

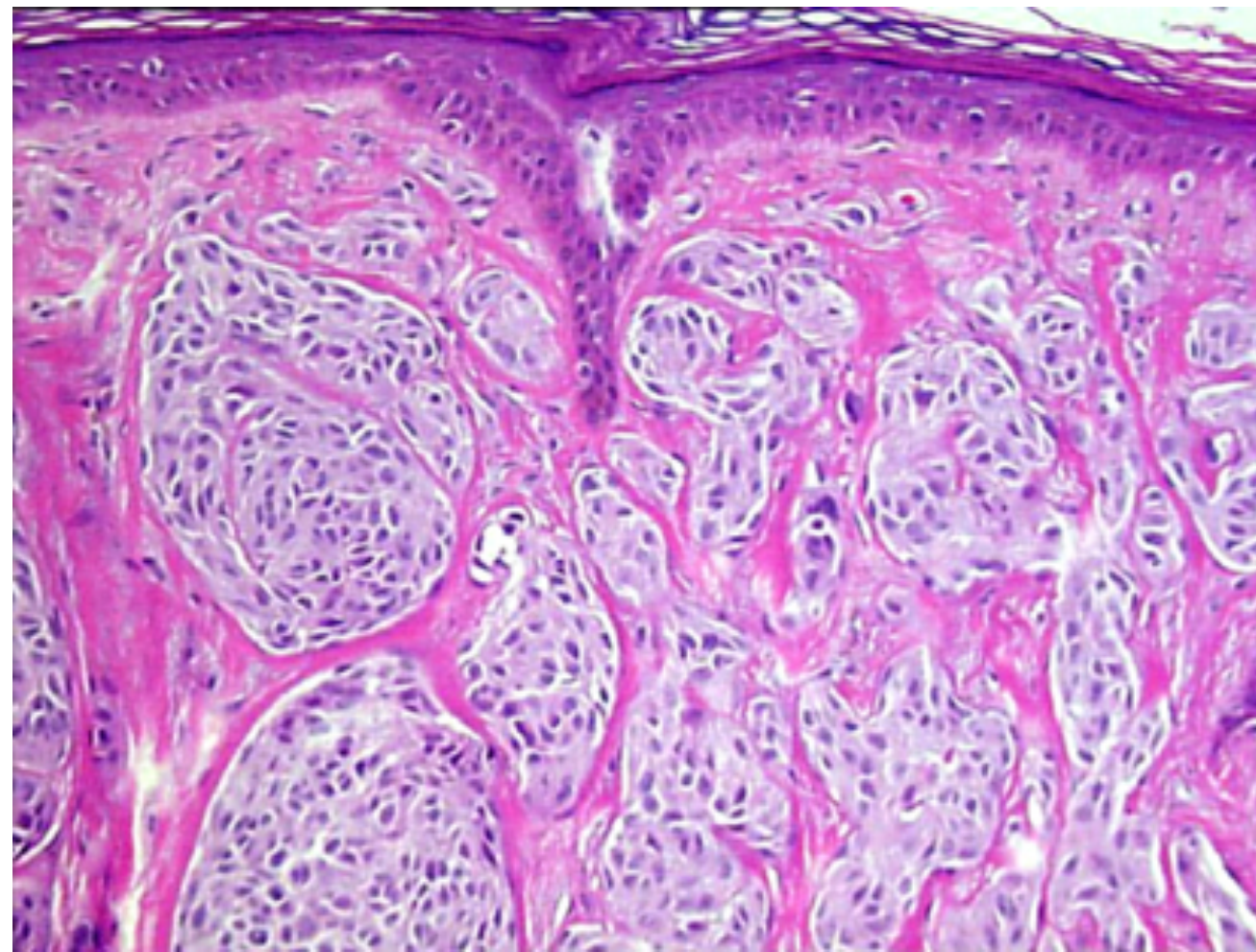
Detecting and quantifying variants

Mark Stenglein, GDW Workshop

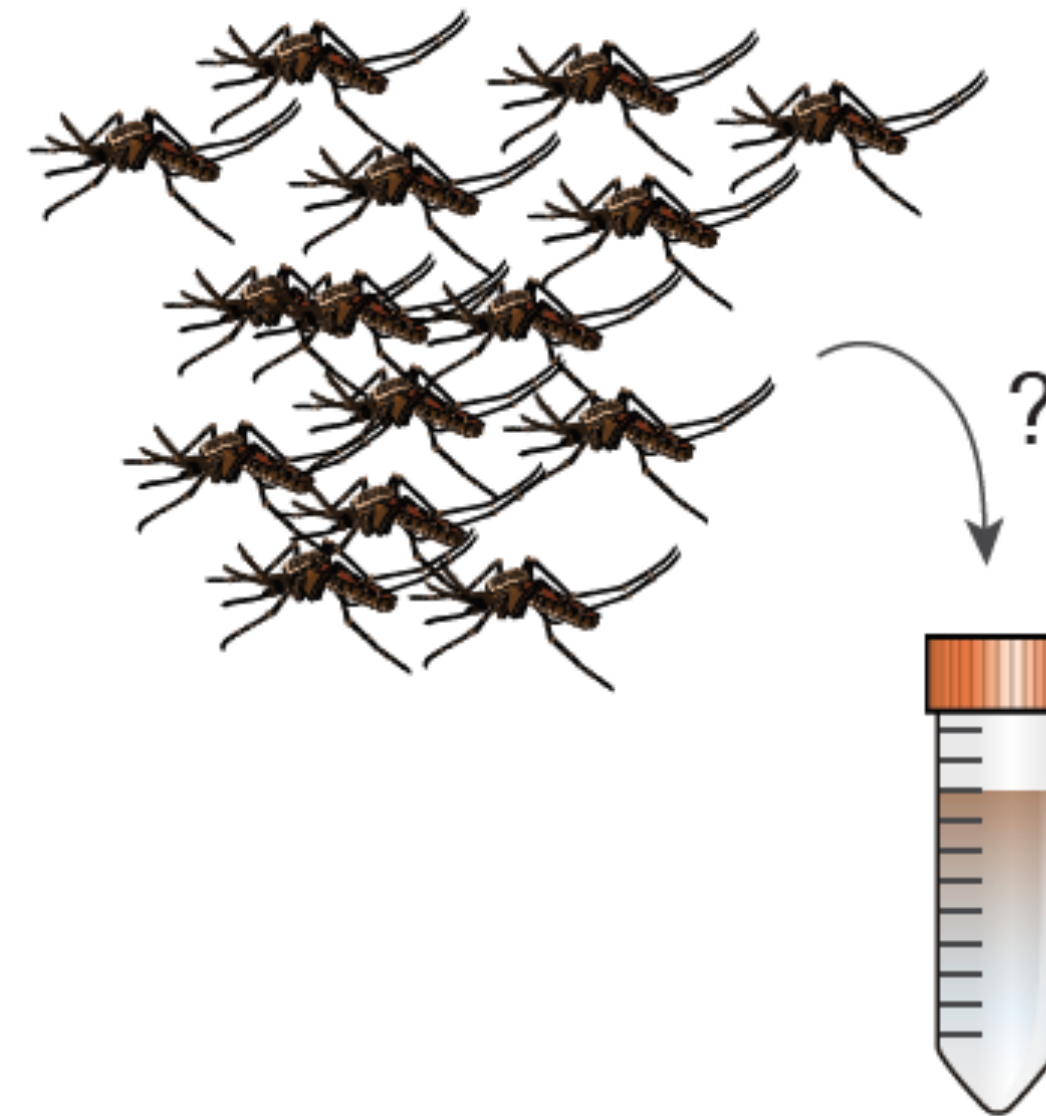


Genomic variation is important in a variety of contexts

Rare somatic variants in cancer
(cancer subclones)



Population genomics using
pools of individuals (Pool-Seq)



