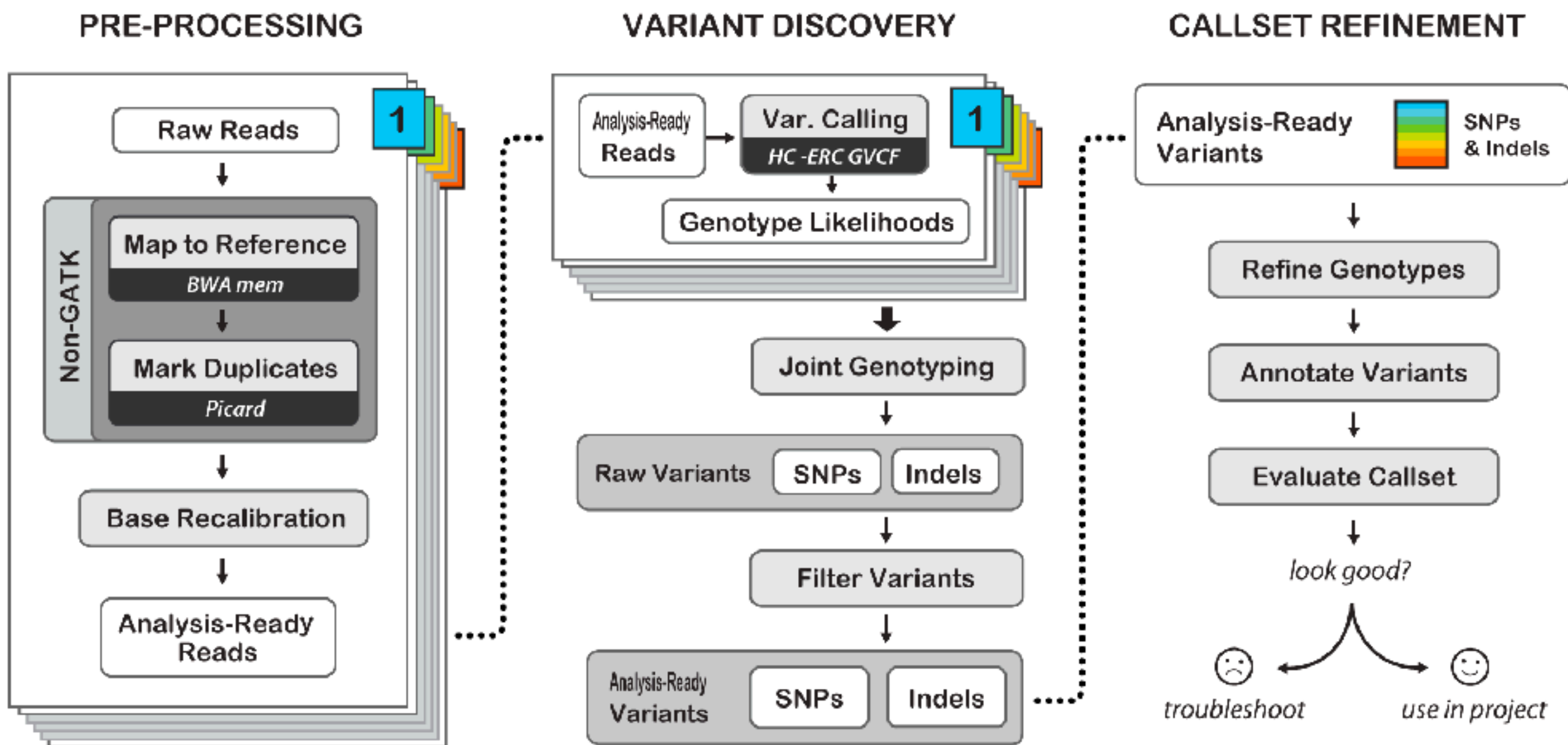


Topic 7: Variant calling using GATK

Learning Goals

- Define the steps involved in SNP calling and what they are doing.
- Understand the reason for haplotype based SNP calling.
- Understand the recalibration approach to variant filtering.
- Define the N+1 problem in genotyping.

GATK Best Practises for Variant Discovery in DNaseq



BAM headers: an essential part of a BAM file

@HD VN:1.0 GO:none SO:coordinate

@SQ SN:chrM LN:16571

@SQ SN:chr1 LN:247249719

@SQ SN:chr2 LN:242951149

[cut for clarity]

@SQ SN:chr9 LN:140273252

@SQ SN:chr10 LN:135374737

@SQ SN:chr11 LN:134452384

[cut for clarity]

