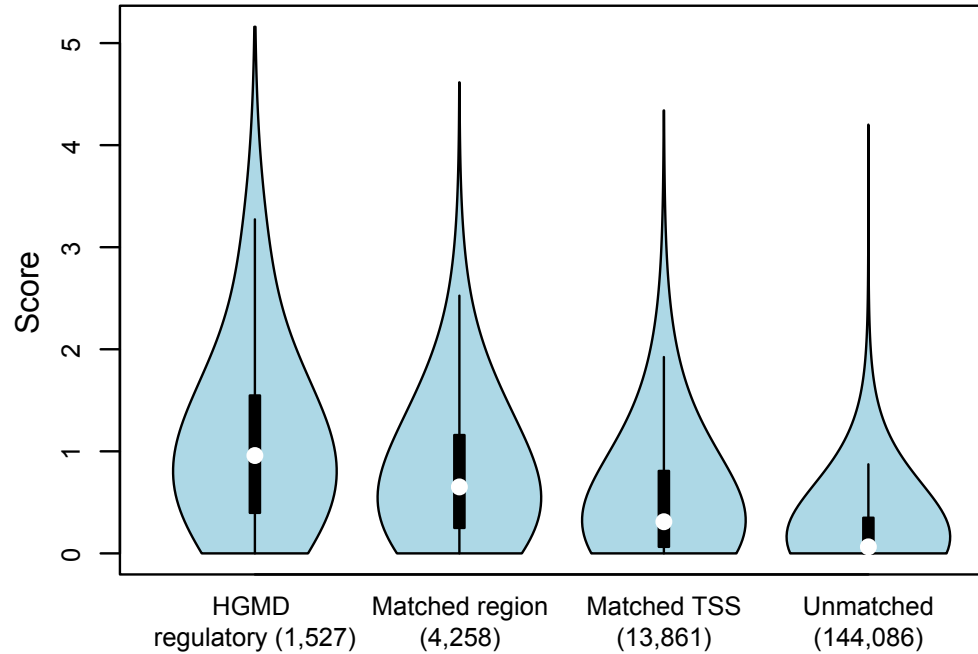


Feature weight: $w_d = 1 + p_d \log_2 p_d + (1 - p_d) \log_2 (1 - p_d)$

$p \uparrow$ $w_d \downarrow$ $p = \text{probability of the feature overlapping natural polymorphisms}$

For a variant: $\text{Score} = \sum w_d$ of observed features

Germline pathogenic variants show higher core scores than controls



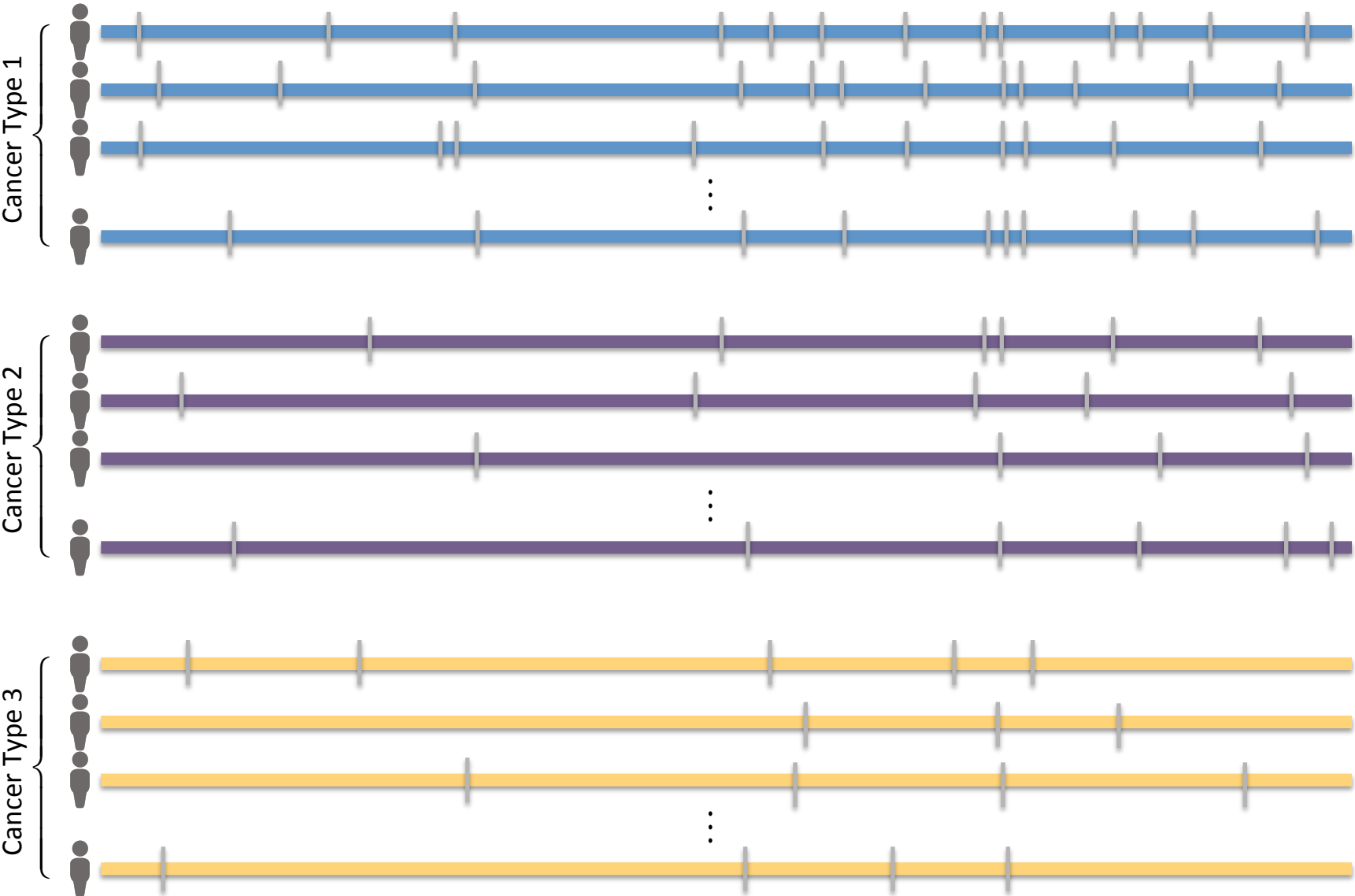
3 controls with natural polymorphisms (allele frequency $\geq 1\%$)