Intrahost viral
variation

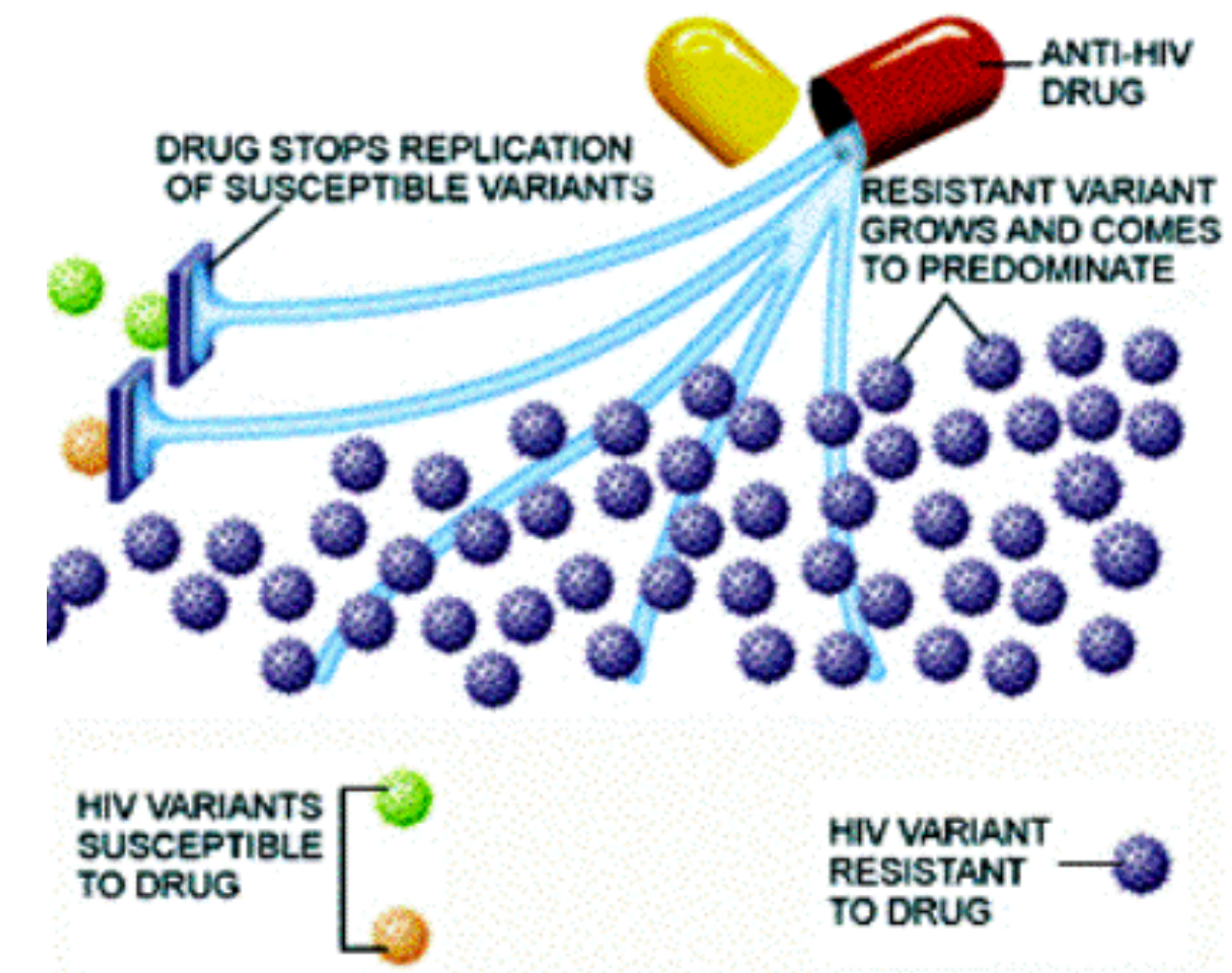
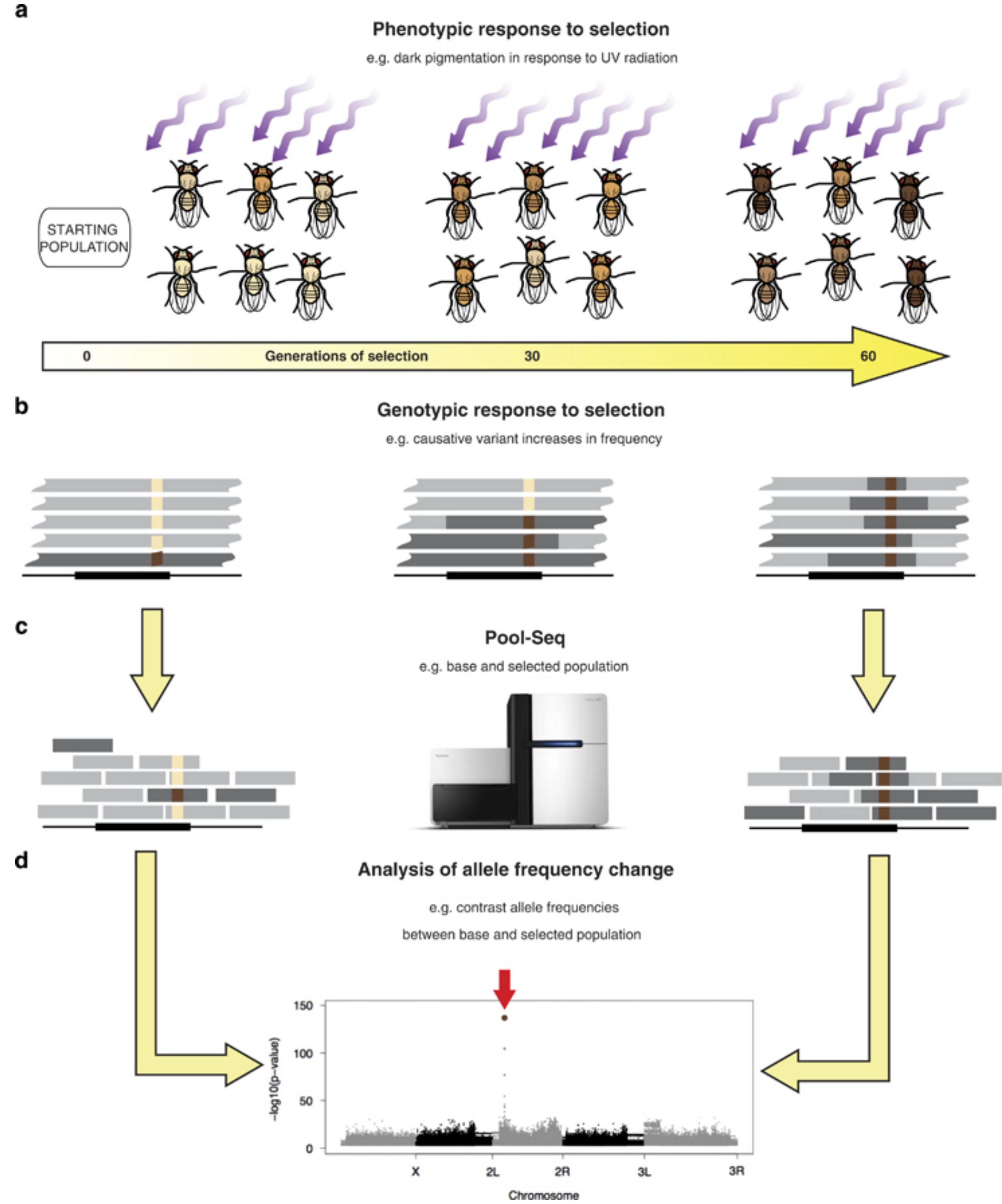
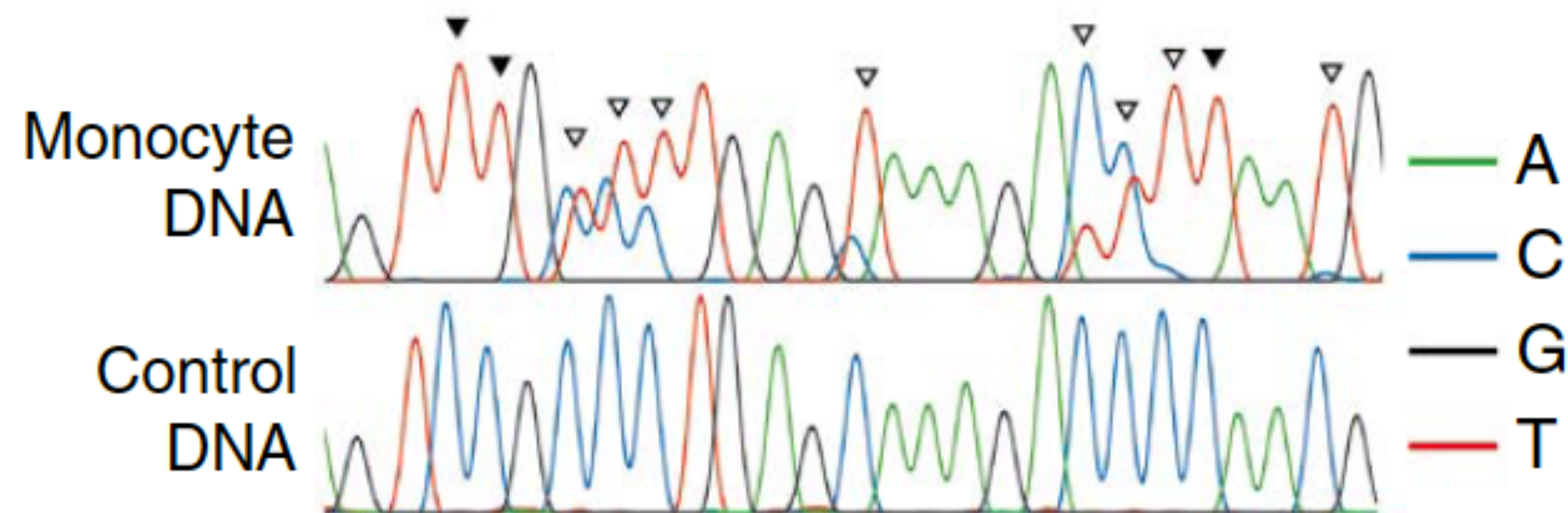
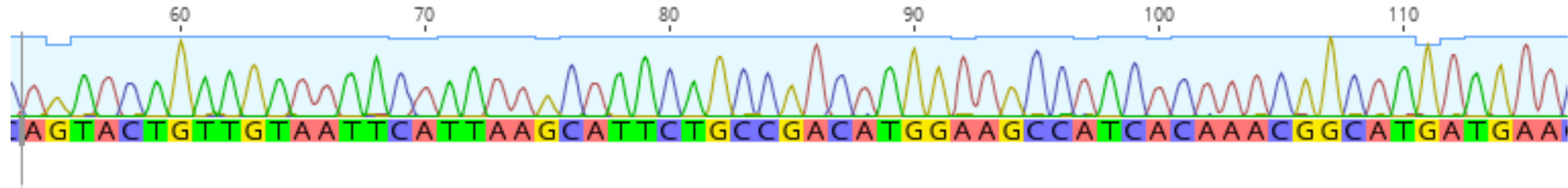


