Thomas Kono

2017-08-02

RIS Interview Seminar
Slides: https://z.umn.edu/TK_RIS

Who I Am

- Undergrad: UC Davis (Biochem. + Molecular Bio.)
- PhD: University of Minnesota (Applied Plant Sciences)
  - Advisors: Peter L. Morrell and Robert M. Stupar
- Postdoc: University of Minnesota (Agronomy/EEB)
  - Advisors: Candice N. Hirsch and Suzanne E. McGaugh

Outline

Can we predict the phenotypic effect of a mutation?

Tools:

SNPMeta: Annotation of SNPs in non-model species

BAD_Mutations: Predicting deleterious SNPs

Applications:

Deleterious variant identification in two crop genomes

A different mutation type: genome content variation

SNPMeta: Questions

- What information on SNPs is available through public data sources?

- How do annotations from GenBank entries compare to those from a reference genome?

SNPMeta:
A Photo Analogy

Purpose: to collect metadata on SNPs

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A Photo Analogy

Purpose: to collect metadata on SNPs

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Modified: August 20, 2011 at 17:02 32
Stationery pad
Locked

▼ More Info:

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Alpha channel: No
Red eye: No
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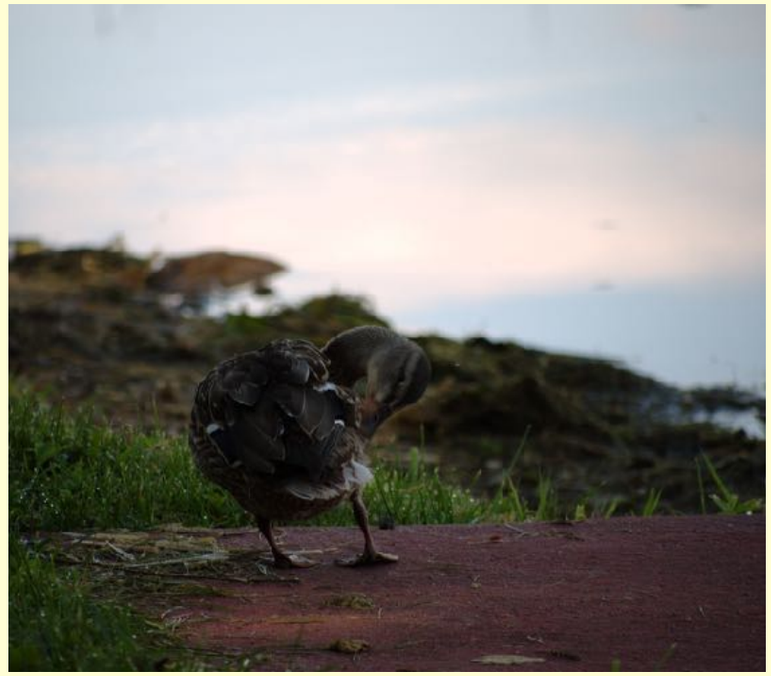
Exposure time: 1/125

→ Date info

→ Camera info

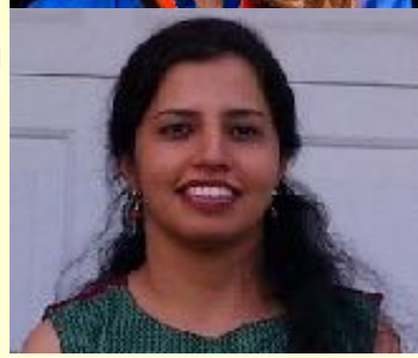
→ Exposure info



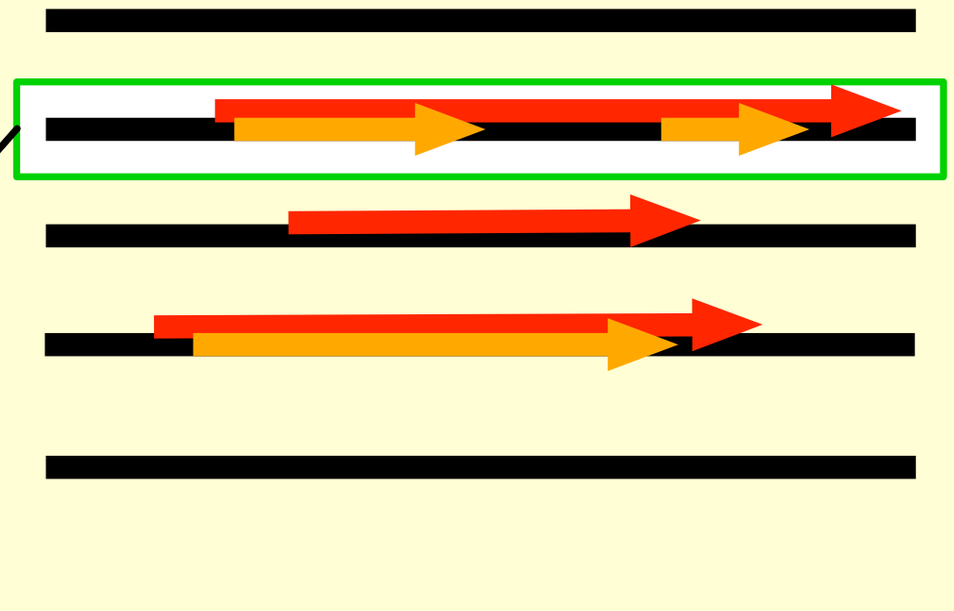
SNPMeta:
Pipeline Development

Amber Eule-Nashoba

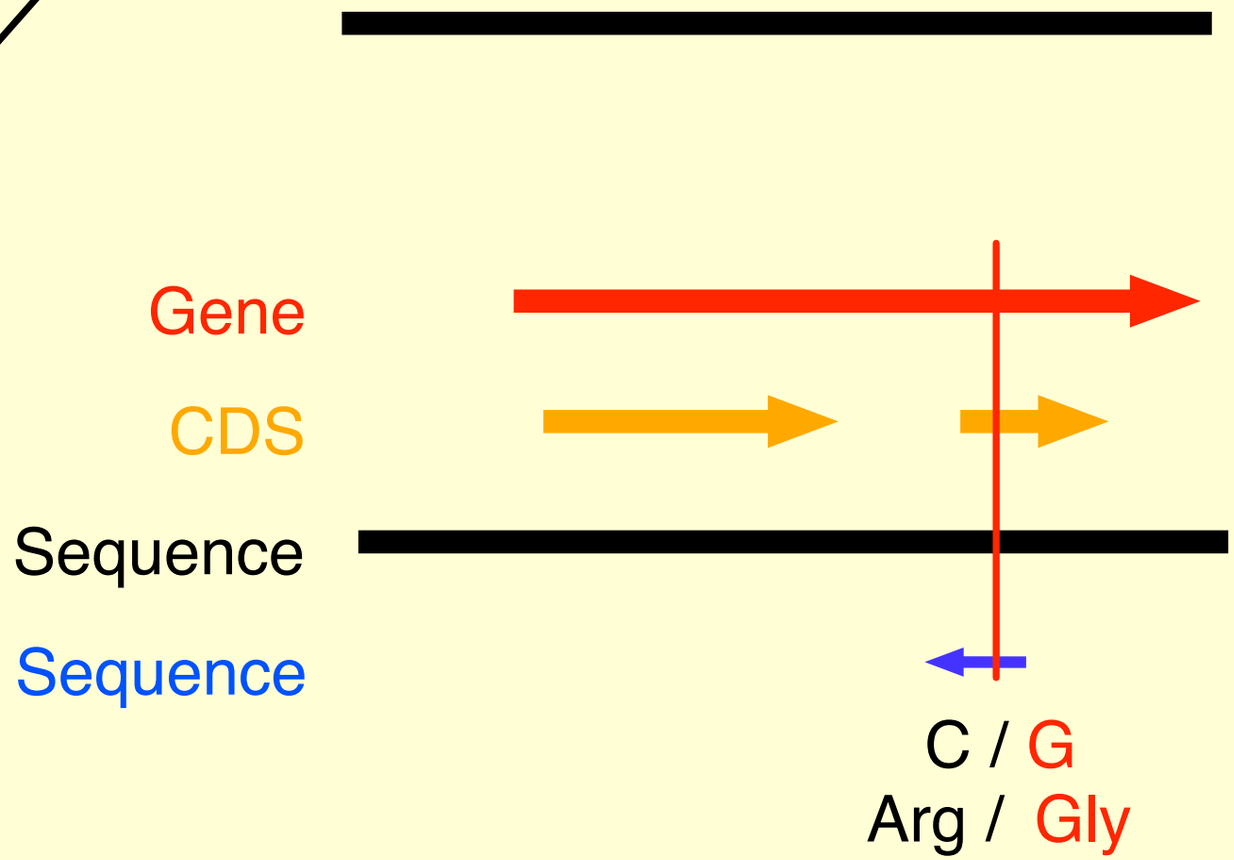
Kiran Seth



BLAST Hits



GenBank Record



SNPMeta: Output to dbSNP

Gene Name

GenBank Number

Protein Impact

```
SNP: RIL01_12001_39
GENENAME: CG4629
ACCESSION: AE014134
COMMENT: nonsynonymous I S
SAMPLESIZE:
LENGTH: ?
5'_FLANK: ATTCACTCCATTTTCCAGAAGAGAGCGGCAGGGACAGCGACGCCGGCTGTAGCGGCGCCA
OBSERVED: T/G
3'_FLANK: TGGCAGCGGCAAAAAGCCCAGTGAGAGAGCCGTCATTTGAGAGGTCGCCGGCGGAGCGCC
||
```