1. Matched region: 1kb around HGMD variants
2. Matched TSS: matched for distance to TSS
3. Unmatched: randomly selected

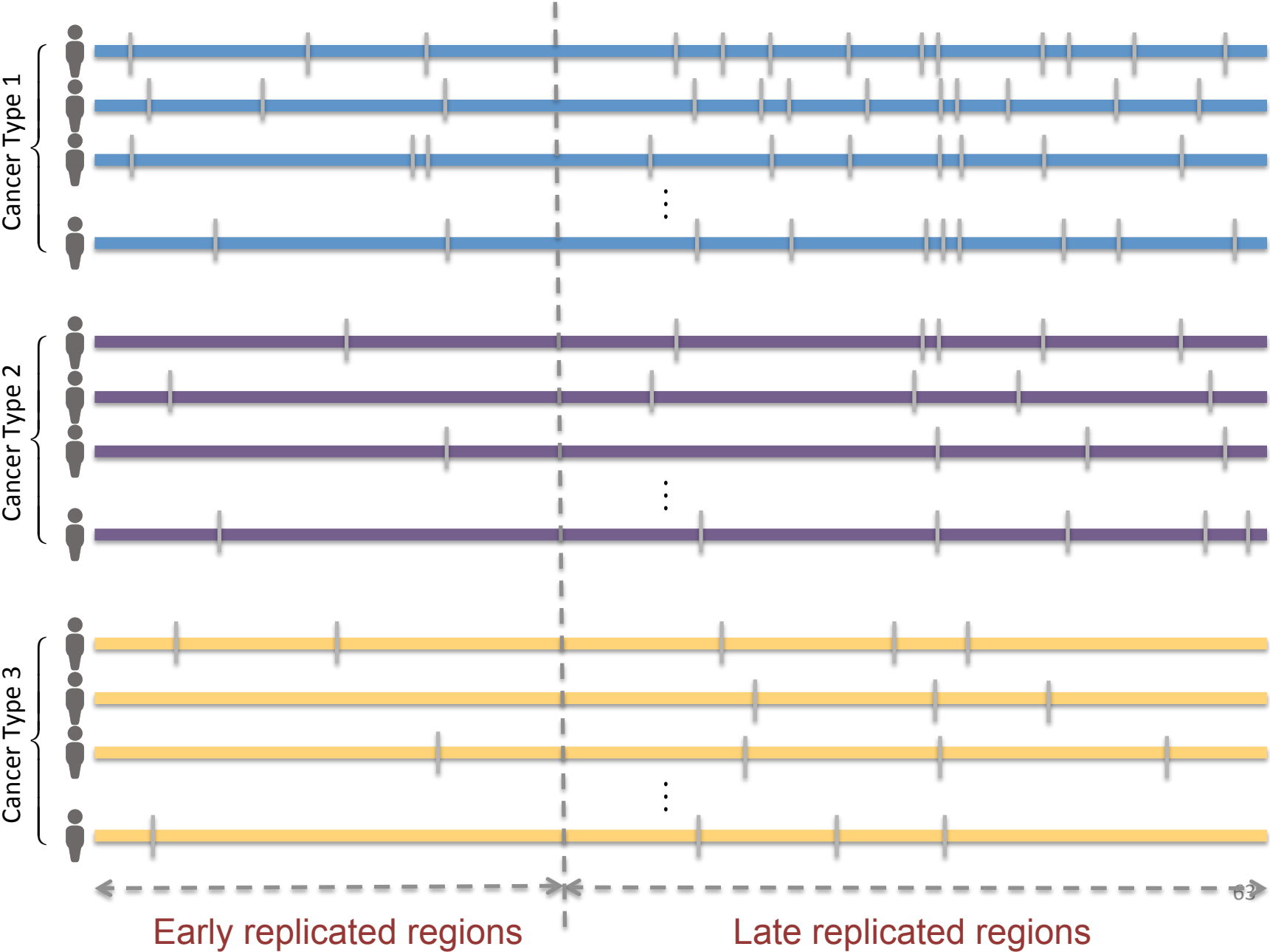
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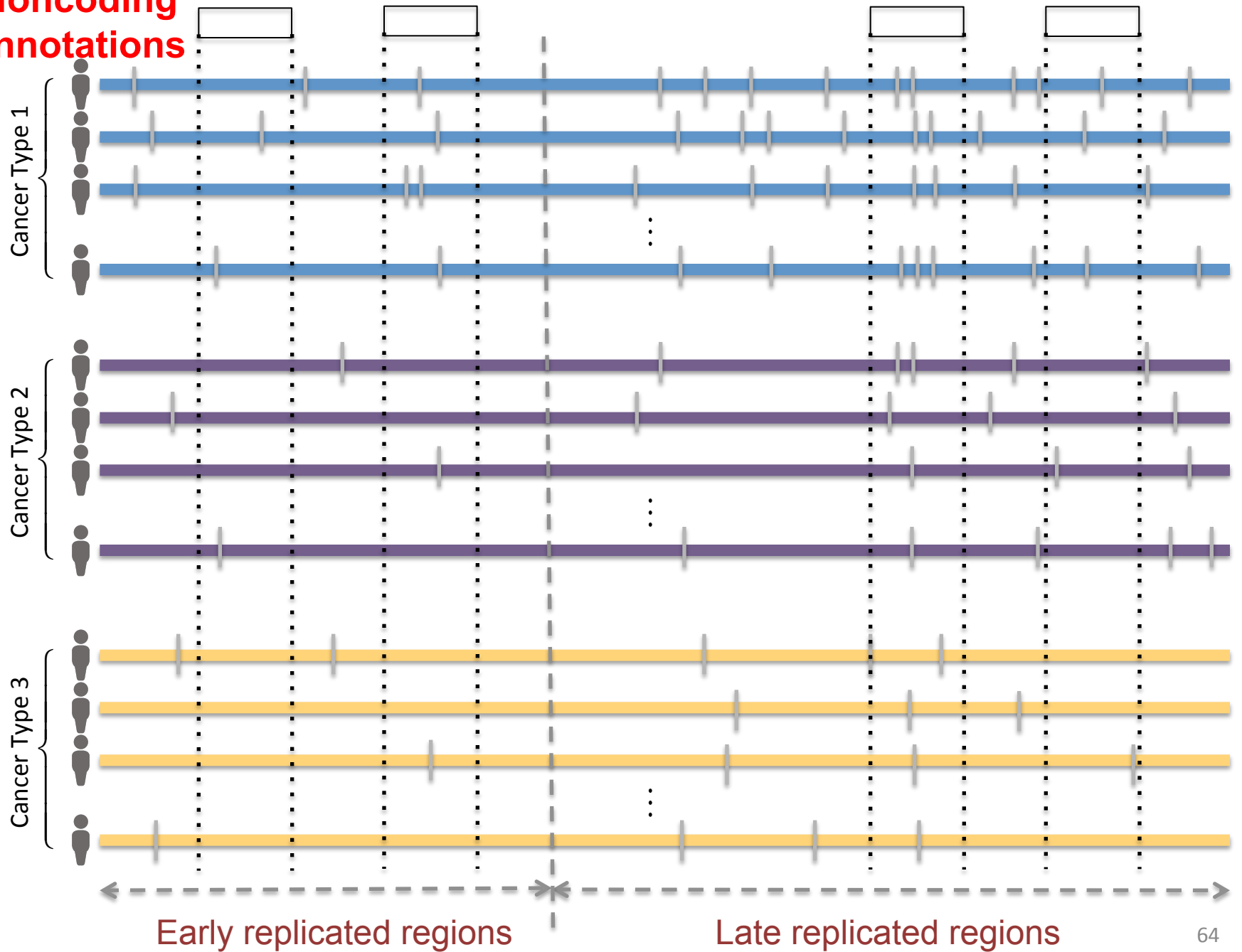
Mutation recurrence