image: Magro et al (2006) Modern Path.

“Evolve & Resequence”

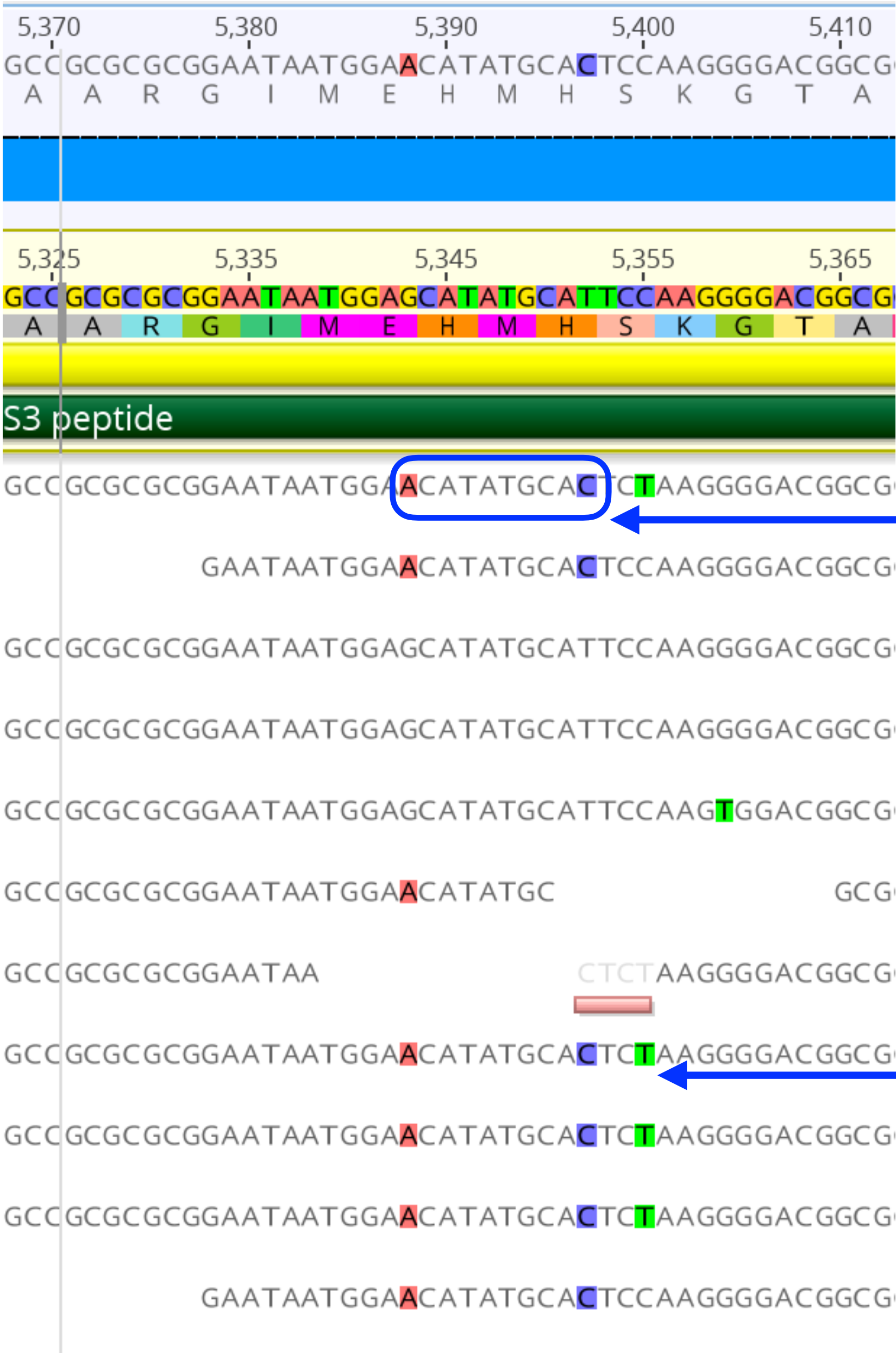


Sanger sequencing typically produces consensus sequence



It is possible to analyze chromatograms to obtain variant frequencies - but it's difficult to quantify and not really done