SNP States

Kono et al. 2014

SNPMeta: Availability

Software available in GitHub
https://github.com/MorrellLAB/SNPMeta

MOLECULAR ECOLOGY
RESOURCES

Molecular Ecology Resources (2014) 14, 419–425 doi: 10.1111/1755-0998.12183

SNPMeta: SNP annotation and SNP metadata collection without a reference genome

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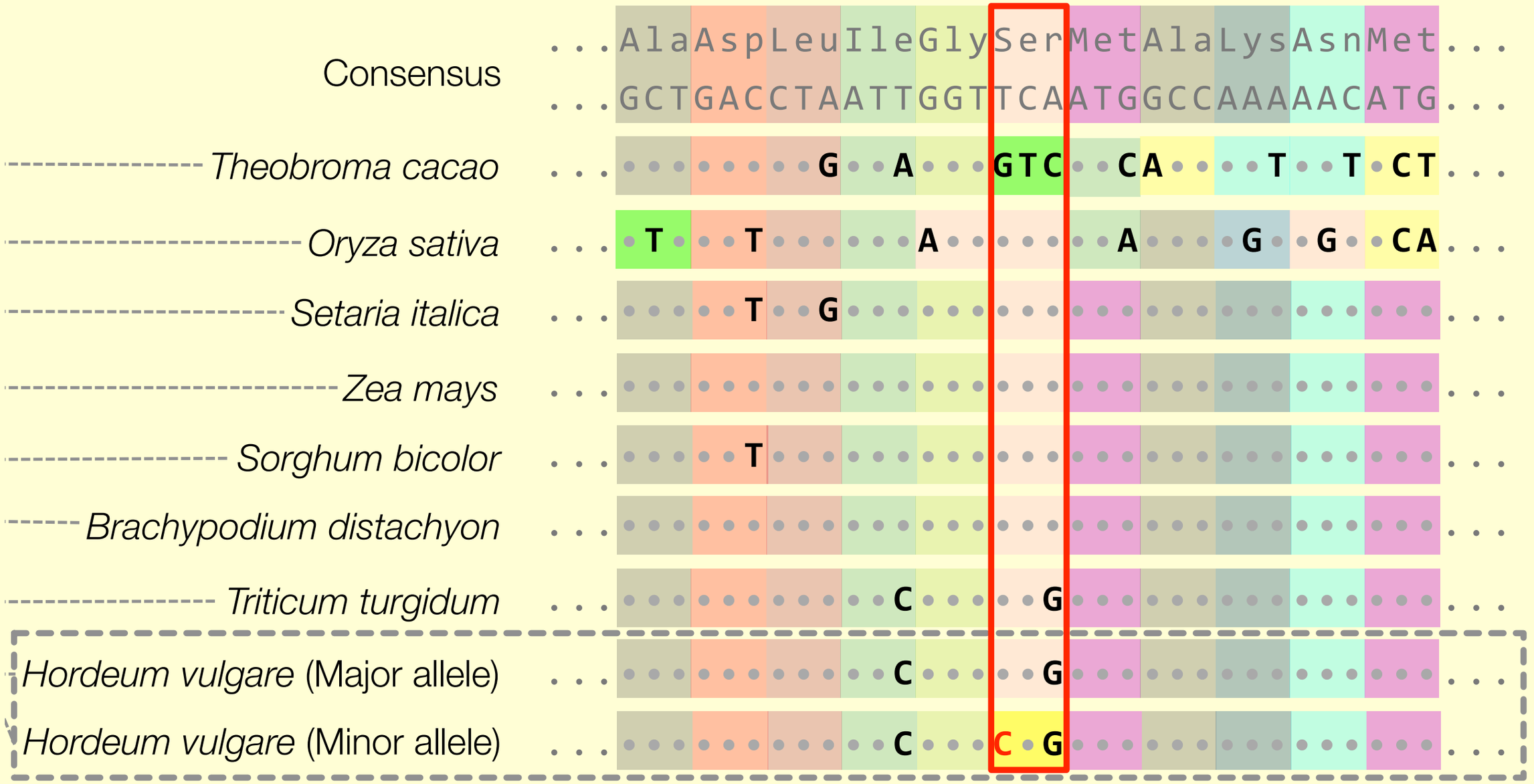
BAD_Mutations:
Yet Another Deleterious Prediction Program

- Why make another deleterious variant prediction program?
  - SIFT, PolyPhen2, PROVEAN, MAPP, GERP++, etc...
- Ideal program:
  - Is species-agnostic
  - Uses consistent high-quality data for each gene
  - Is hypothesis-driven
  - Corrects for reference bias[1]

1: Simons et al. 2014

BAD_Mutations:
What a Deleterious Variant Looks Like



BAD_Mutations: Hypothesis Test

Based on a likelihood ratio test (LRT) of sequence constraint from Chun and Fay (2009)

$$LLR = \log \frac{L(D|T, \theta, d_N = C d_S)}{L(D|T, \theta, d_N = d_S)}$$

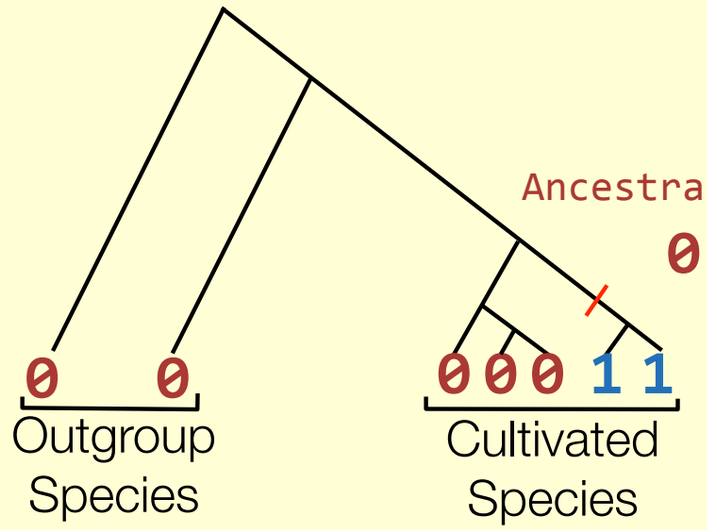
D = Codon alignment
T = Phylogeny
θ = Local substitution rate

BAD_Mutations: Addressing Reference Bias

	Morrex (Reference)	Stepstoe	Harrington	Kindred
SNP 1	A	G	G	A
SNP 2	T	C	T	T
SNP 3	C	C	T	T
Diff. From Reference	**0**	**2**	**2**	**1**

BAD_Mutations: Addressing Reference Bias

	Ancestral	Morex (Reference)	Steptoe	Harrington	Kindred
SNP 1	A	A	G	G	A
SNP 2	C	T	C	T	T
SNP 3	T	C	C	T	T
Diff. From Ancestral	**0**	**2**	**2**	**2**	**1**