@SQ SN:chr22 LN:49691432

@SQ SN:chrX LN:154913754

@SQ SN:chrY LN:57772954

@RG ID:20FUK.1 PL:illumina PU:20FUKAAXX100202.1 LB:Solexa-18483 SM:NA12878 CN:BI

@RG ID:20FUK.2 PL:illumina PU:20FUKAAXX100202.2 LB:Solexa-18484 SM:NA12878 CN:BI

@RG ID:20FUK.3 PL:illumina PU:20FUKAAXX100202.3 LB:Solexa-18483 SM:NA12878 CN:BI

@RG ID:20FUK.4 PL:illumina PU:20FUKAAXX100202.4 LB:Solexa-18484 SM:NA12878 CN:BI

@RG ID:20FUK.5 PL:illumina PU:20FUKAAXX100202.5 LB:Solexa-18483 SM:NA12878 CN:BI

@RG ID:20FUK.6 PL:illumina PU:20FUKAAXX100202.6 LB:Solexa-18484 SM:NA12878 CN:BI

@RG ID:20FUK.7 PL:illumina PU:20FUKAAXX100202.7 LB:Solexa-18483 SM:NA12878 CN:BI

@RG ID:20FUK.8 PL:illumina PU:20FUKAAXX100202.8 LB:Solexa-18484 SM:NA12878 CN:BI

@PG ID:BWA VN:0.5.7 CL:tk

@PG ID:GATK TableRecalibration VN:1.0.2864

20FUKAAXX100202:1:1:12730:189900 163 chrM 1 60 101M = 282 381

GATCACAGGTCTATCACCTATTAACCACTCACGGGAGCTCTCCATGCATTTGGTA...[more bases]

?BA@A>BBBBACBBAC@BBCBBCBC@BC@CAC@:BBCBBCACAACBABCBCBCCAB...[more quals]

RG:Z:20FUK.1 NM:i:1 SM:i:37 AM:i:37 MD:Z:72G28 MQ:i:60 PG:Z:BWA UQ:i:33

Required: Standard header

Essential: contigs of aligned reference sequence. Should be in karyotypic order.

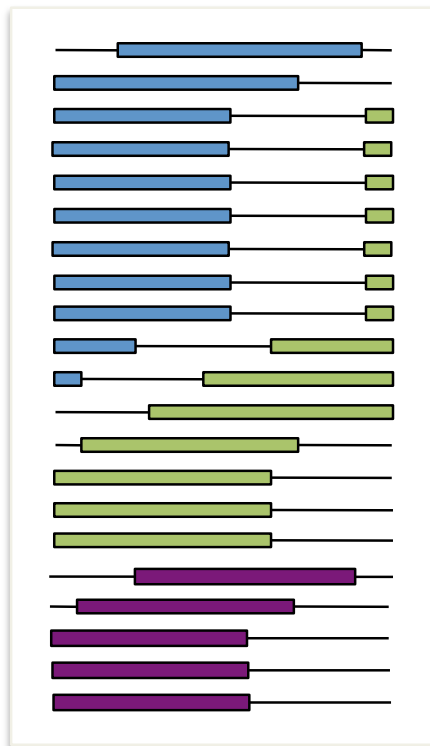
Essential: read groups. Carries platform (PL), library (LB), and sample (SM) information. Each read is associated with a read group

Useful: Data processing tools applied to the reads

Official specification in <http://samtools.sourceforge.net/SAM1.pdf>

Mapping short reads to a reference is simple in principle

Enormous pile of short reads from NGS

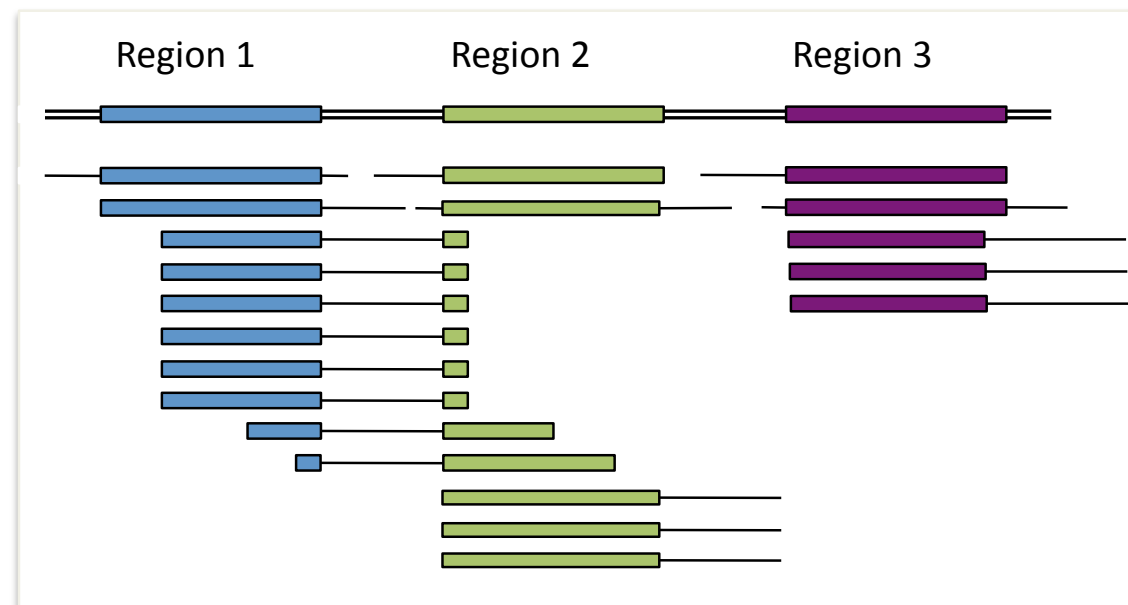


Mapping and alignment algorithms

Identify where the read matches the reference sequence and record match details as CIGAR string