Goal: identify variants, their frequencies, and potential functional impact



Consensus sequence

Reference sequence

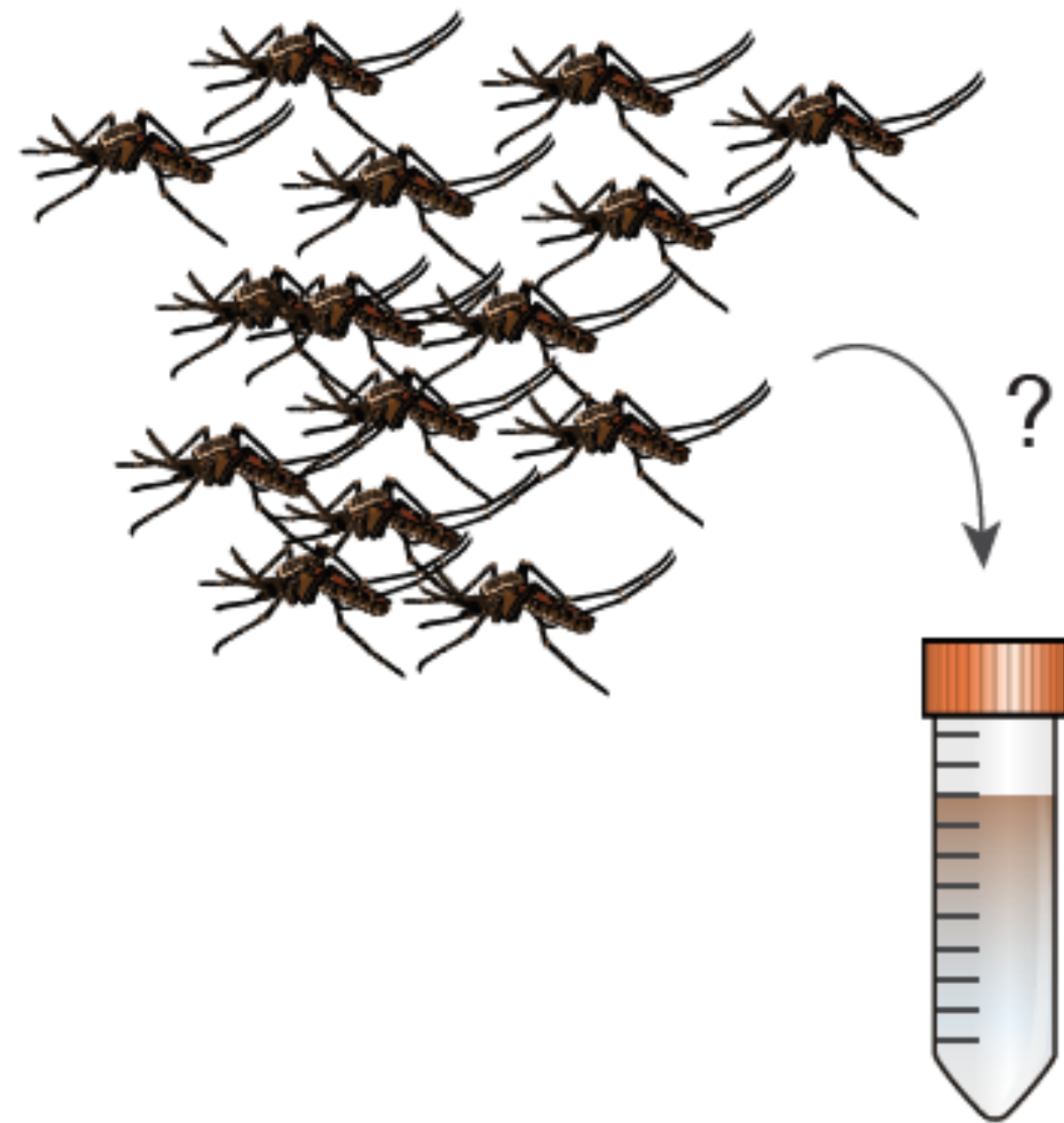
These 2 variants are at a >50% allele frequency and so are consensus changing variants

They are also both synonymous mutations

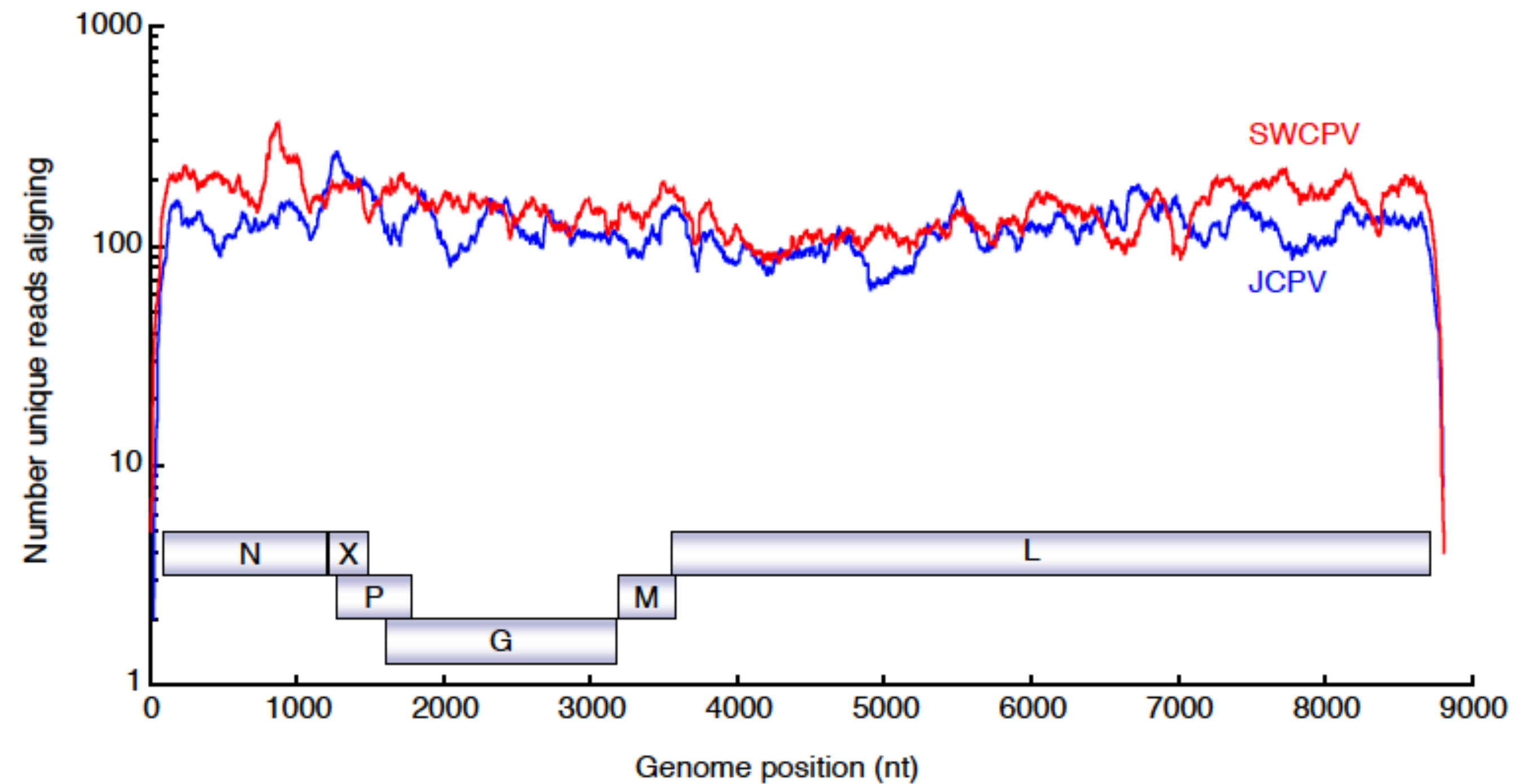
This T's allele frequency is 42% -> no consensus change

Biological and technical limitations to the ability to detect rare variants

Pool size could limit the ability to detect rare variants



unlikely to observe variants with frequency $< 1\%$ in these datasets



carpet python bornaviruses



Distinguishing sequencing errors from true rare variants can be a challenge

GGAATAATGGAACATATGCACCTCTAAGGGGACGGCGCTCATGTAT

GAATAATGGAACATATGCACCTCCAAGGGGACGGCGCTCATGTAT

GGAATAATGGAGCATATGCATTCCAAGGGGACGGCGCTCATGTAT

GGAATAATGGAGCATATGCATTCCAAGGGGACGGCGCTCATGTAT

GGAATAATGGAGCATATGCATTCCAAGTGGACGGCGCTCATGTAT

GGAATAATGGAACATATGC GCGCTCATGTAT

GGAATAA CTCTAAGGGGACGGCGCTCATGTAT



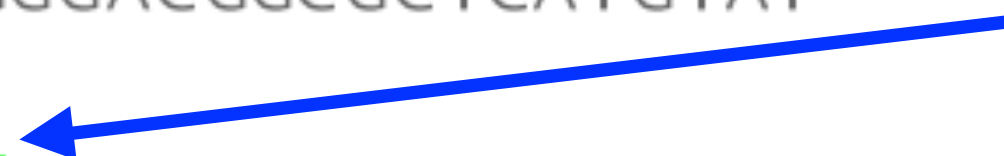
GGAATAATGGAACATATGCACCTCTAAGGGGACGGCGCTCATGTAT

GGAATAATGGAACATATGCACCTCTAAGGGGACGGCGCTCATGTAT

GGAATAATGGAACATATGCACCTCTAAGGGGACGGCGCTCATGTAT

GAATAATGGAACATATGCACCTCCAAGGGGACGGCGCTCATGTAT

sequencing error, or real low frequency variant?