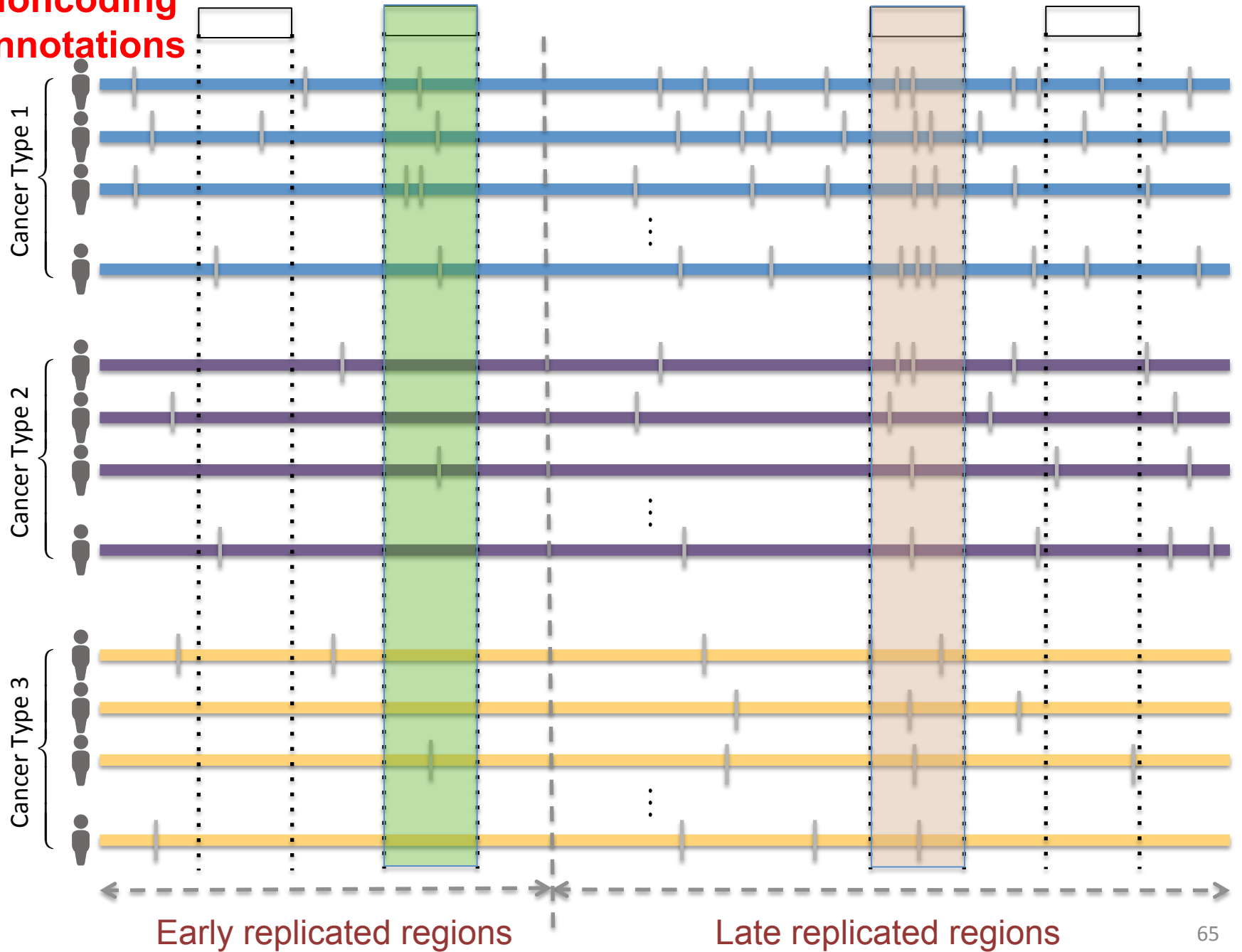
Mutation recurrence



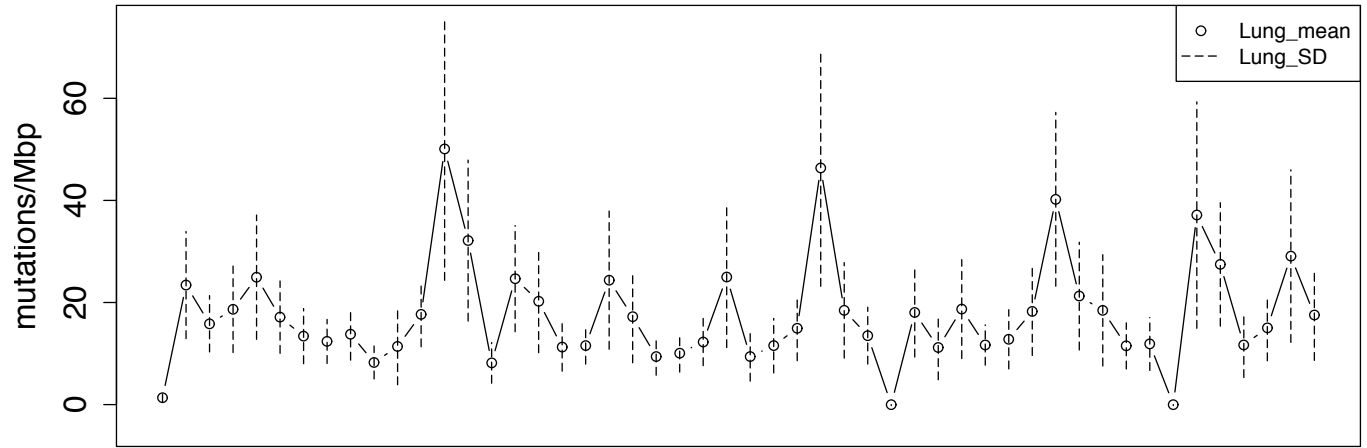