RefPos:	1	2	3	4	5	6	7	8	9
Reference:	C	C	A	T	A	C	T	-	G
Read:		C	A	T	-	C	T	A	G

POS: 2
CIGAR: 3M1D2M1I1M

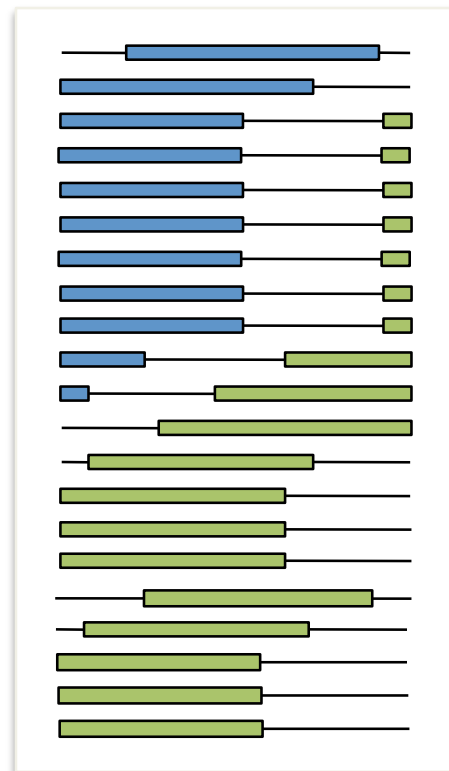


Reference genome

Reads mapped to reference

But mapping is actually very hard because of mismatches (true mutations or sequencing errors), duplicated regions etc.

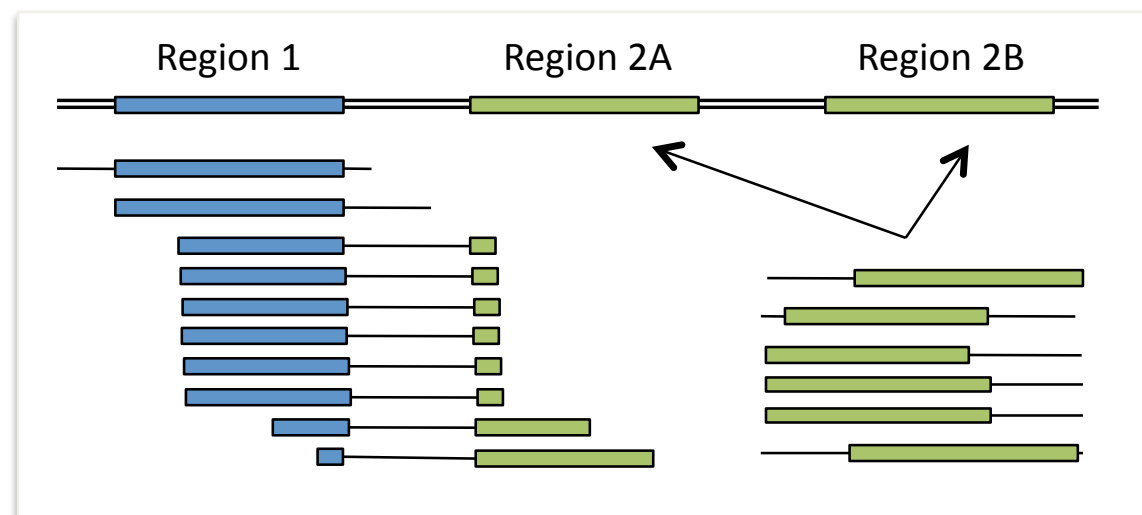
Enormous pile of short reads from NGS



Mapping and alignment algorithms

Mapping algorithms account for this by choosing the most likely placement

→ mapping quality (MQ)