Variant calling is also sensitive to mapping

GGAATAATGGAACATATGCACCTCTAAGGGGACGGCGCTCATGTAT

GAATAATGGAACATATGCACCTCCAAGGGGACGGCGCTCATGTAT

GGAATAATGGAGCATATGCATTCCAAGGGGACGGCGCTCATGTAT

GGAATAATGGAGCATATGCATTCCAAGGGGACGGCGCTCATGTAT

GGAATAATGGAGCATATGCATTCCAAGTGGACGGCGCTCATGTAT

GGAATAATGGAACATATGC GCGCTCATGTAT

GGAATAA CTCTAAGGGGACGGCGCTCATGTAT

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GGAATAATGGAACATATGCACCTCTAAGGGGACGGCGCTCATGTAT

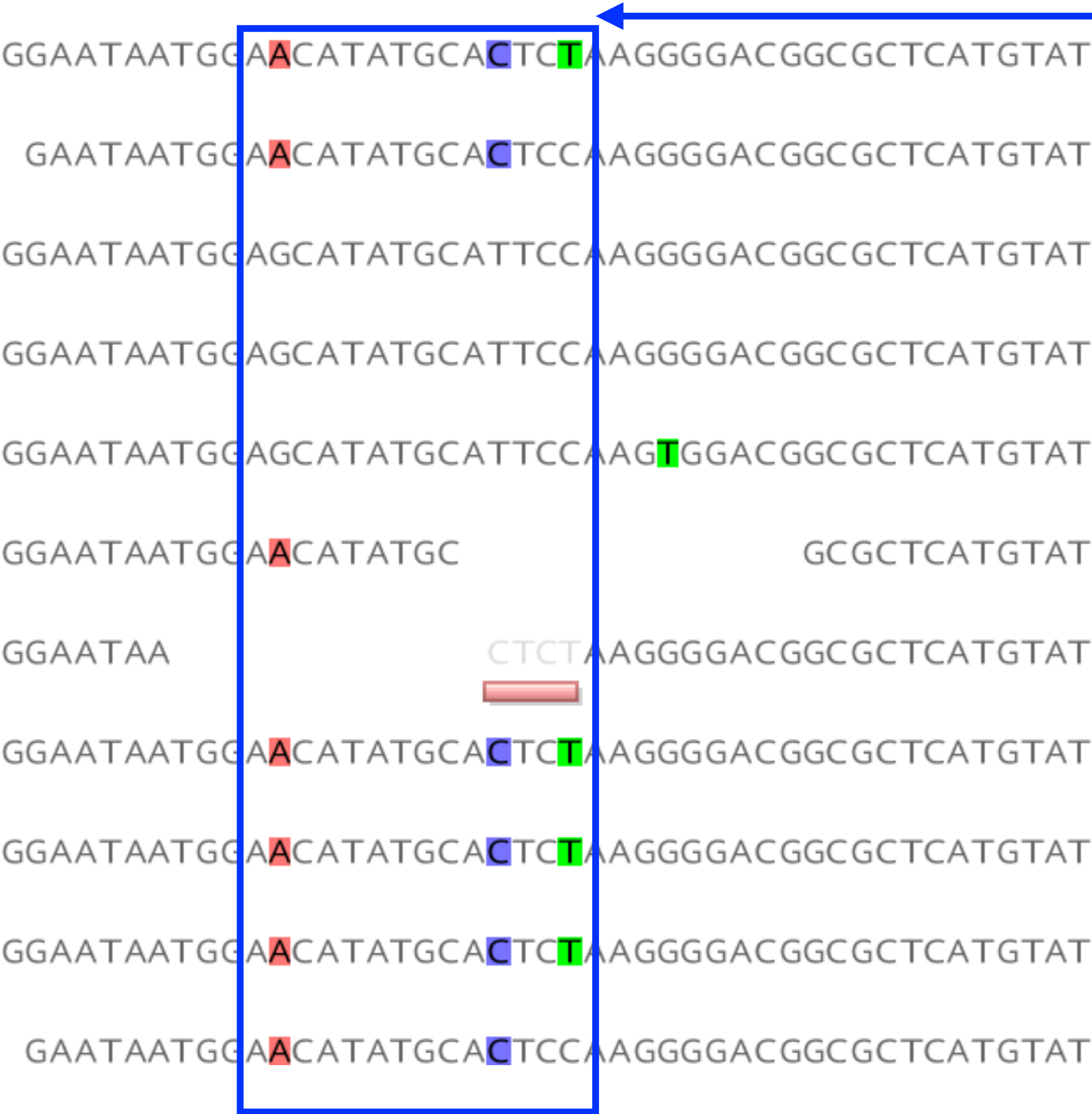
GGAATAATGGAACATATGCACCTCTAAGGGGACGGCGCTCATGTAT

GAATAATGGAACATATGCACCTCCAAGGGGACGGCGCTCATGTAT

These bases were soft-trimmed
(not aligned), but they support variant
basecalls

Different mapping software could well
produce different results.

Another issue is linking or ‘phasing’ variants (haplotype reconstruction)



3 haplotypes evident here

G T C [reference sequence]

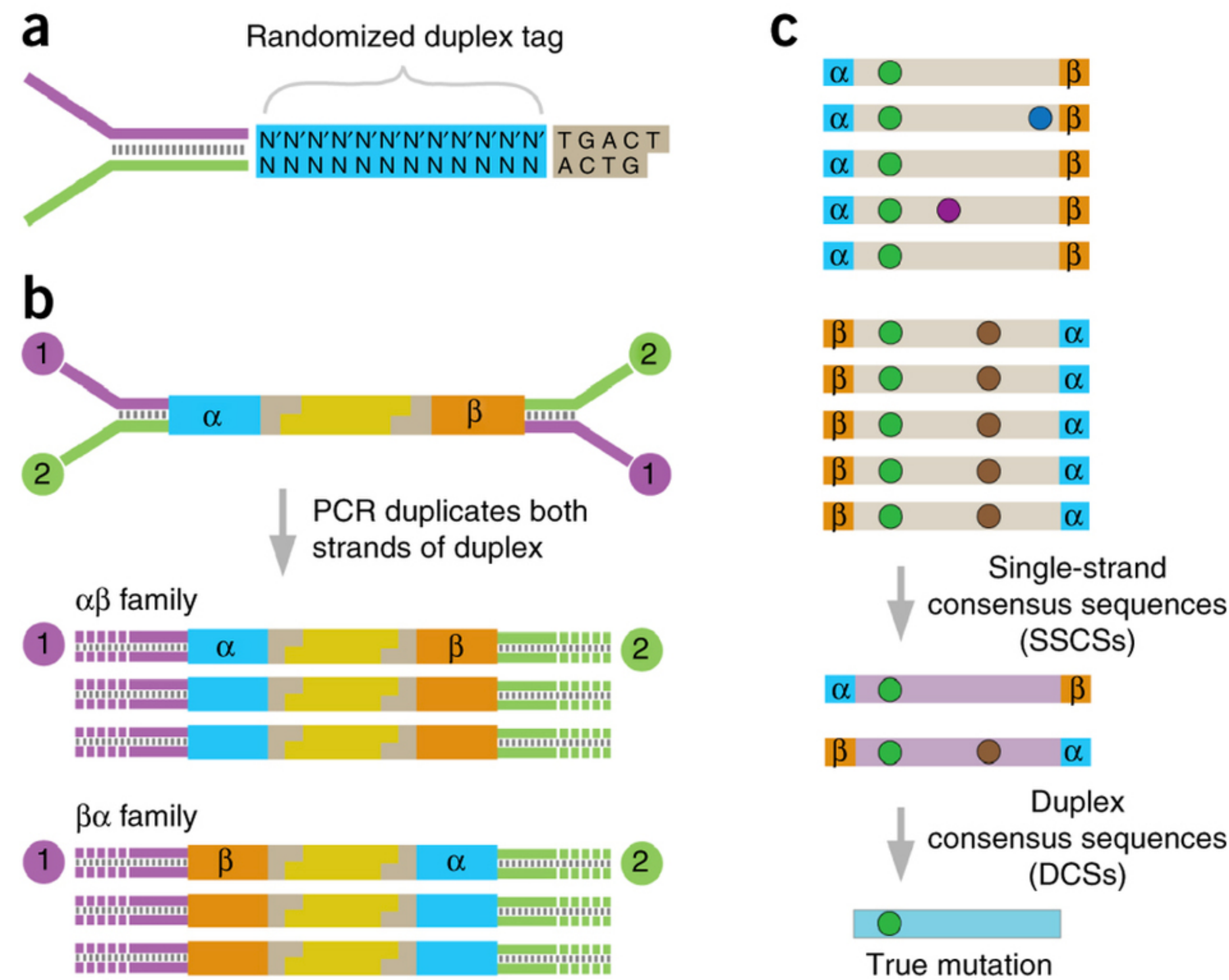
A C C [2 mutations]