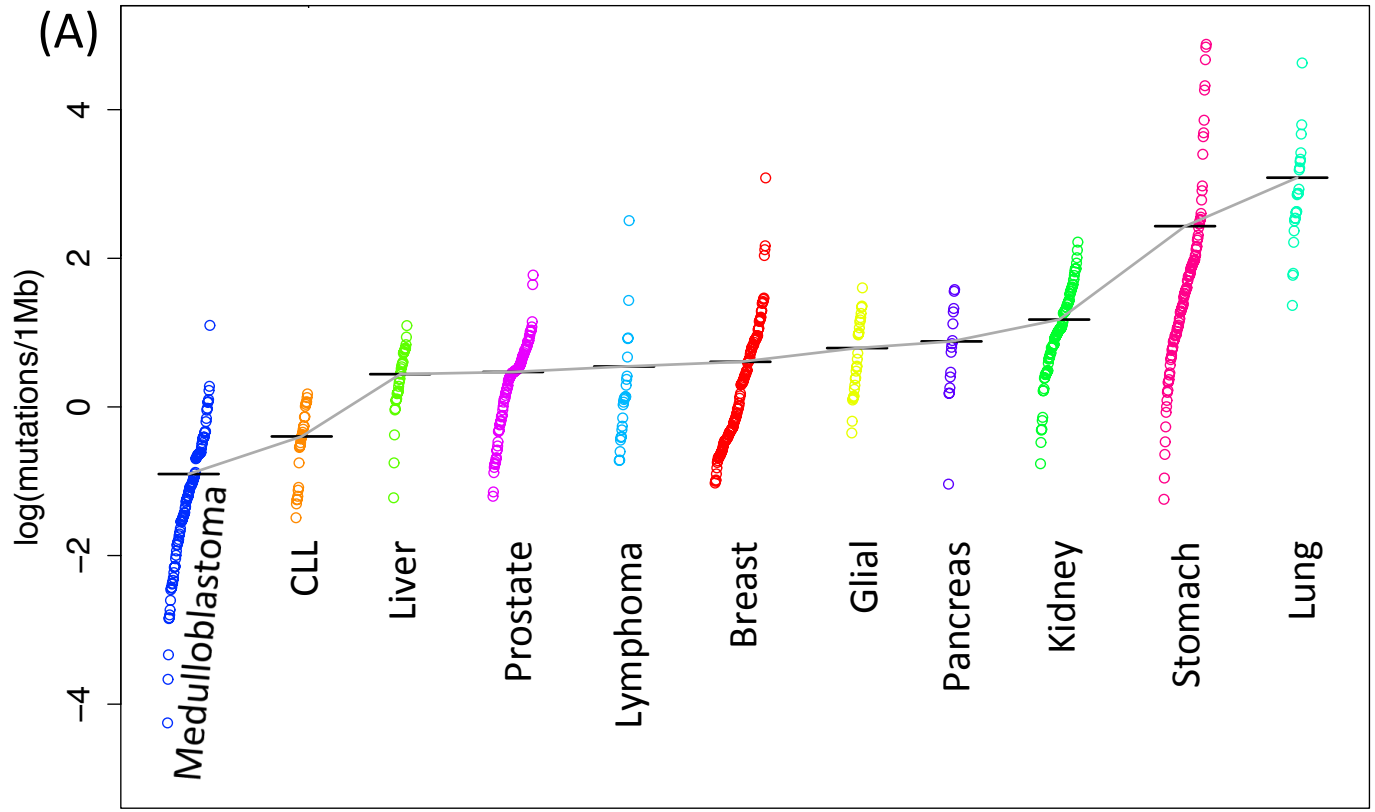
Noncoding annotations