Reference genome

High MQ

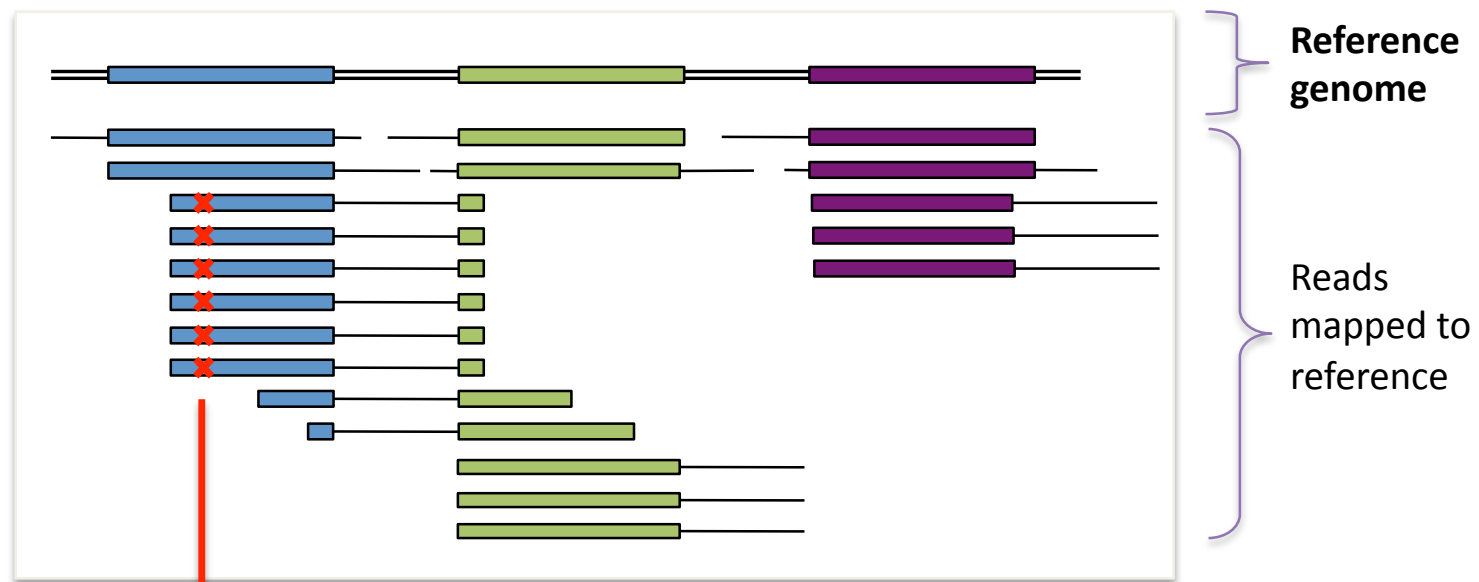
Low MQ

For more information see:

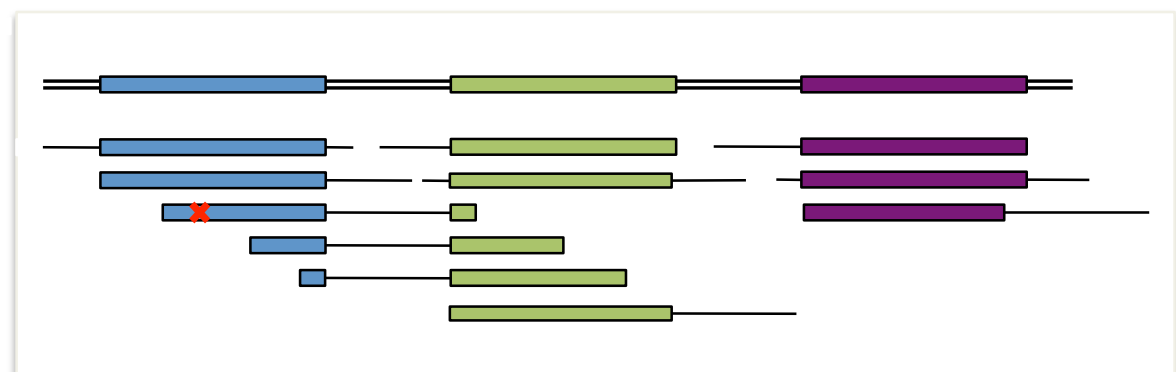
Li and Homer (2010). A survey of sequence alignment algorithms for next-generation sequencing. *Briefings in Bioinformatics*.