A C T [3 mutations]

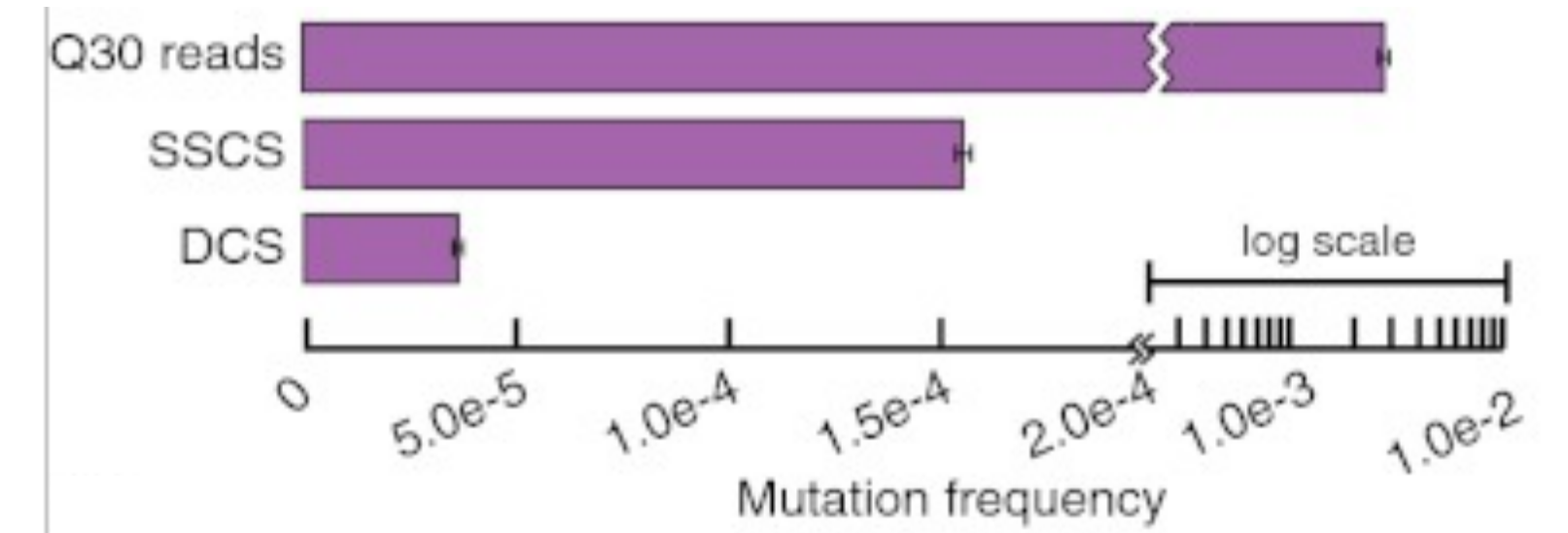
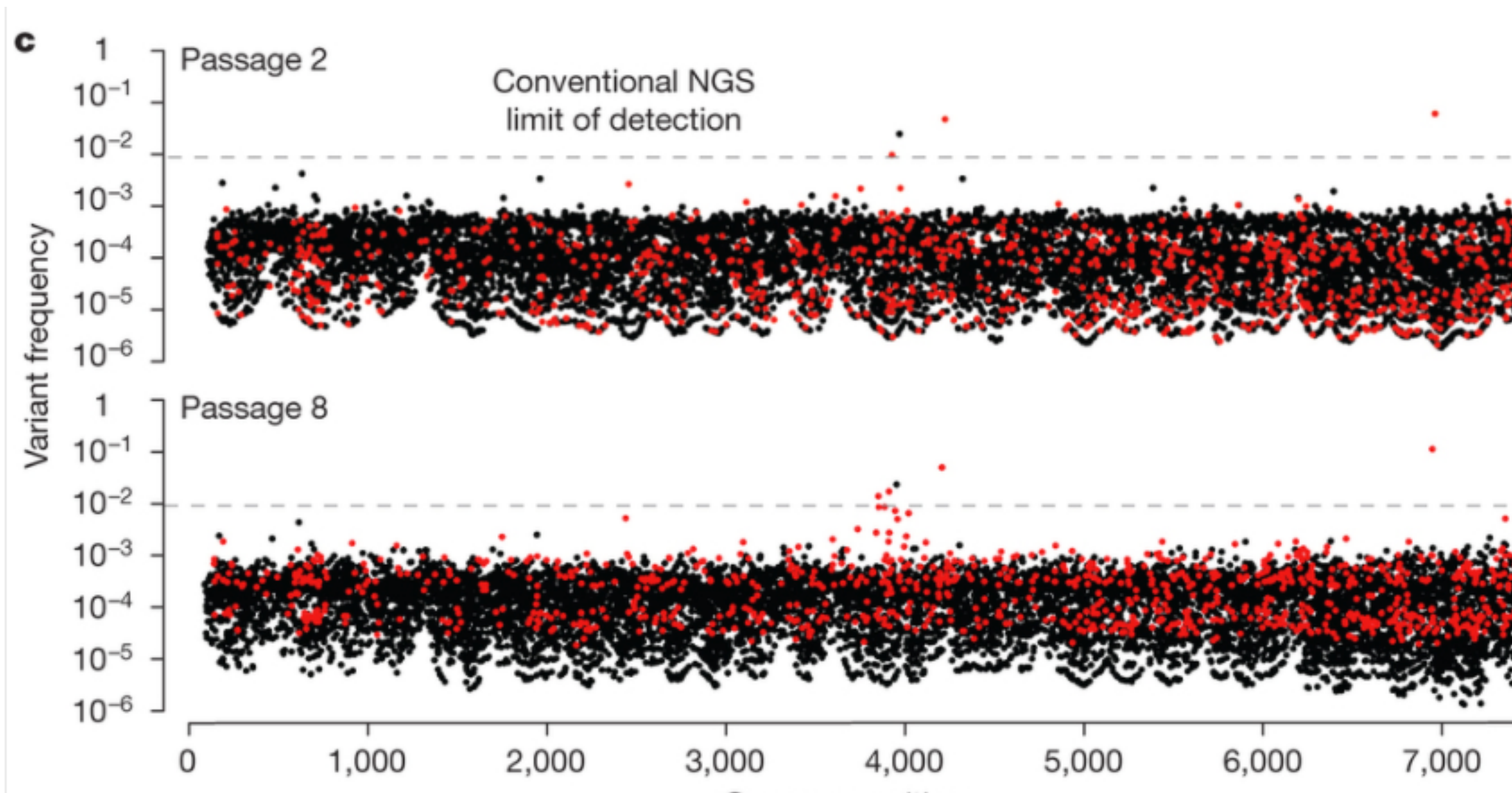
Much harder to link distant variants using short read data

Several clever methods have been developed to get beyond the limit of detection due to sequencing errors

Some protocols take advantage of PCR duplicates to sequence the same original molecule multiple times