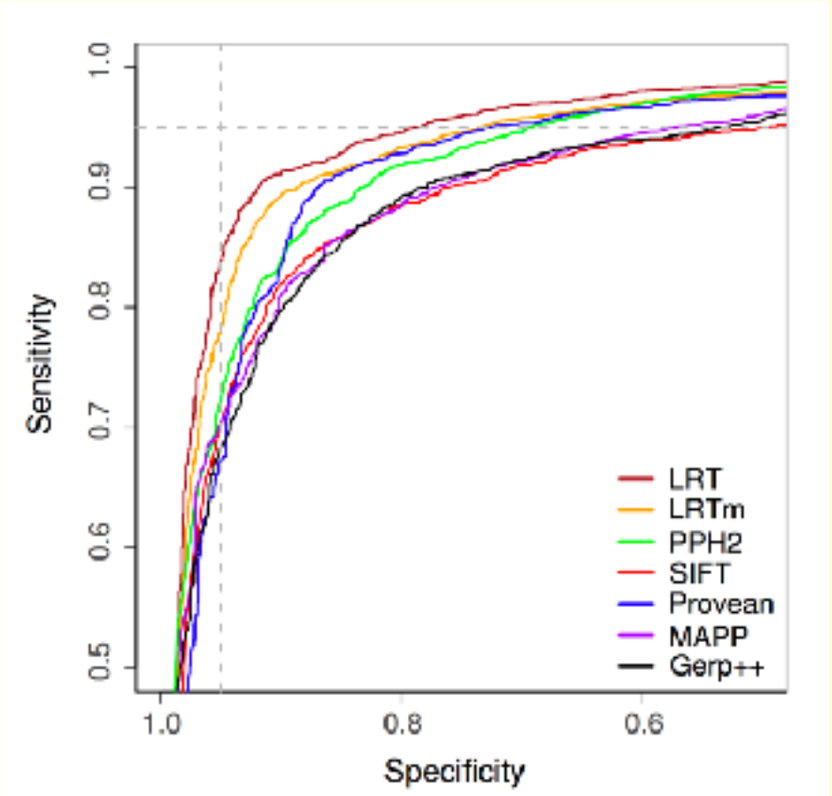
BAD_Mutations: Modular Design

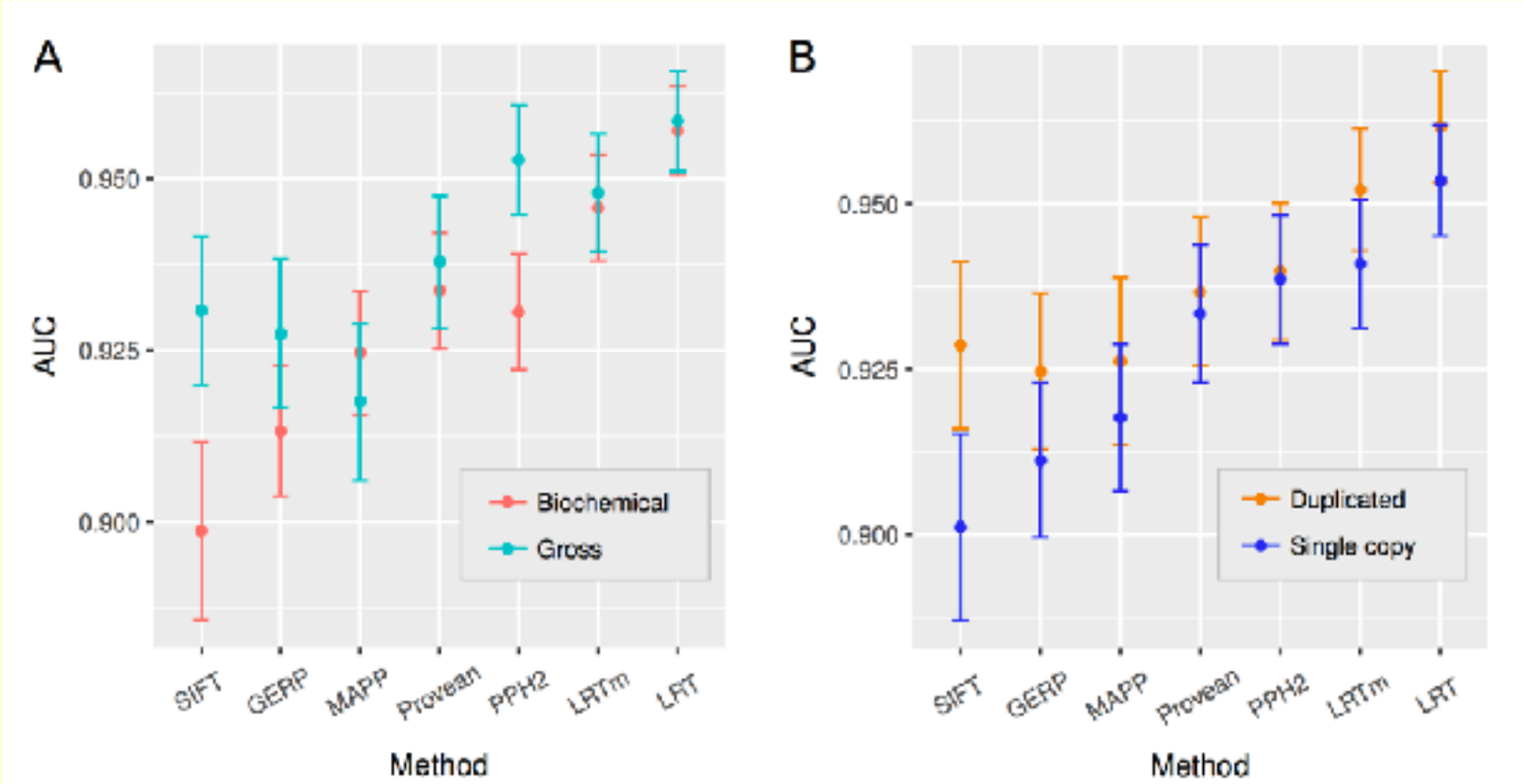
BAD_Mutations.py

setup	fetch	align	predict	compile
Generate config file	Download and unzip CDS files	Find and align orthologues	Run test on query codons	Generate report and p-values
Use config for controlling other subcommands	Download databases once, refresh when needed	Parallelize on a gene-basis for a genome wide analysis	Parallelize on a gene-basis for a genome wide analysis. Slow.	Run locally, parses HYPHY text reports.

BAD_Mutations: High Accuracy

Used a curated set of 2,910 SNPs in *A. thaliana* with mutant phenotypic effects and 1,583 SNPs at high frequency (neutral)





BAD_Mutations: Availability

- Manuscript in BioRxiv

New Results

Comparative genomics approaches accurately predict deleterious variants in plants

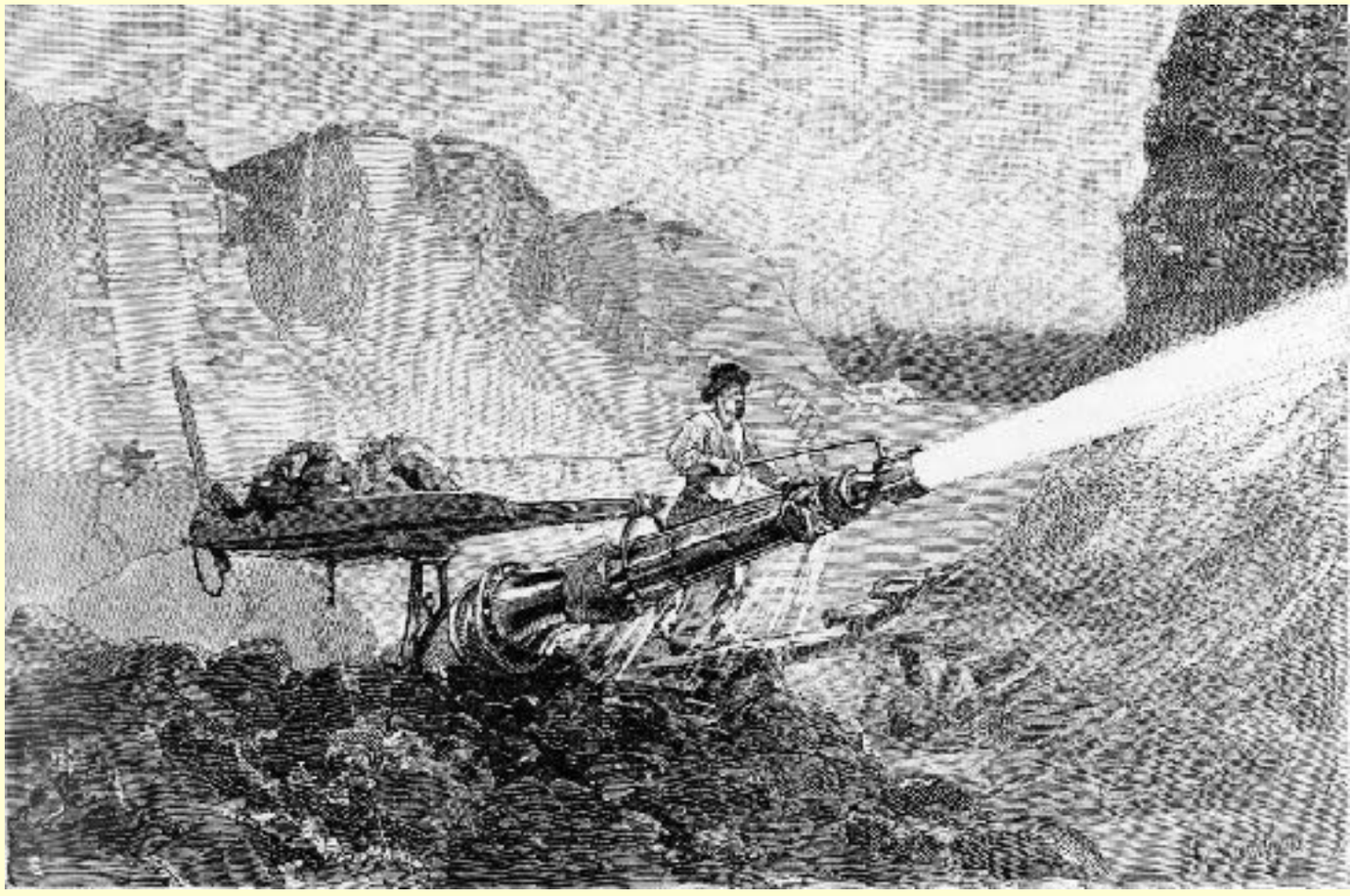
Thomas John Y Kono, Li Lei, Ching-Hua Shih, Paul J Hoffman, Peter L Morrell, Justin C. Fay

doi: https://doi.org/10.1101/112318

Software available in GitHub

- https://github.com/MorrellLAB/BAD_Mutations
- Manual: https://github.com/MorrellLAB/BAD_Mutations/blob/master/Manual/Manual_v1.0.md

Deleterious Variants: A “Gold Rush”

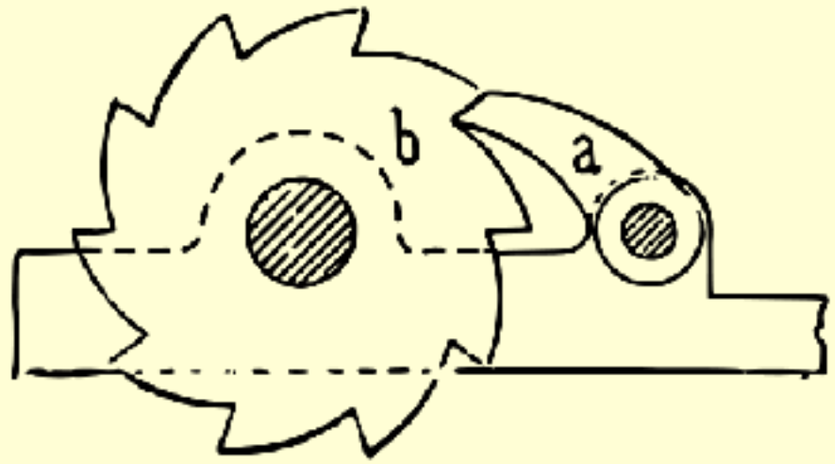


Lewontin 1974
Rockman 2012

Deleterious Variants: Theoretical Basis

- Purging effects - Finite N_e limits the effectiveness of purifying selection[1]

- "Muller's Ratchet"[2] - Deleterious mutations fix in low recombination regions



- Linked selection effects - genetic hitchhiking[3]