The reason why duplicates are bad

✗ = sequencing error propagated in duplicates

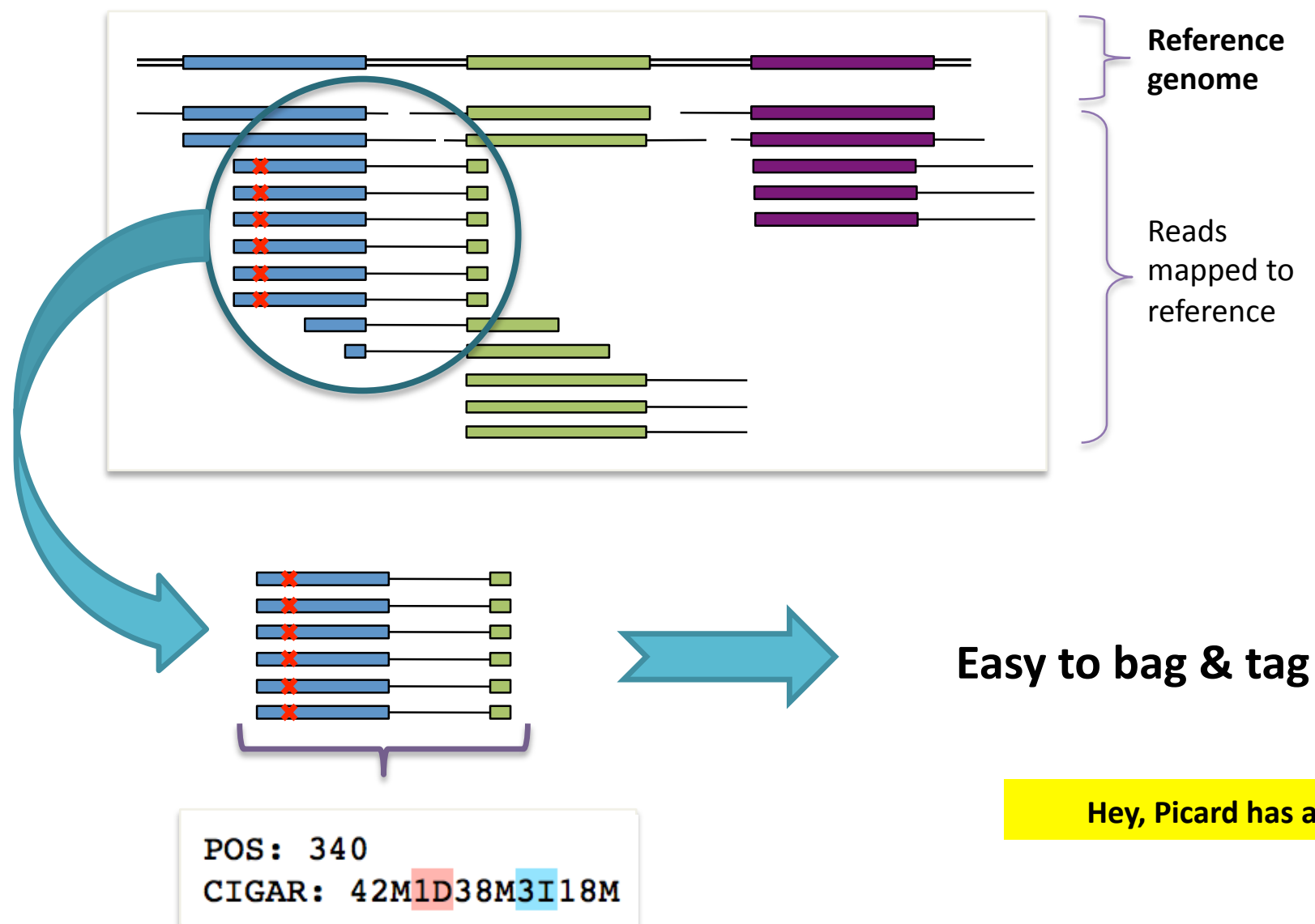


After marking duplicates, the GATK will only see :



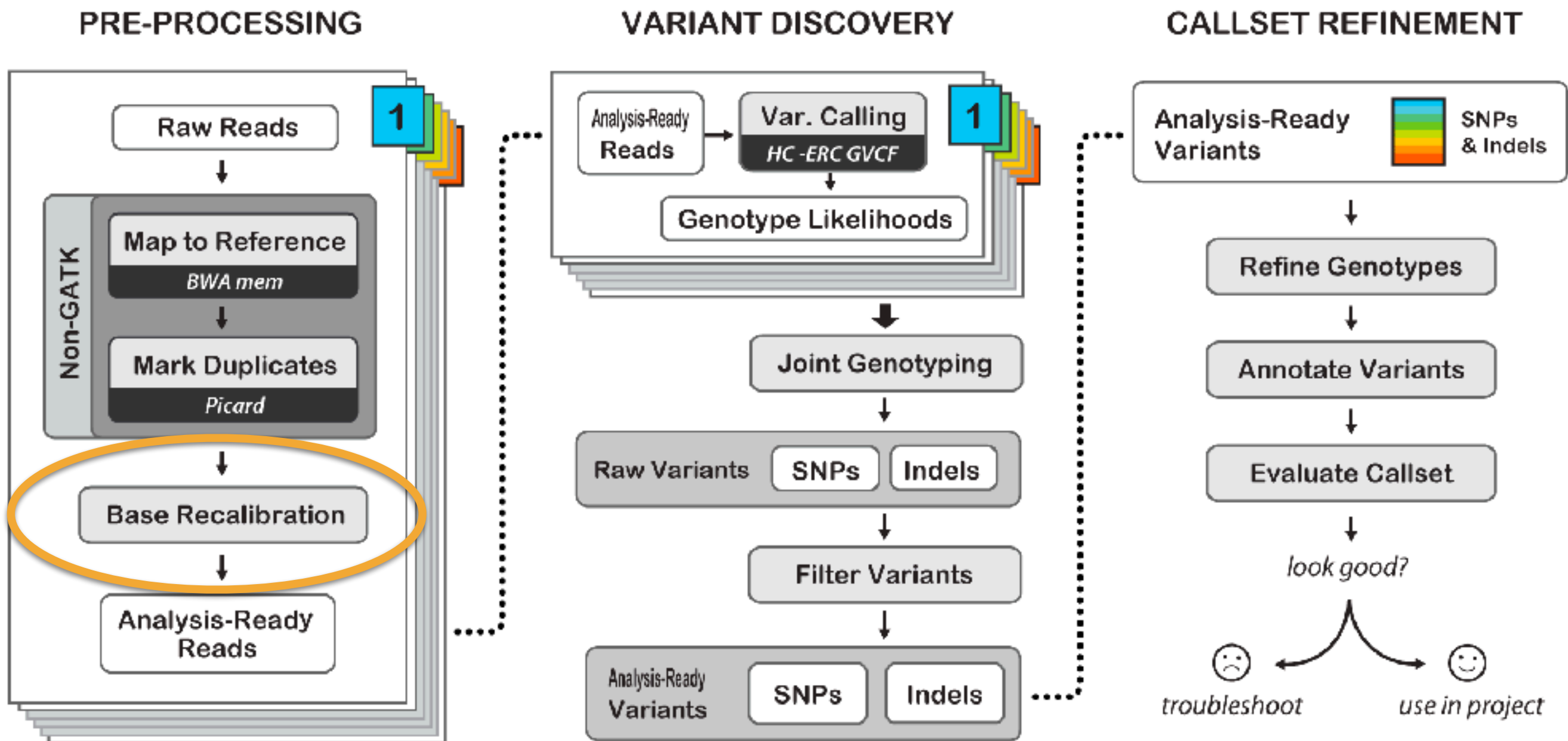
... and thus be more likely to make the right call

Easy to identify: duplicate reads have the same starting position and same CIGAR string



Why wouldn't we do this for GBS?