Noncoding annotations



Cancer Somatic Mutational Heterogeneity, across cancer types, samples & regions



1 Mbp genome regions (locations chosen at random)

Cancer Somatic Mutation Modeling

- 3 models to evaluate the significance of mutation burden
- Suppose there are k genome elements. For element i , define:
 - n_i : total number of nucleotides
 - x_i : the number of mutations within the element
 - p_i : the mutation rate
 - R : the replication timing bin of the element

Model 1: Constant Background Mutation Rate (Model from Previous Work)

$$x_i : \text{Binomial}(n_i, p)$$

Model 2: Varying Mutation Rate

$$x_i | p_i : \text{Binomial}(n_i, p_i)$$

$$p_i : \text{Beta}(\mu, \sigma)$$

Model 3: Varying Mutation Rate with Replication Timing Correction

$$x_i | p_i : \text{Binomial}(n_i, p_i)$$

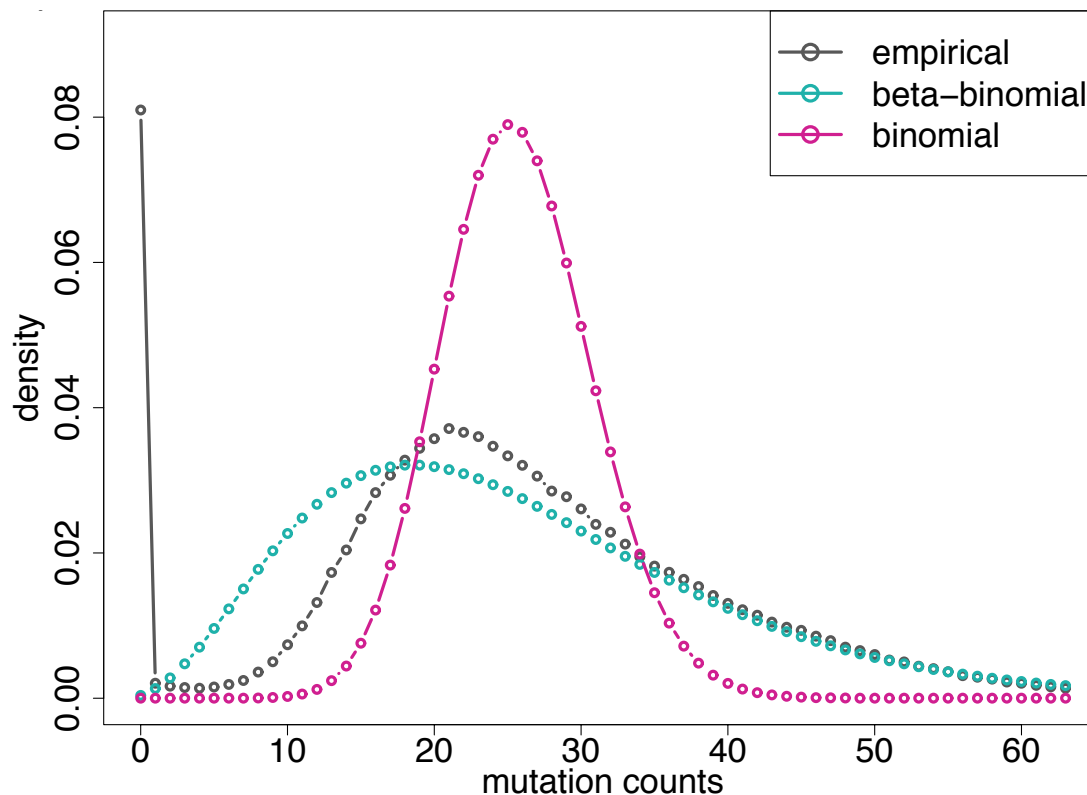
$$p_i : \text{Beta}(\mu | \mathbf{R}, \sigma | \mathbf{R})$$

$$\mu | \mathbf{R}, \sigma | \mathbf{R} : \text{constant within the same } \mathbf{R} \text{ bin}$$