1:Takebayashi and Morrell 2001
2: Muller 1964
3: Hill and Robertson 1966

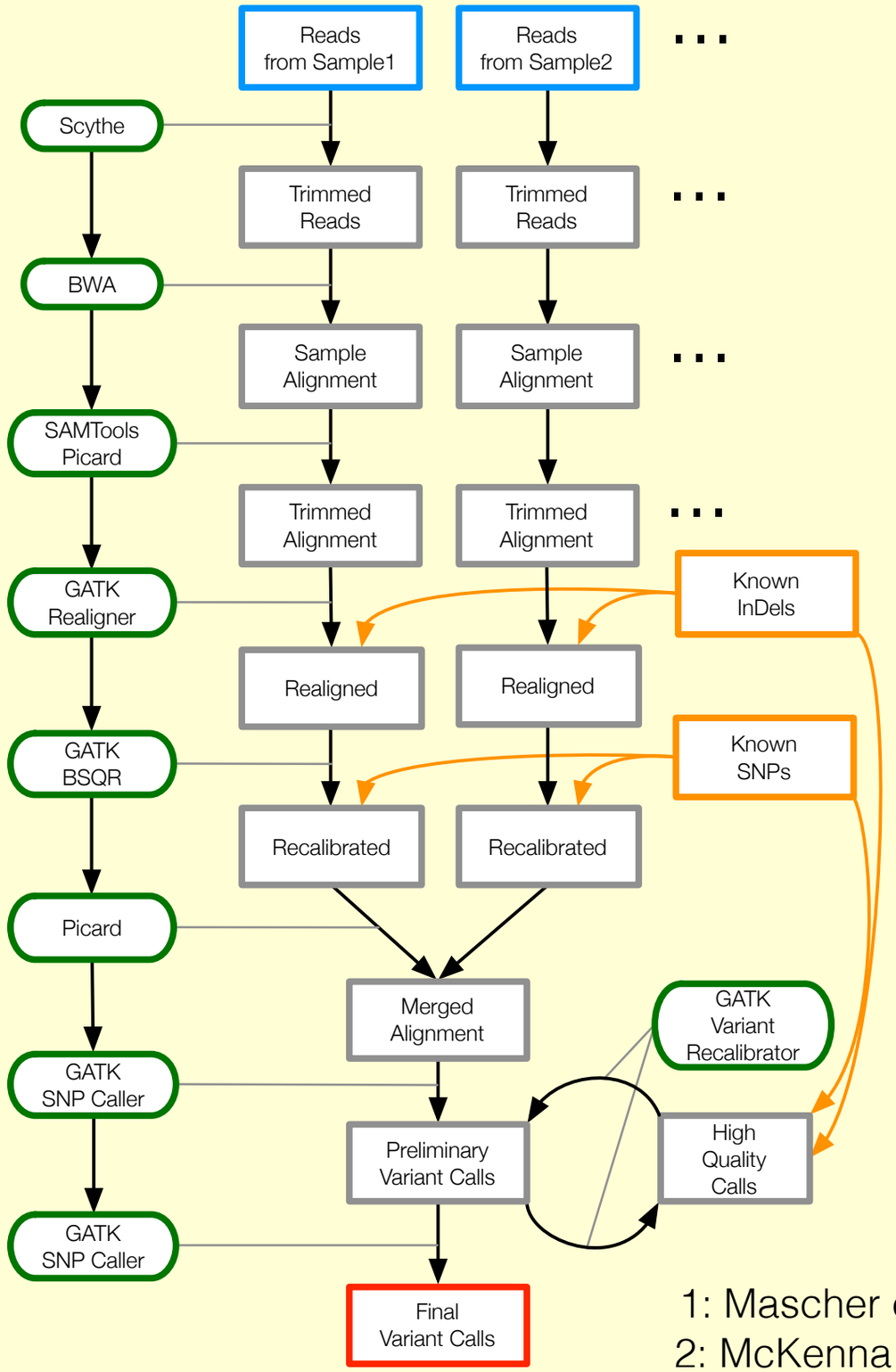
Deleterious Variants: Questions

- How many putatively deleterious SNPs segregate in two crop species?

- Are SNPs that are causative for a phenotypic variant more likely to be annotated as deleterious, as compared to those without known phenotypic effects?

Deleterious Variants: Resequencing Data Analysis Pipeline

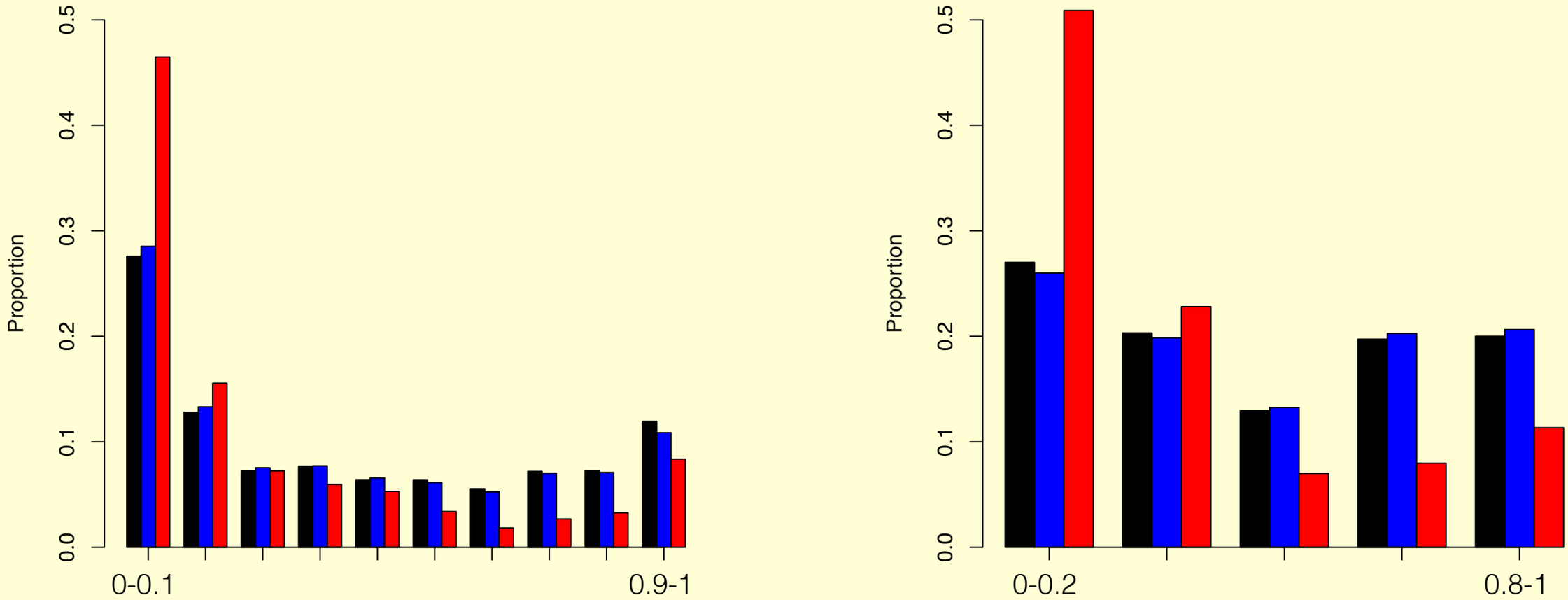
- Exome resequencing[1] of 15 barley accessions
- Whole genome resequencing of 8 soybean accessions
- Workflow based on GATK best practices[2,3]



1: Mascher et al. 2013
2: McKenna et al 2010
3: DePristo et al. 2011

Deleterious Variants: Enrichment for Low Frequency

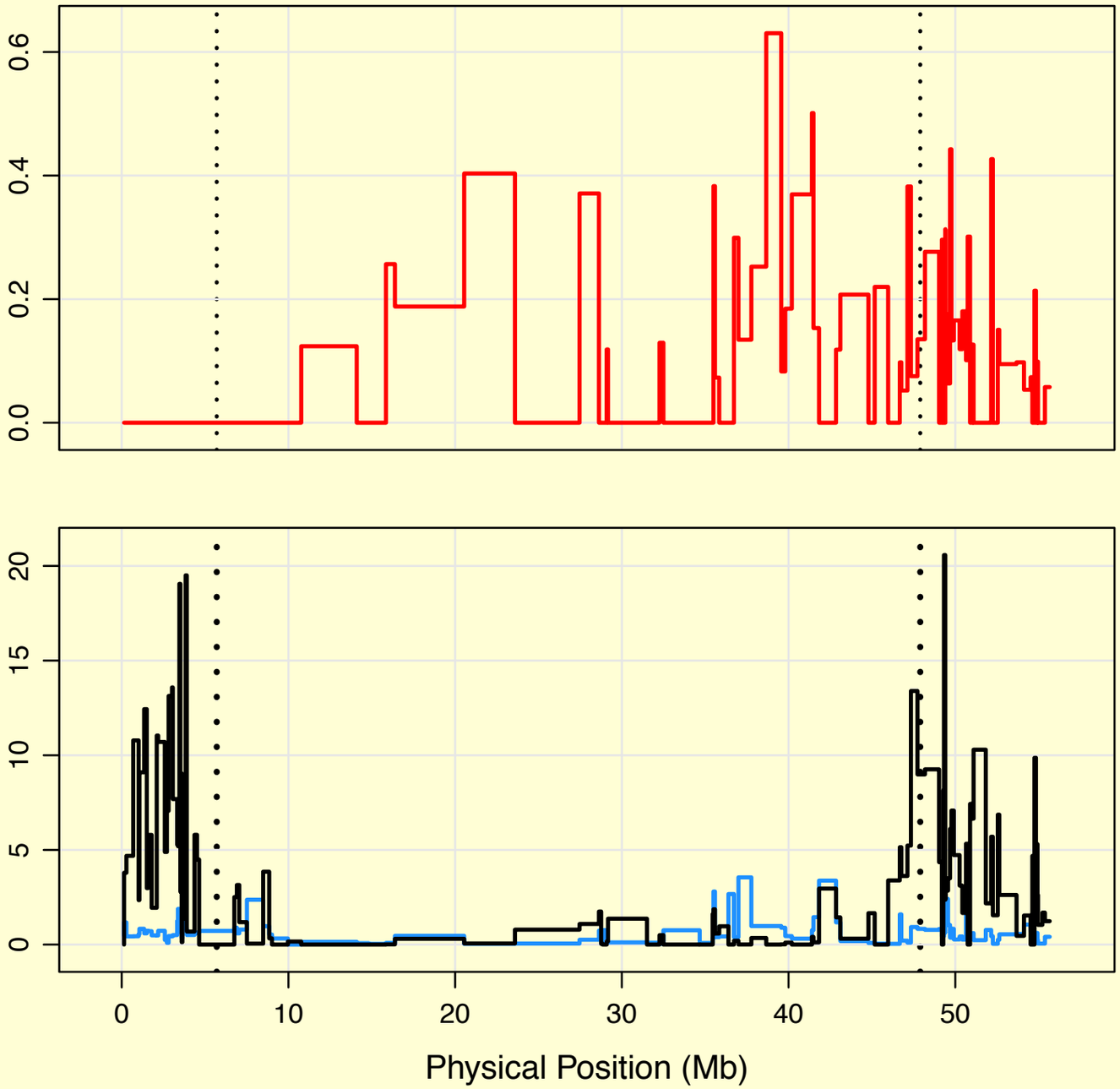
- Deleterious variants tend to be at lower derived frequency than “tolerated” variants