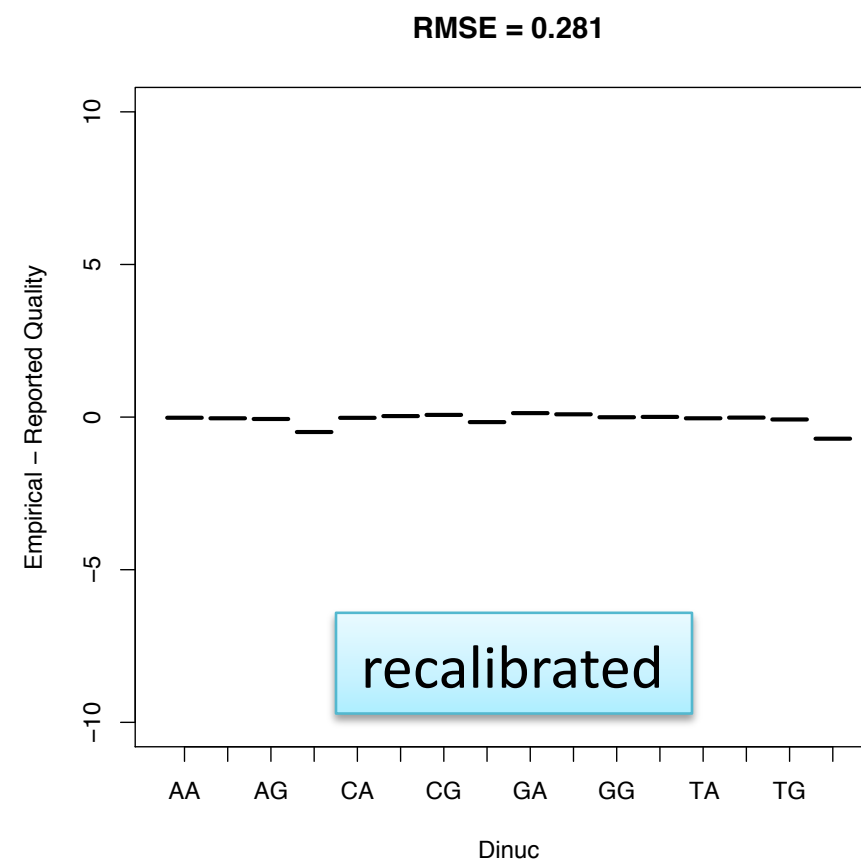
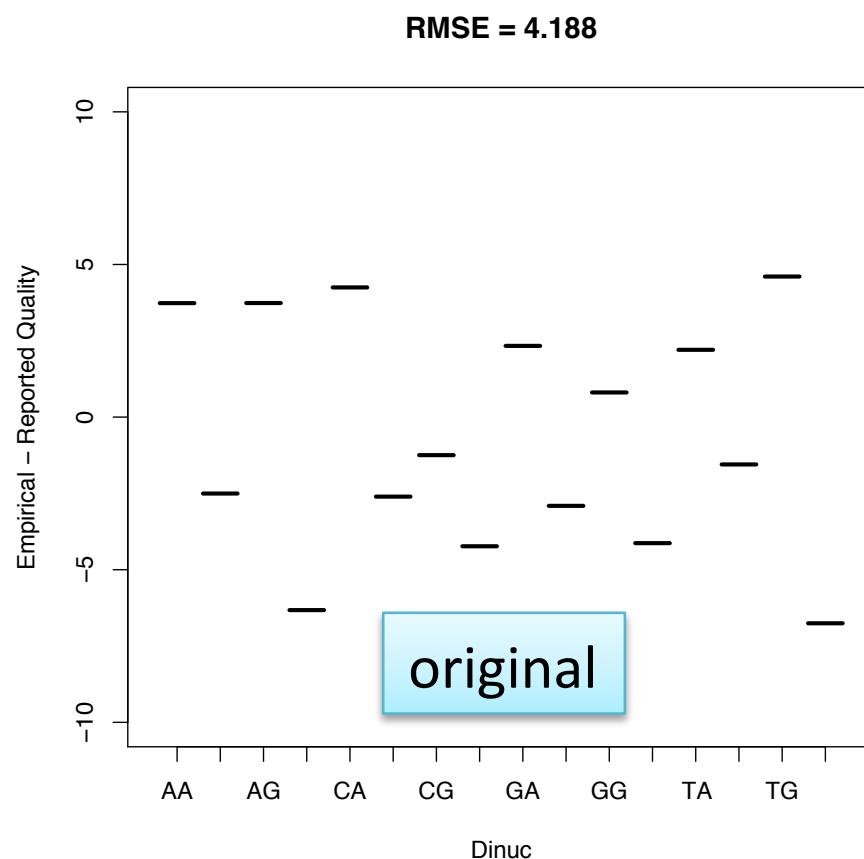
Base recalibration



Quality scores issued by sequencers are **inaccurate** and **biased**

- Quality scores are critical for all downstream analysis
- Systematic biases are a major contributor to bad calls

Example of bias: qualities reported depending on nucleotide context



BQSR identifies patterns in how errors correlate with base features

- Empowered by looking at entire lane of data
- Analyze covariation among several features of a base, e.g.:
 - Reported quality score
 - Position within the read (machine cycle)
 - Preceding and current nucleotide (sequencing chemistry effect)
- Based on the patterns identified:
Apply corrections to recalibrate the quality scores of all reads in the BAM file.