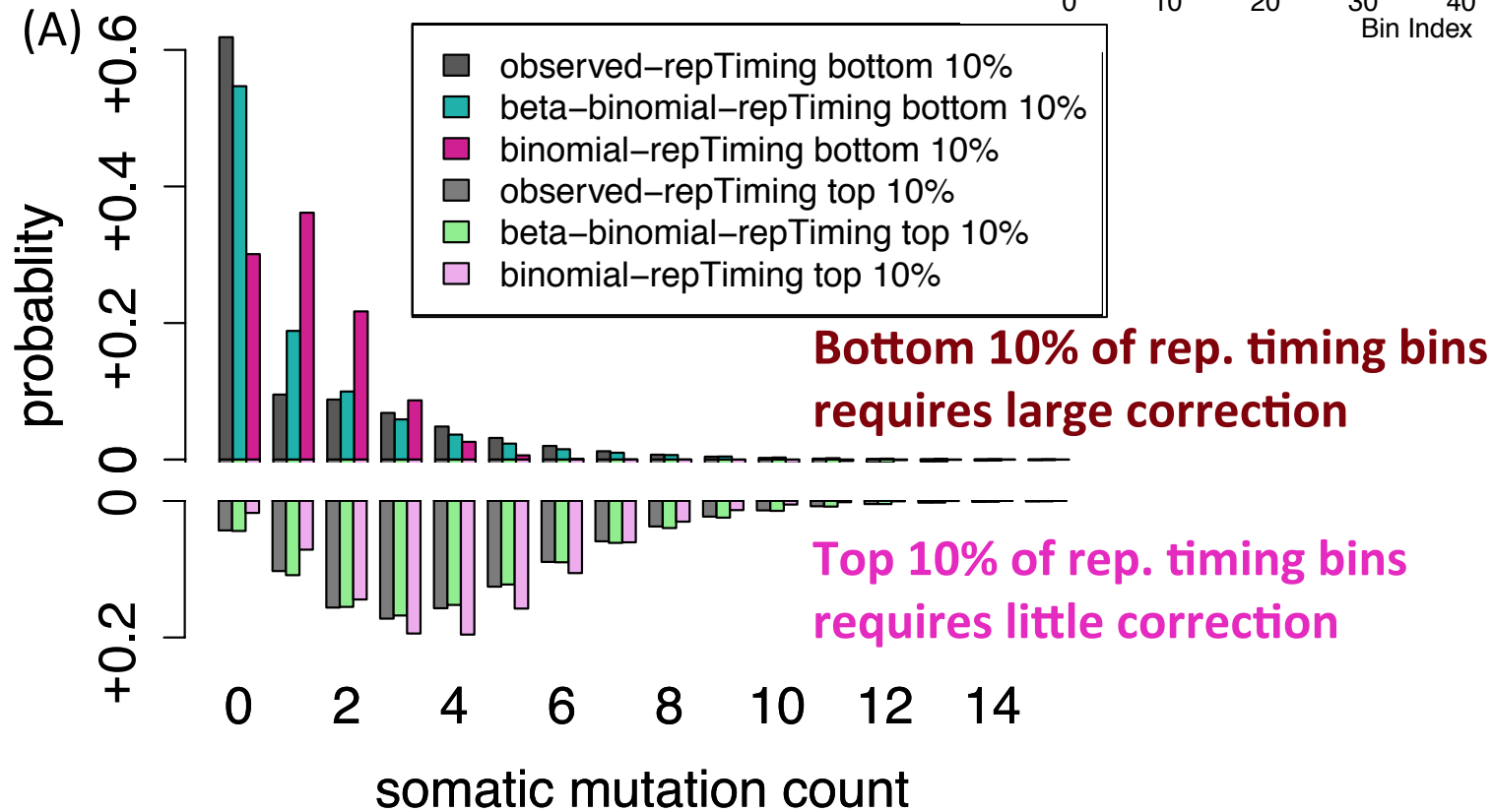
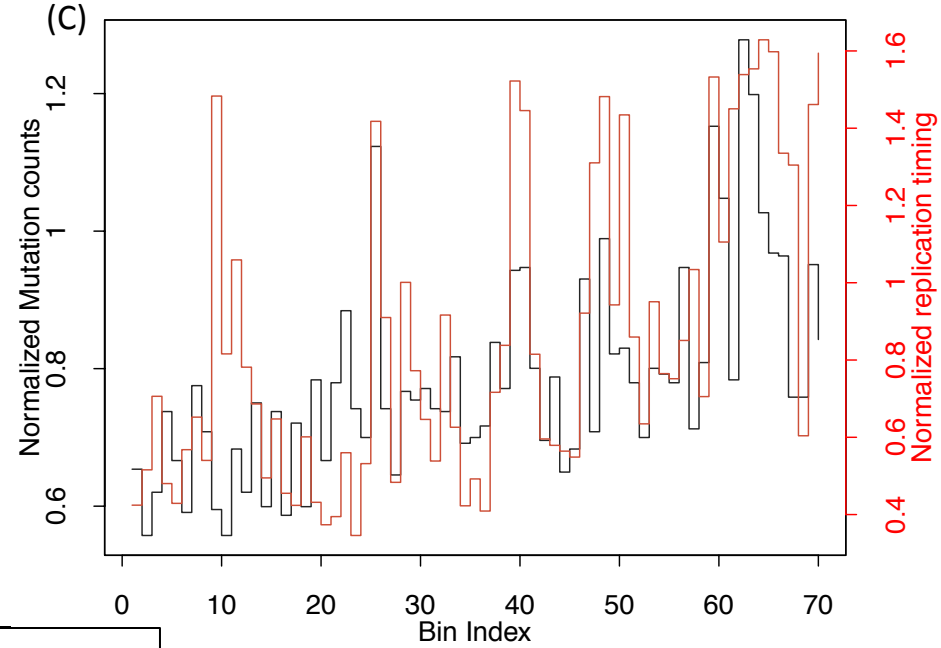
[Lochovsky et al. *NAR* ('15)]

LARVA Model Comparison

- Comparison of mutation count frequency implied by the binomial model (model 1) and the beta-binomial model (model 2) relative to the empirical distribution
- The beta-binomial distribution is significantly better, especially for accurately modeling the over-dispersion of the empirical distribution