Kono et al. 2016

Deleterious Variants: Enrichment in Low Recombination Regions

- Tend to occur in low recombination regions



Pericentromere boundary

Prop. Deleterious SNPs

Recom. rate (cM/Mb)

Nucleotide diversity

Kono et al. 2016

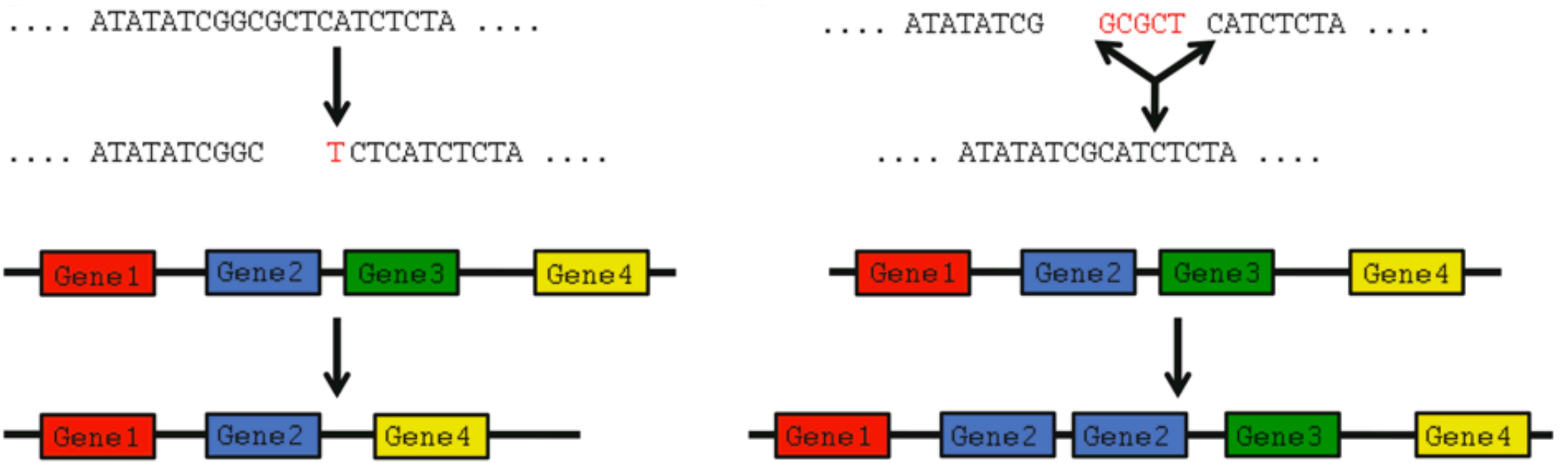
Deleterious Variants: Causative SNPs are "Deleterious"

- Causative variants tend to be called deleterious more frequently than those without *a priori* known phenotypic impacts

	Tolerated	Deleterious	Total
Causative	23 (**67.6%**)	11 (**32.4%**)	34
No Known Phenotype	29,259 (**94.2%**)	1,790 (**5.8%**)	31,046

Kono et al. 2016

A Different Mutation Type: Genome Content Variation



Tandem Duplicate Evolution: Background

- Tandem duplicates may be particularly compelling because they are segmental duplications of genes or gene fragments

- May have interesting evolutionary outcomes because they are duplications in the same genomic "neighborhood."

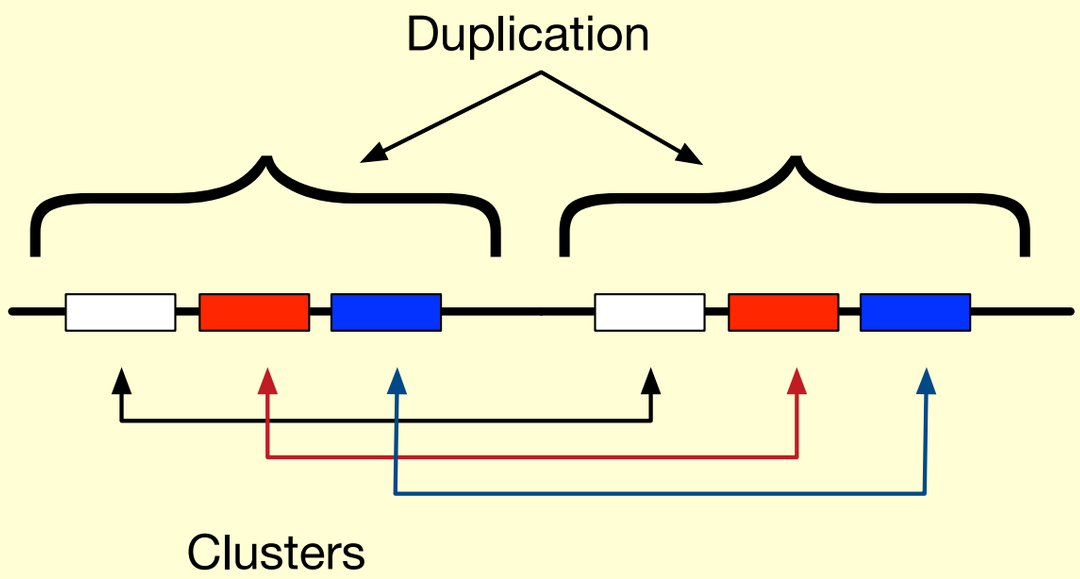
- New long read assembly in maize allows for better resolution of tandem duplicate sequences

Tandem Duplicate Evolution: Questions

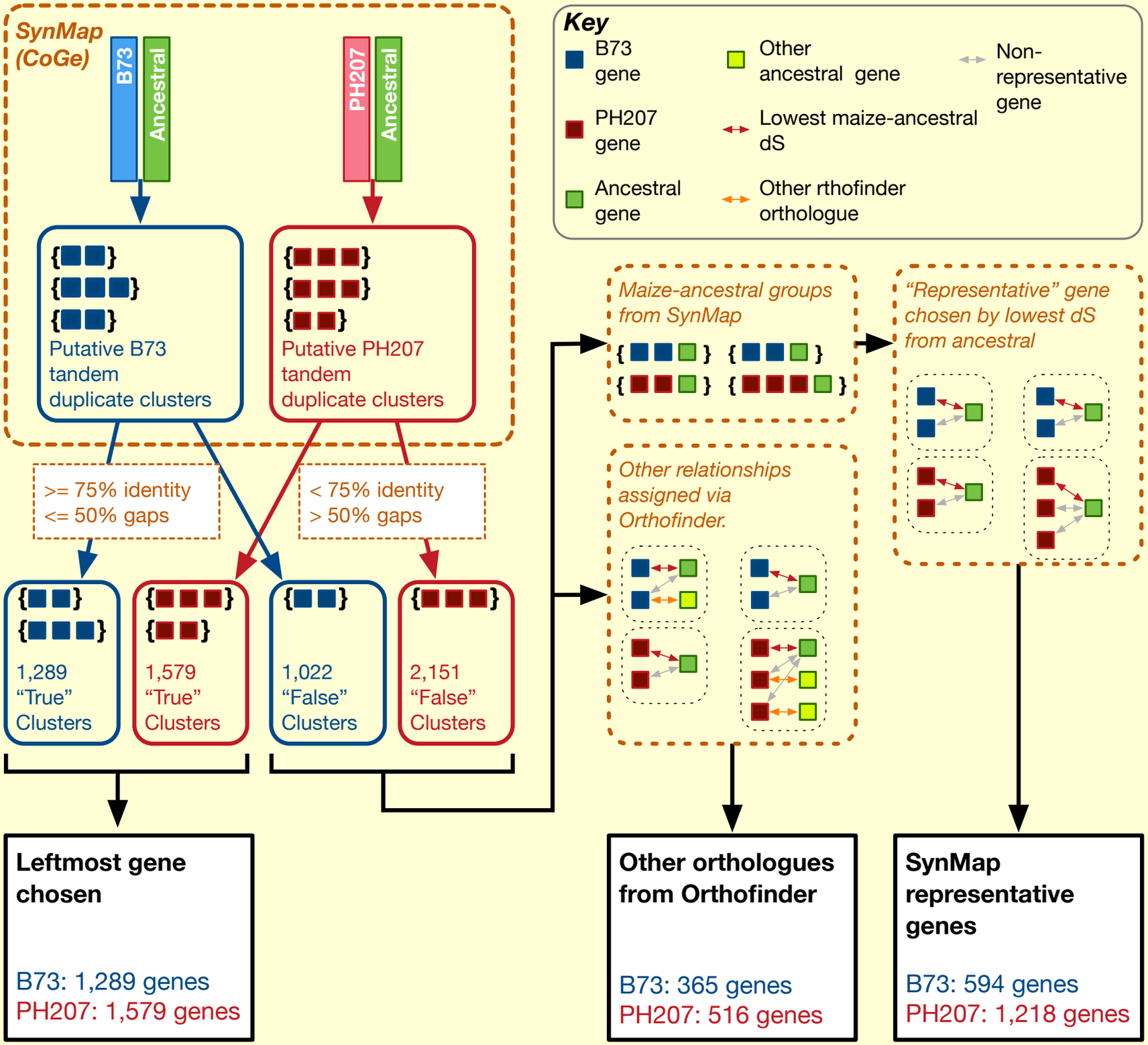
- Where are tandem duplicate genes in maize? Is there a genomic feature that explains their distribution?