These methods aim to decrease variant frequency limit of detection



These approaches have practical limitations

That's a lot of (poly-A) RNA

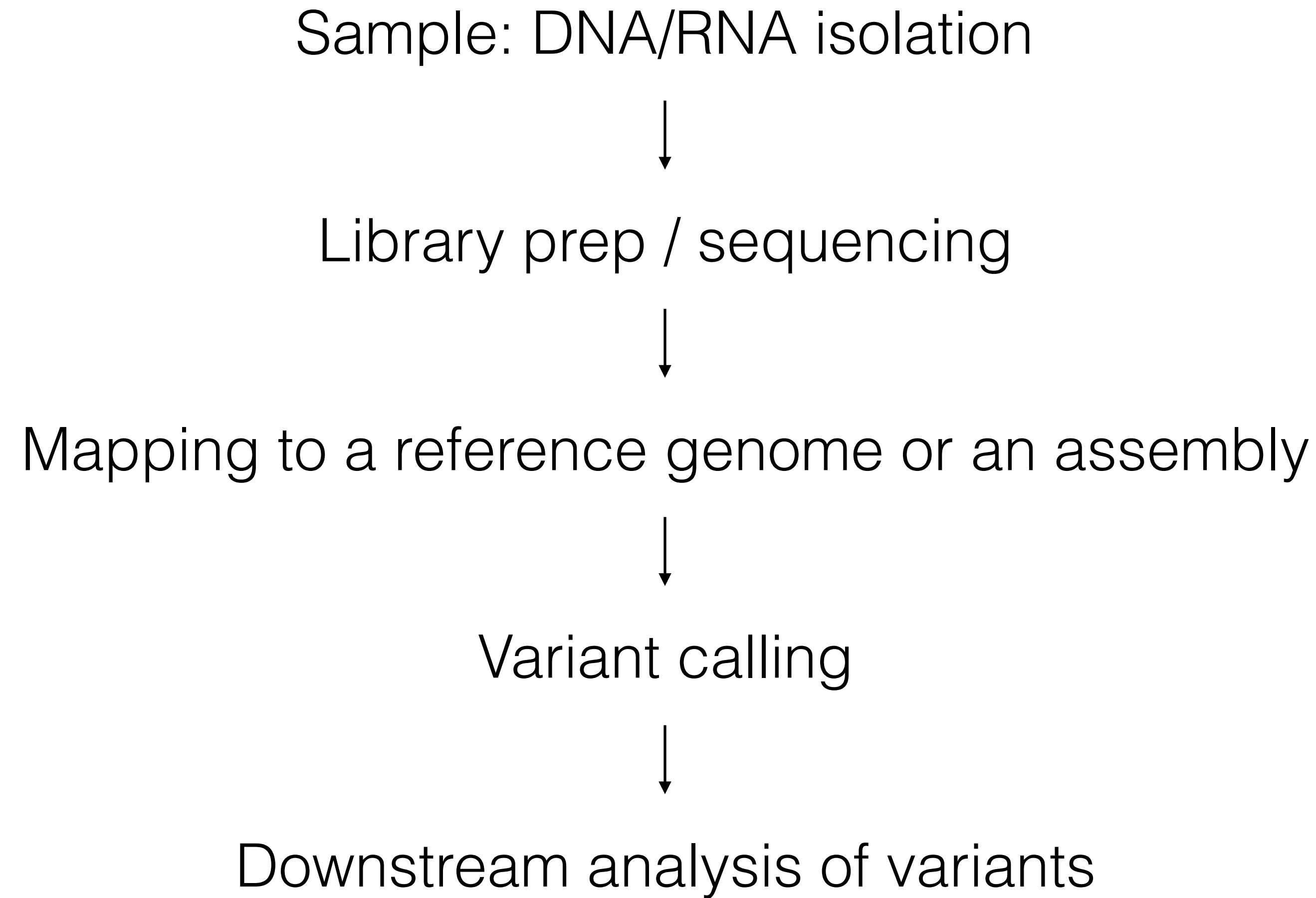


according to the manufacturer guidelines. Then 2–5 μg of poly(A)-containing RNA was fragmented with fragmentation reagent (Ambion) for 7.5 min at 70°C. A practical minimum for this library preparation is 1 μg to ensure that enough fragmented RNA is obtained to produce a library with sufficient complexity and handle reproducibly. Approximately 80–90-base RNA fragments

The good news!

You don't necessarily or even often need linked variants or ultra low frequency variants to infer population genetic parameters (or otherwise answer your question of interest)

A typical workflow for variant identification



The standard format for variant data is the vcf file (variant call format)

```
##fileformat=VCFv4.3
##fileDate=20090805
##source=myImputationProgramV3.1
##reference=file:///seq/references/1000GenomesPilot-NCBI36.fasta
##contig=<ID=20,length=62435964,assembly=B36,md5=f126cdf8a6e0c7f379d618ff66beb2da,species="Homo sapiens",taxonomy=x>
##phasing=partial
##INFO=<ID=NS,Number=1,Type=Integer,Description="Number of Samples With Data">
##INFO=<ID=DP,Number=1,Type=Integer,Description="Total Depth">
##INFO=<ID=AF,Number=A,Type=Float,Description="Allele Frequency">
##INFO=<ID=AA,Number=1,Type=String,Description="Ancestral Allele">
##INFO=<ID=DB,Number=0,Type=Flag,Description="dbSNP membership, build 129">
##INFO=<ID=H2,Number=0,Type=Flag,Description="HapMap2 membership">
##FILTER=<ID=q10,Description="Quality below 10">
##FILTER=<ID=s50,Description="Less than 50% of samples have data">
##FORMAT=<ID=GT,Number=1,Type=String,Description="Genotype">
##FORMAT=<ID=GQ,Number=1,Type=Integer,Description="Genotype Quality">
##FORMAT=<ID=DP,Number=1,Type=Integer,Description="Read Depth">
##FORMAT=<ID=HQ,Number=2,Type=Integer,Description="Haplotype Quality">
#CHROM POS ID REF ALT QUAL FILTER INFO FORMAT NA00001 NA00002 NA00003
20 14370 rs6054257 G A 29 PASS NS=3;DP=14;AF=0.5;DB;H2 GT:GQ:DP:HQ 0|0:48:1:51,51 1|0:48:8:51,51 1/1:43:5:.,.
20 17330 . T A 3 q10 NS=3;DP=11;AF=0.017 GT:GQ:DP:HQ 0|0:49:3:58,50 0|1:3:5:65,3 0/0:41:3
20 1110696 rs6040355 A G,T 67 PASS NS=2;DP=10;AF=0.333,0.667;AA=T;DB GT:GQ:DP:HQ 1|2:21:6:23,27 2|1:2:0:18,2 2/2:35:4
20 1230237 . T . 47 PASS NS=3;DP=13;AA=T GT:GQ:DP:HQ 0|0:54:7:56,60 0|0:48:4:51,51 0/0:61:2
20 1234567 microsat1 GTC G,GTCT 50 PASS NS=3;DP=9;AA=G GT:GQ:DP 0/1:35:4 0/2:17:2 1/1:40:3
```

<https://github.com/samtools/hts-specs>

A couple reviews to get you started

Schlötterer et al (2014) Nat Rev Gen
doi:10.1038/nrg3803

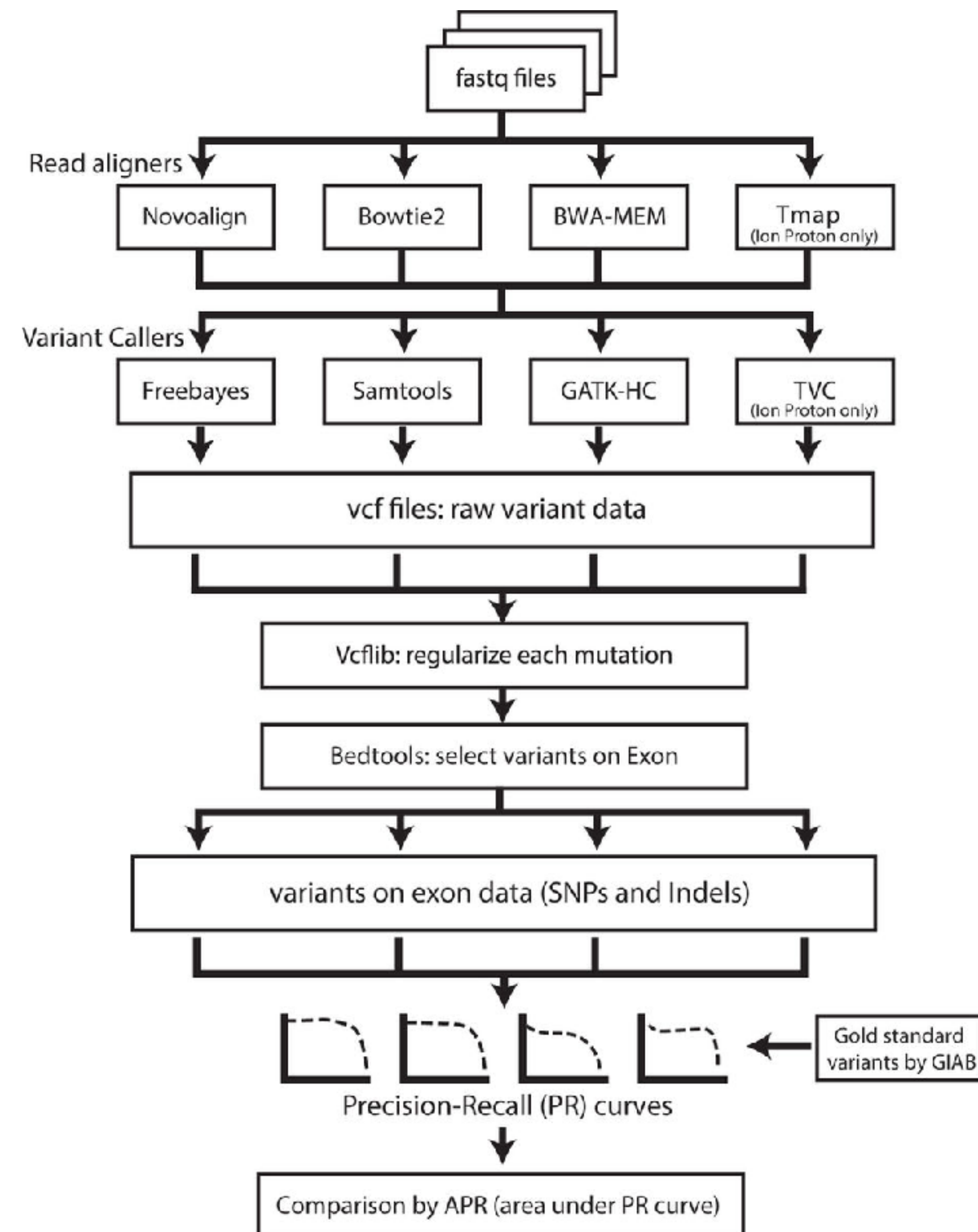
Posada-Céspedes et al (2016) Virus Res
doi:10.1016/j.virusres.2016.09.016