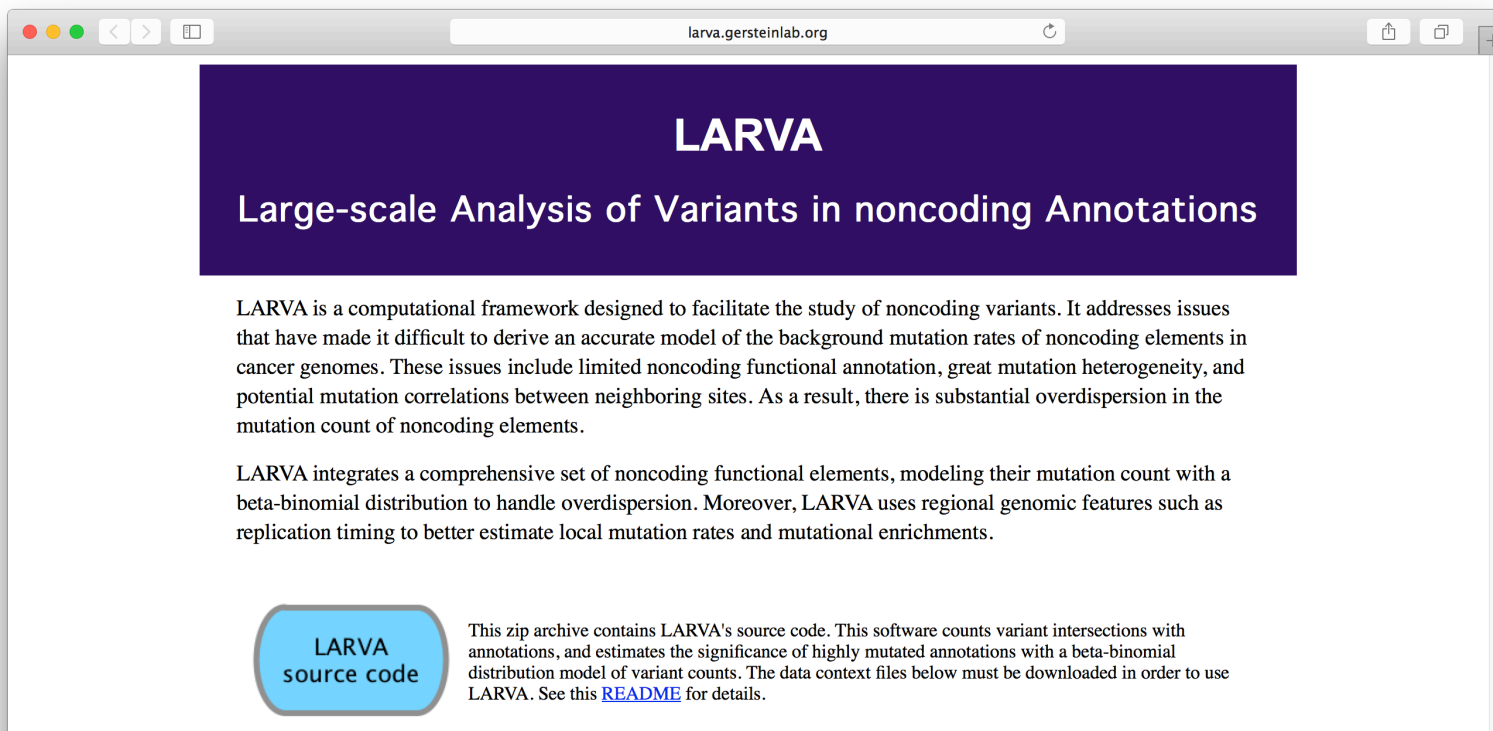


Adding DNA replication timing correction further improves the beta-binomial model



LARVA Implementation

- <http://larva.gersteinlab.org/>
- Freely downloadable C++ program
 - Verified compilation and correct execution on Linux
- A Docker image is also available to download
 - Runs on any operating system supported by Docker
- Running time on transcription factor binding sites (a worst case input size) is ~80 min
 - Running time scales linearly with the number of annotations in the input

A screenshot of a web browser displaying the LARVA website. The browser's address bar shows 'larva.gersteinlab.org'. The main content area features a dark purple header with the text 'LARVA' in white, followed by the subtitle 'Large-scale Analysis of Variants in noncoding Annotations' in white. Below this, there is a paragraph of text describing the framework's purpose and challenges. A second paragraph explains the computational model used. At the bottom, there is a blue button labeled 'LARVA source code' and a link to a README file.

LARVA
Large-scale Analysis of Variants in noncoding Annotations

LARVA is a computational framework designed to facilitate the study of noncoding variants. It addresses issues that have made it difficult to derive an accurate model of the background mutation rates of noncoding elements in cancer genomes. These issues include limited noncoding functional annotation, great mutation heterogeneity, and potential mutation correlations between neighboring sites. As a result, there is substantial overdispersion in the mutation count of noncoding elements.