- How old are tandem duplications in maize? Do they arise continuously, or happen in “bursts?”

- What are the estimated functional outcomes of tandem duplicate genes in maize? Is there a relationship between the age of a duplication and its outcome?



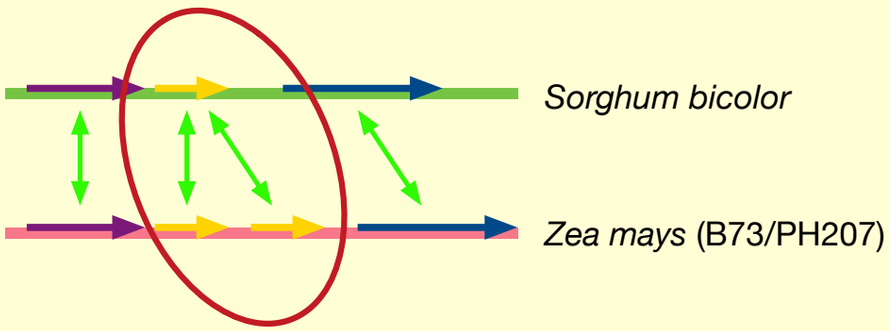
Tandem Duplicate Evolution: Identifying Tandem Duplicates



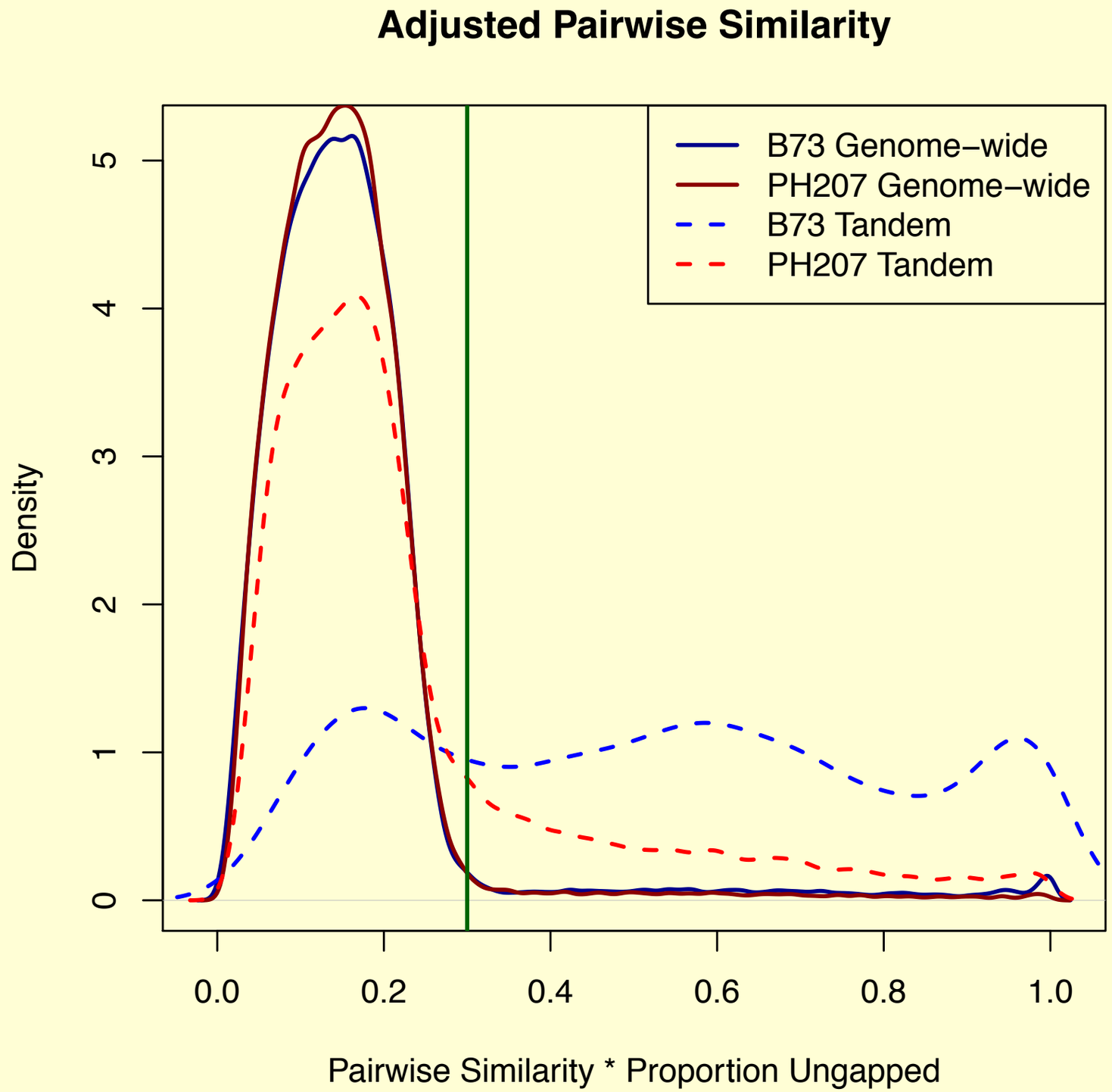
Brohammer et al. *In prep*

Tandem Duplicate Evolution: Identifying Tandem Duplicates

- Had to filter tandem duplicates - CoGe identification procedure was over-calling



- "Adjusted pairwise similarity" = pairwise similarity, down-weighted for gapping



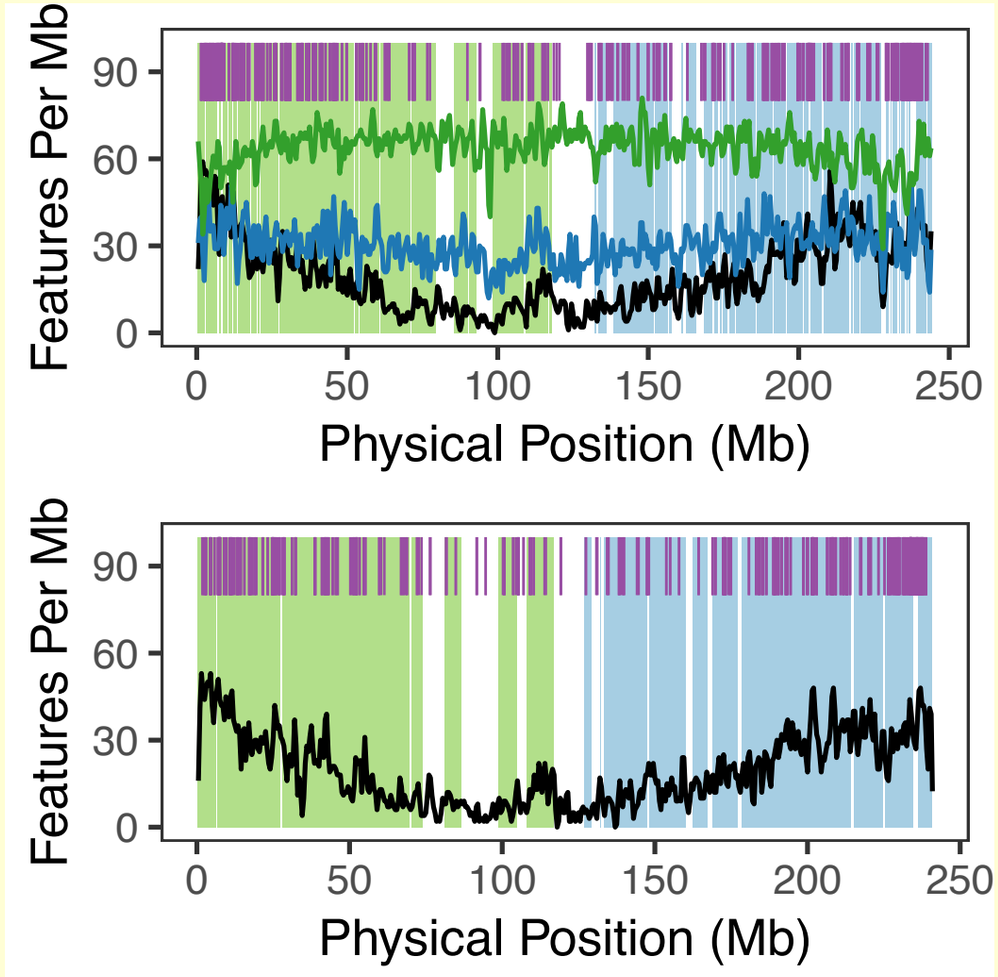
Tandem Duplicate Evolution: Most Duplicates are Shared