How covariates are analyzed to identify patterns

- Any sequence mismatch = error *except known variants!*
- Keep track of number of observations and number of errors as a function of various error covariates

(lane, original quality score, machine cycle, and sequencing context)

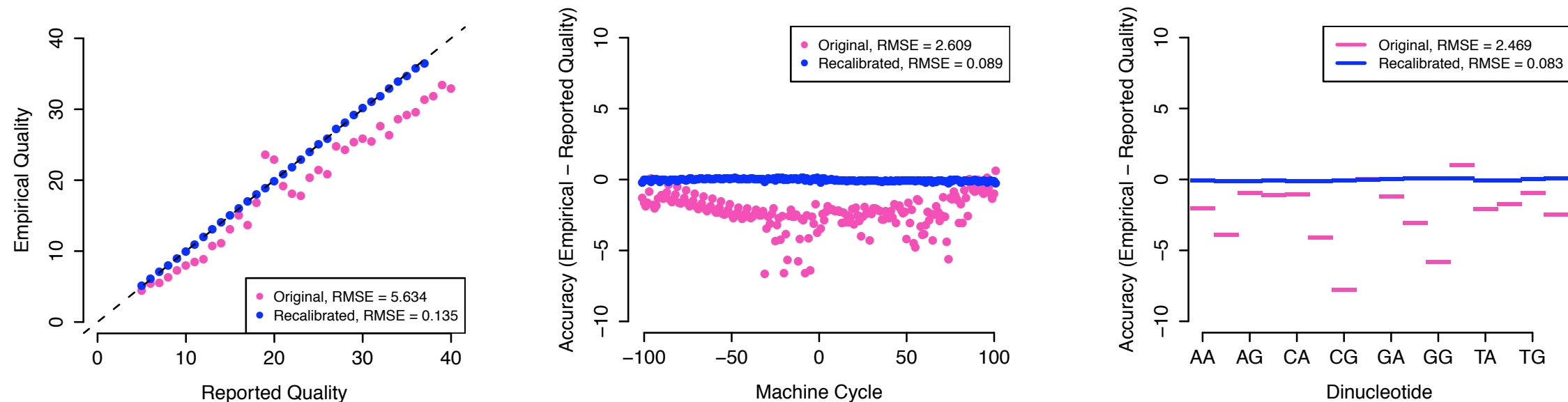
$$\frac{\# \text{ of reference mismatches} + 1}{\# \text{ of observed bases} + 2}$$



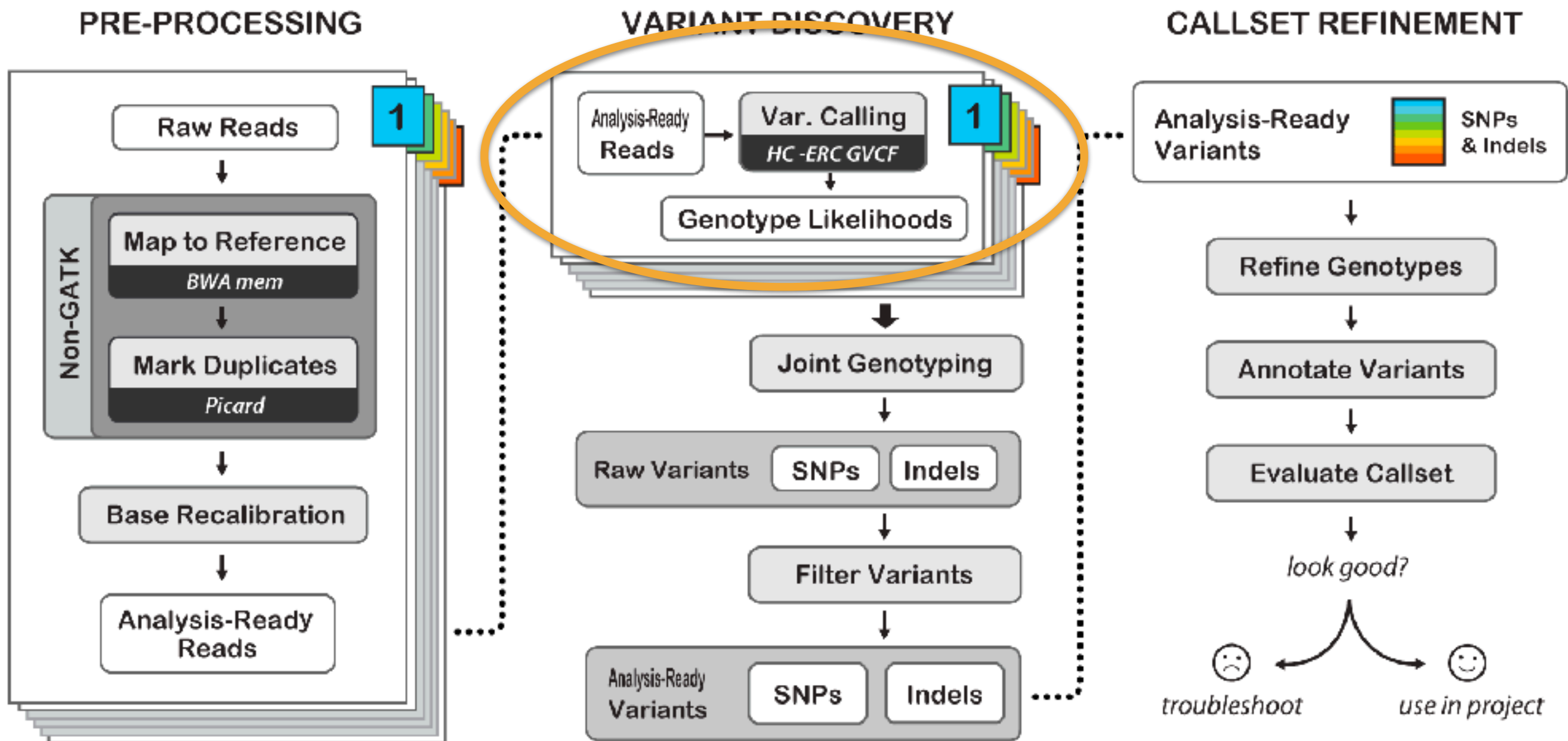
PHRED-scaled
quality score

Did the recalibration work properly?