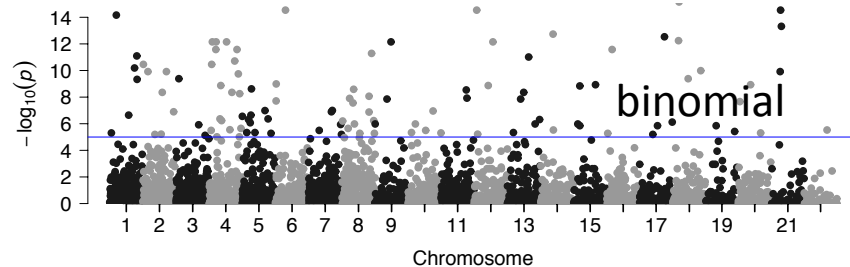
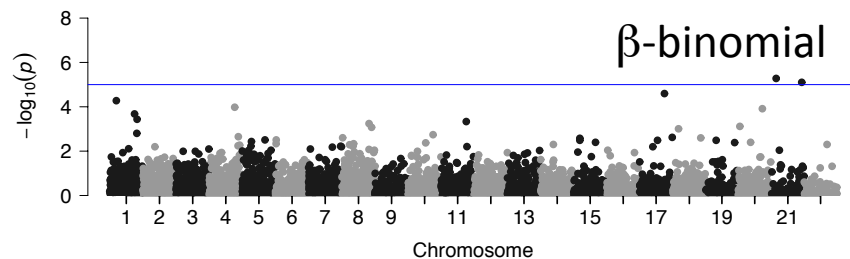
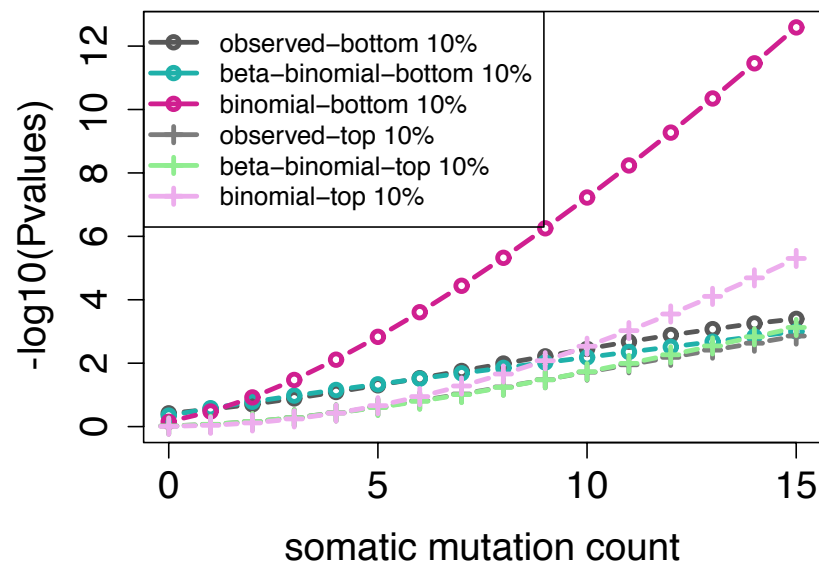
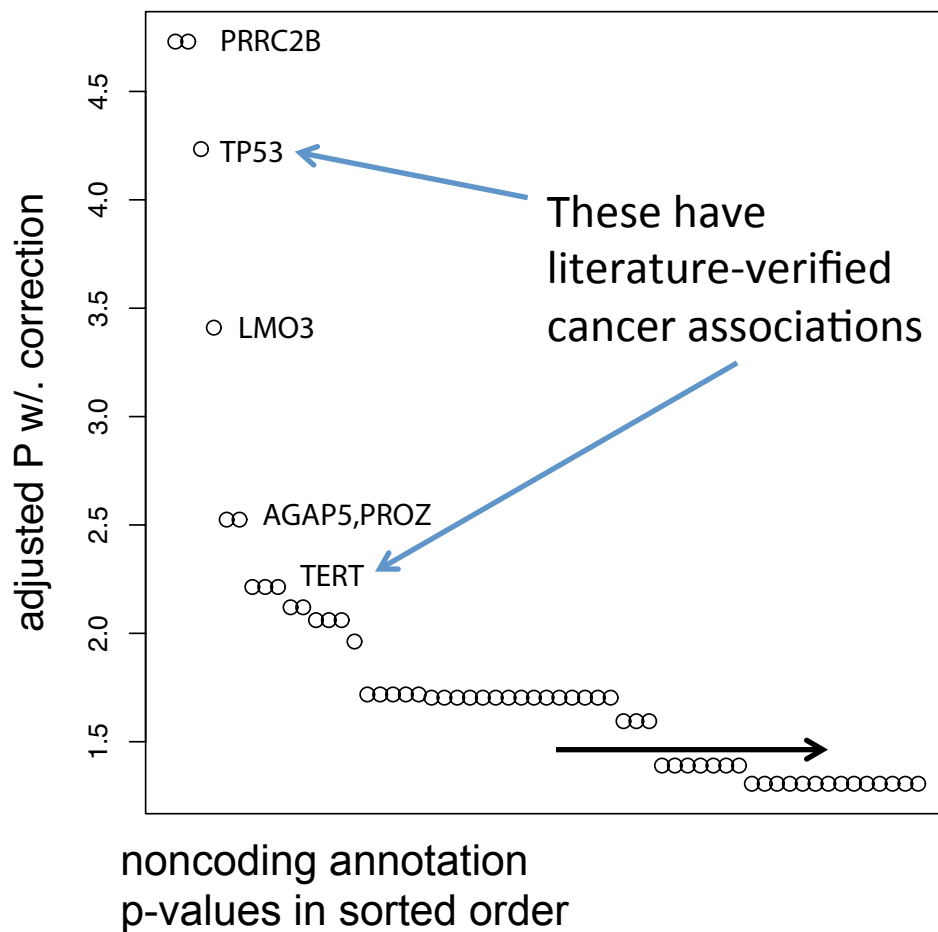
LARVA integrates a comprehensive set of noncoding functional elements, modeling their mutation count with a beta-binomial distribution to handle overdispersion. Moreover, LARVA uses regional genomic features such as replication timing to better estimate local mutation rates and mutational enrichments.

LARVA source code

This zip archive contains LARVA's source code. This software counts variant intersections with annotations, and estimates the significance of highly mutated annotations with a beta-binomial distribution model of variant counts. The data context files below must be downloaded in order to use LARVA. See this [README](#) for details.

LARVA Results

TSS LARVA results



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AlleleDB.gersteinlab.org
J **Chen**, J **Rozowsky**,
TR **Galeev**, A Harmanci,
R Kitchen, J Bedford,
A Abyzov, Y Kong, L Regan

CostSeq2

P **Muir**, S Li, S Lou,
D Wang, DJ Spakowicz,
L Salichos, J Zhang, F Isaacs,
J Rozowsky

FunSeq.gersteinlab.org

- & -

FunSeq2.gersteinlab.org

Y **Fu**, E **Khurana**, Z Liu,
S Lou, J Bedford, XJ Mu, KY
Yip, V Colonna, XJ Mu, ... ,

1000 Genomes

Project Consortium, et al

LARVA.gersteinlab.org
L **Lochovsky**,
J **Zhang**, Y Fu,
E Khurana

STRESS.molmovdb.org
D **Clarke**, A **Sethi**, S Li,
S Kumar, R W.F. Chang,
J Chen



Acknowledgments

Hiring Postdocs. See gersteinlab.org/jobs

Extra