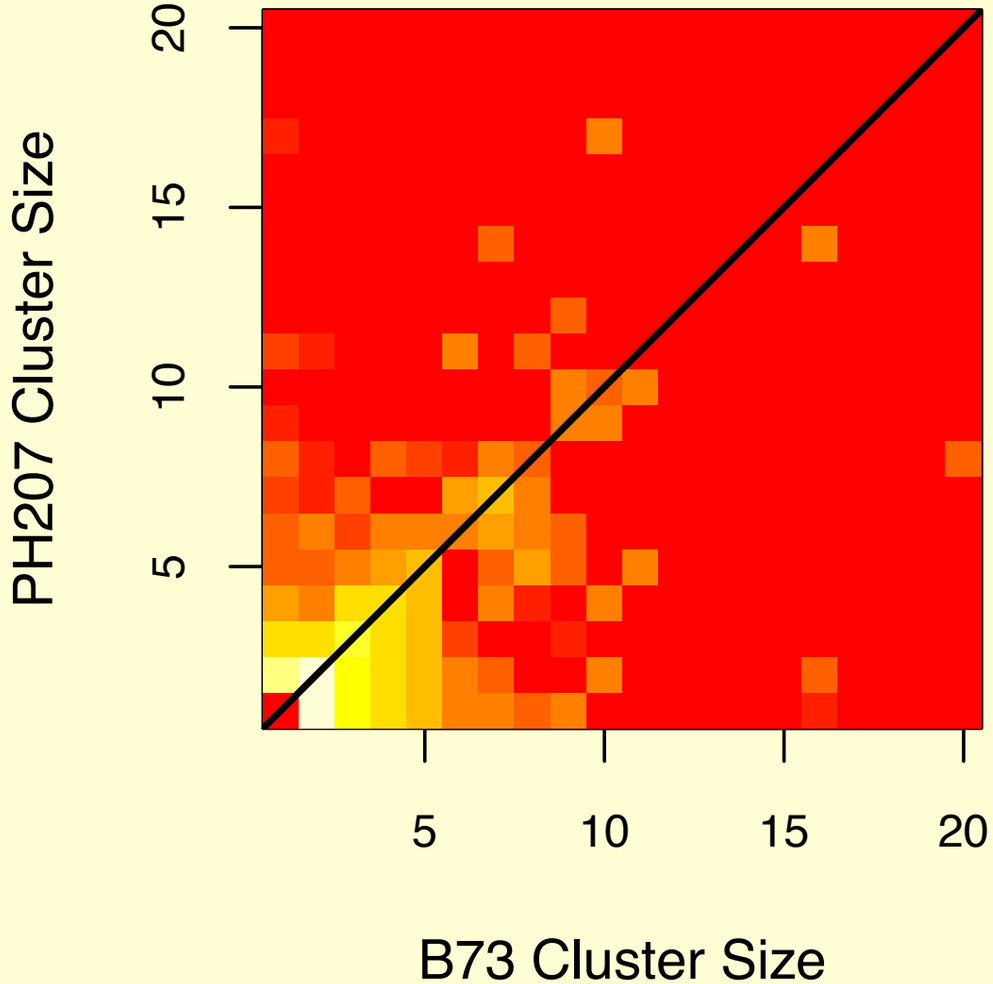
Tandem duplications happen where there are genes

Most tandem duplicates are shared between B73 and PH207

B73

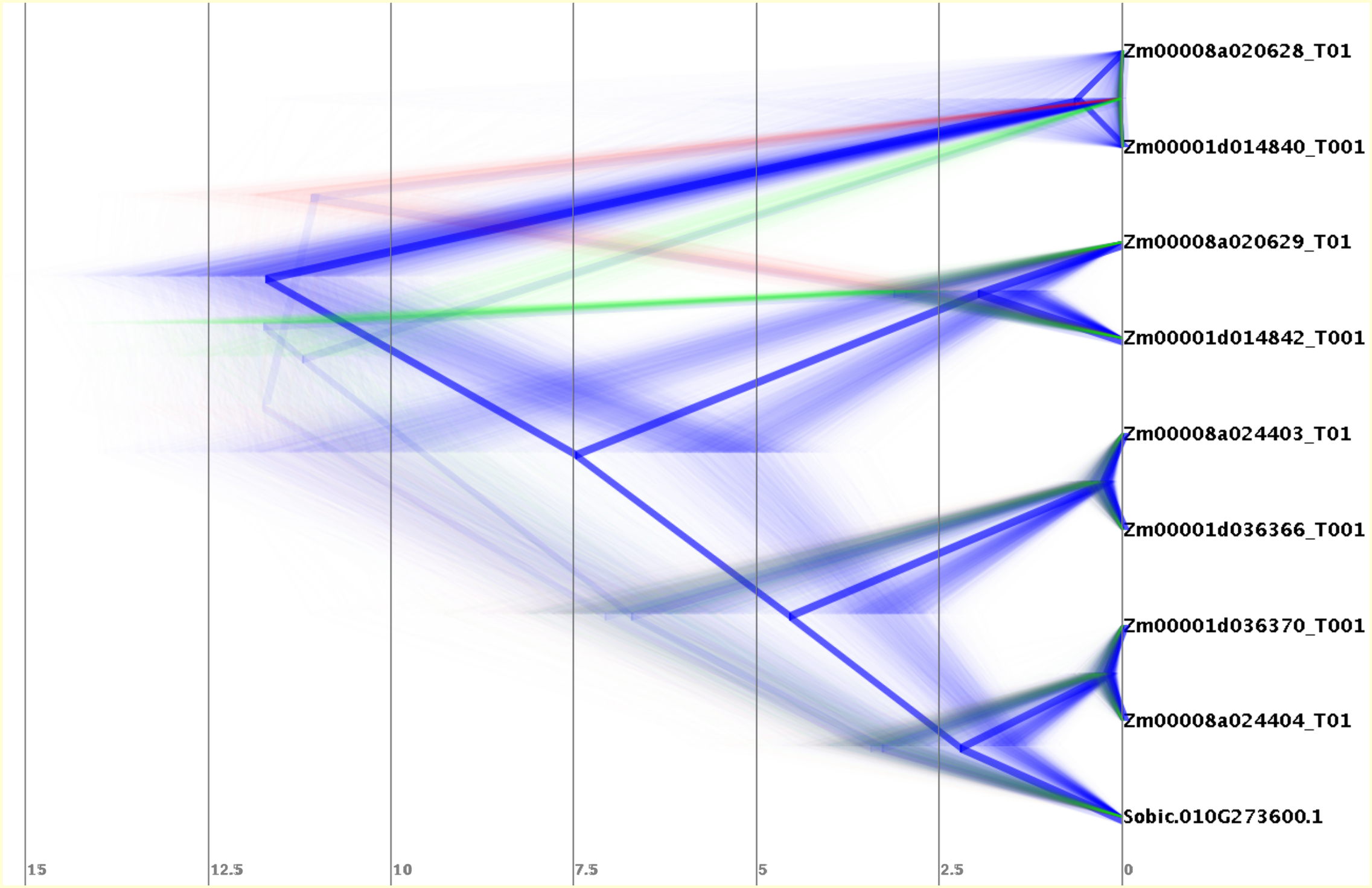
PH207





Kono et al. *In prep*

Tandem Duplicate Evolution: Diverge Date Estimation



Genome Content Variation: Background

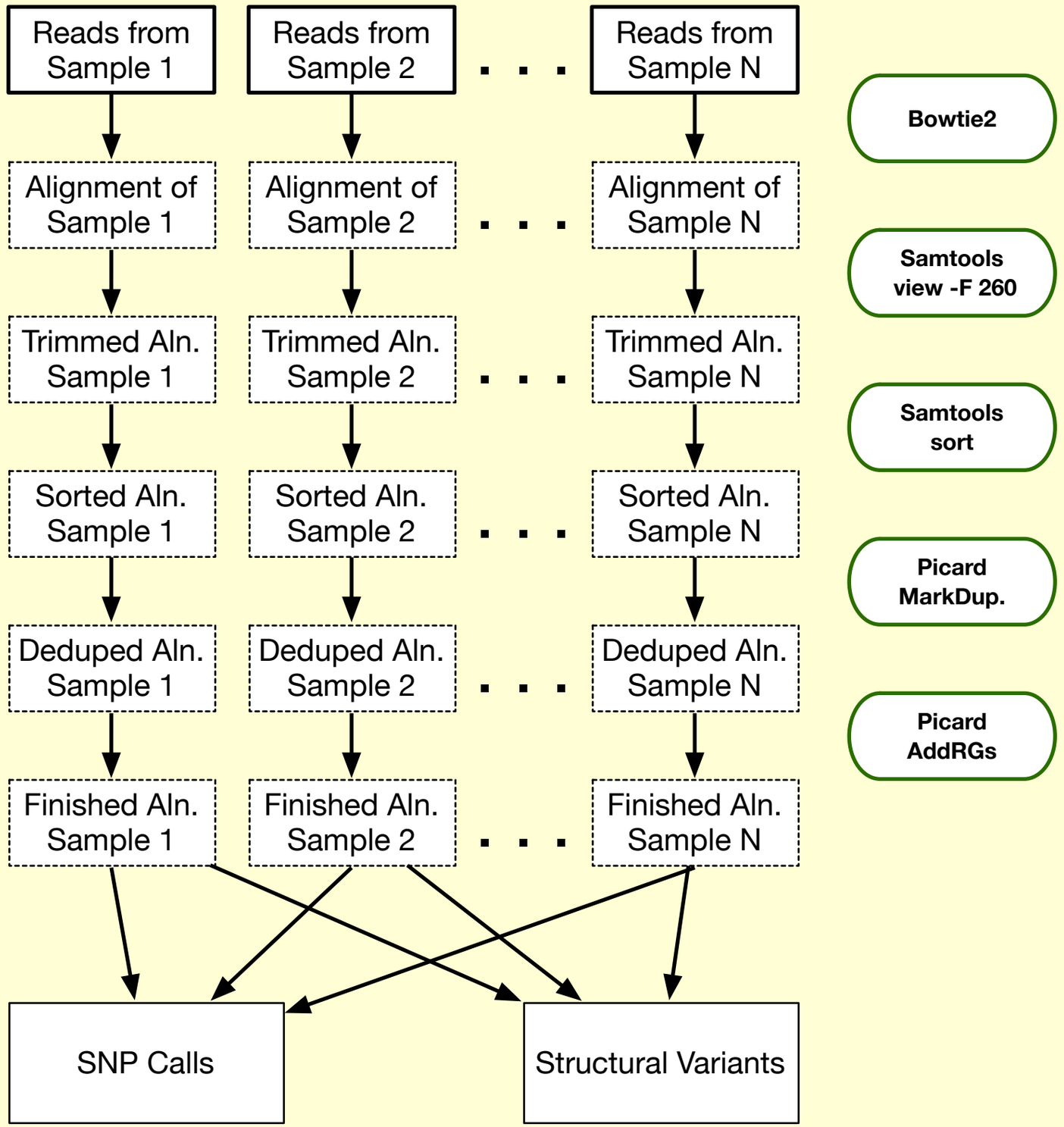
- Presence-absence variation and copy number variation may play a large role in phenotypic variation