Table 2 | To pool or not to pool?

Scenario	Pool-seq recommended?
Small sample size (<40 individuals)	Yes, but only appropriate when carried out on genomic windows containing multiple SNPs instead of on individual SNPs
Phenotypes of individuals are or will be available	RAD-seq of individuals is probably better suited for many cases
Linkage disequilibrium is key to data analysis	RAD-seq of individuals is probably better suited for many cases
High confidence about low-frequency SNPs is needed	Not with current protocols; sequencing of individuals is preferred
Simple population genetic analyses, such as population differentiation or average heterozygosity	Yes, but when coverage is low it results in a lower confidence of the allele frequency estimate of individual SNPs
Identification of selective sweeps	Yes, but only limited information about linkage disequilibrium can be obtained
Time series with large sample sizes and many replicates	Yes
Mapping of induced mutations	Yes, identification of the causative site is possible
GWAS	Yes, provided that replicates and large pool sizes are available, but other approaches should also be considered
QTL mapping	Yes, but no effect sizes are estimated
Intraspecific polymorphism of bacterial and viral populations	Yes
Information about dominance and effect size is important	No
Cancer	Pool-seq is a natural approach to analyse the cell population

GWAS, genome-wide association study; QTL, quantitative trait locus; RAD-seq, restriction-site-associated DNA sequencing; SNP, single-nucleotide polymorphism.

Several papers fairly recently compared variant calling software



Fairly good overlap from different pipelines using Illumina data

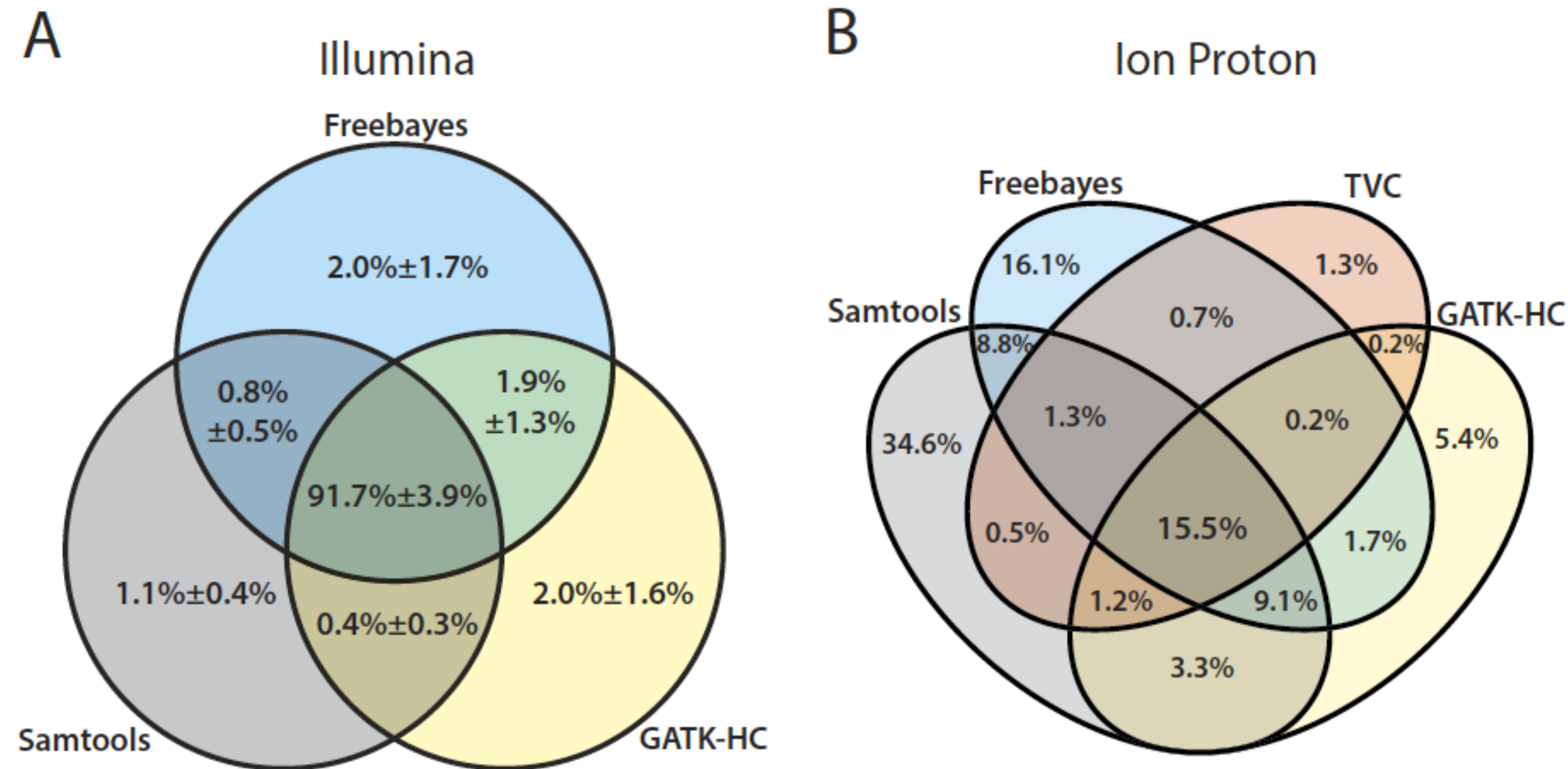


Figure 3. Venn diagrams summarizing called variants by different callers. The mean percentage with

Different s/w had different biases
Avoid using Ion Proton data for variant calling

We'll call some variants later this morning

GGAATAATGGA~~A~~CATATGCAC~~C~~TC~~T~~AAGGGGACGGCGCTCATGTAT

GAATAATGGA~~A~~CATATGCAC~~C~~TCCAAGGGGACGGCGCTCATGTAT

GGAATAATGGAGCATATGCATTCCAAGGGGACGGCGCTCATGTAT

GGAATAATGGAGCATATGCATTCCAAGGGGACGGCGCTCATGTAT

GGAATAATGGAGCATATGCATTCCAAG~~T~~GGACGGCGCTCATGTAT

GGAATAATGGA~~A~~CATATGCGCGCTCATGTAT

GGAATAACTCTAAGGGGACGGCGCTCATGTAT



GGAATAATGGA~~A~~CATATGCAC~~C~~TC~~T~~AAGGGGACGGCGCTCATGTAT

GGAATAATGGA~~A~~CATATGCAC~~C~~TC~~T~~AAGGGGACGGCGCTCATGTAT

GGAATAATGGA~~A~~CATATGCAC~~C~~TC~~T~~AAGGGGACGGCGCTCATGTAT

GAATAATGGA~~A~~CATATGCAC~~C~~TCCAAGGGGACGGCGCTCATGTAT