- SNPs can only explain so much variation in GWAS, and most SNPs are thought to have neutral or very small effects on phenotypic variation

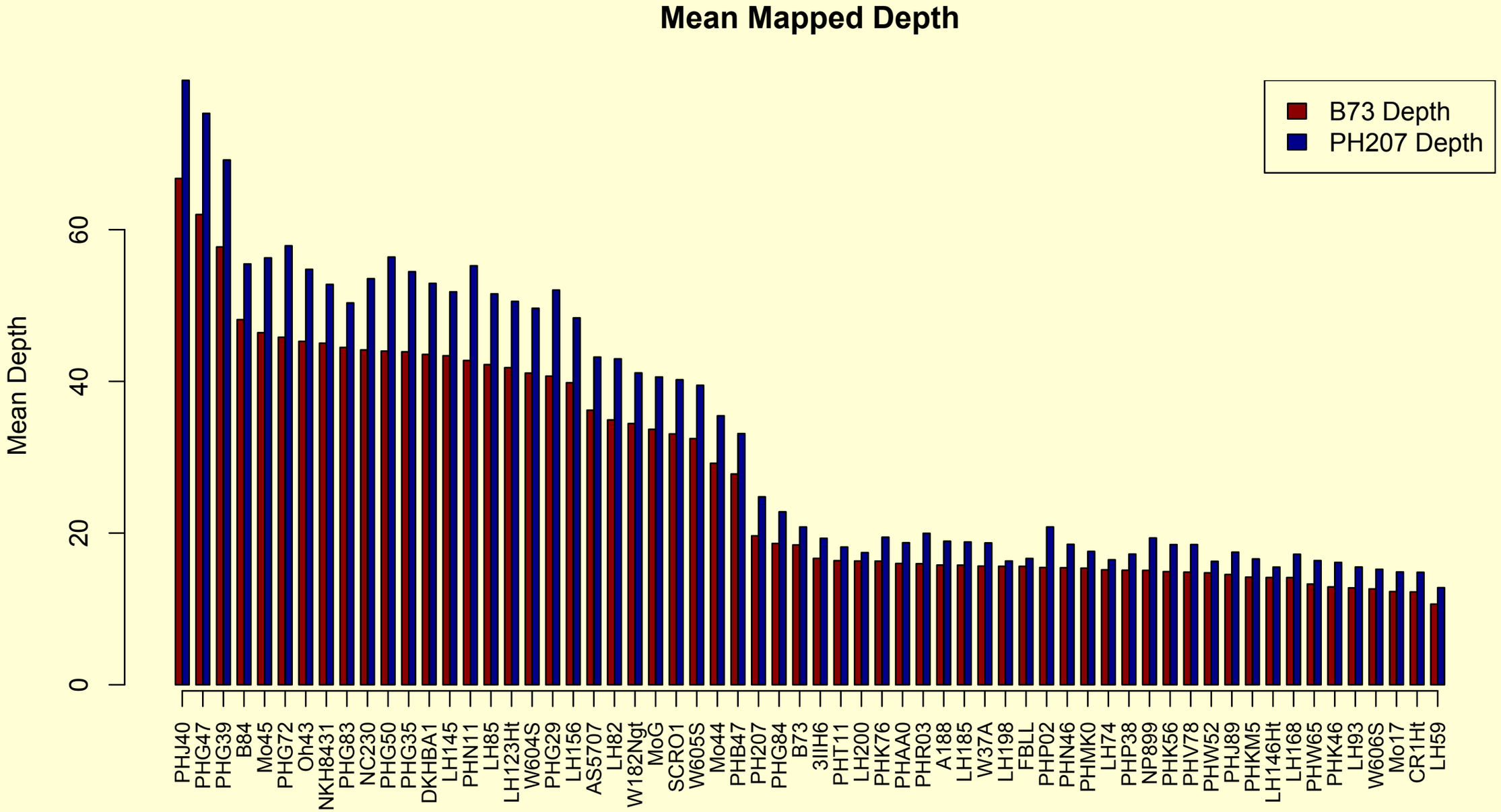
- Gene deletions/duplications, on the other hand, may have much greater impact, as they more drastically alter protein function and regulation

Genome Content Variation: Sequence Analysis Pipeline

- Whole genome resequencing of 62 maize inbred lines
- Currently have short read resequencing, but will collect long read data
- Mapped against two reference genomes

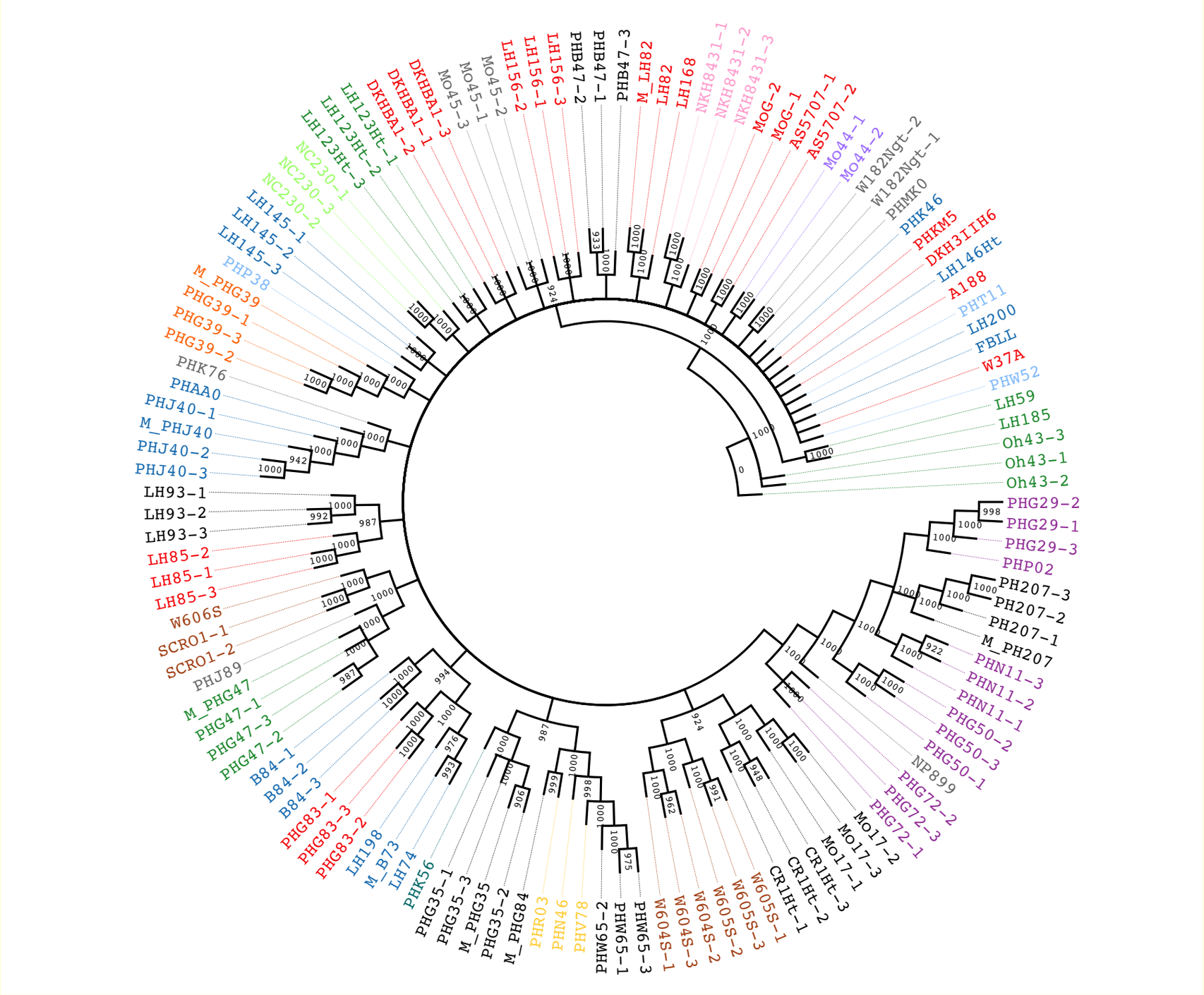


Genome Content Variation: Varying Depths of Sequencing



Genome Content Variation: A "Biological QC"

- Bootstrapped NJ tree for sample verification
- Samples from multiple libraries and data sources cluster by genotype



Genome Content Variation: Next Steps

- First: downsampling analysis with the high-coverage samples
  - Identify the nature of the tradeoff between sequencing depth and variant identification sensitivity
    - What depth gives a good balance between variant discovery and cost?
- Later: Call genome content variants, and estimate the frequencies of gene loss and duplication

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Jean-Michel Michno
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