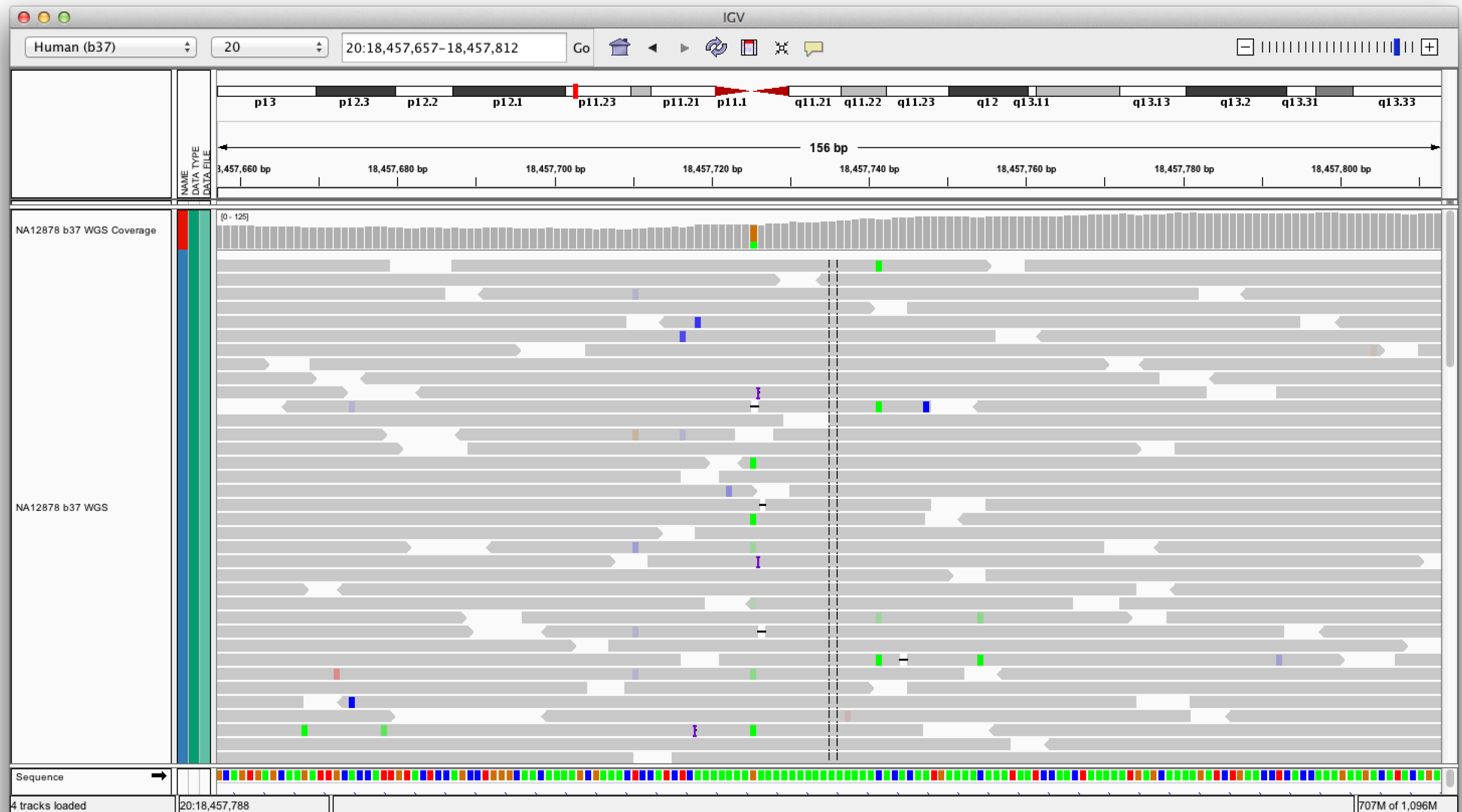
Post-recalibration quality scores should fit the empirically-derived quality scores very well; no obvious systematic biases should remain



Base recalibration



Real mutations are hidden in the noise



Summed up in GATK terms

Bayesian
model

$$\begin{aligned} \Pr\{G|D\} &= \frac{\overbrace{\Pr\{G\}}^{\text{Prior of the genotype}} \overbrace{\Pr\{D|G\}}^{\text{Likelihood of the genotype}}}{\sum_i \Pr\{G_i\} \Pr\{D|G_i\}}, \text{ [Bayes' rule]} \\ \Pr\{D|G\} &= \prod_j \left(\frac{\Pr\{D_j|H_1\}}{2} + \frac{\Pr\{D_j|H_2\}}{2} \right) \text{ where } G = H_1 H_2 \quad \underbrace{\hspace{10em}}_{\text{Diploid assumption}} \\ \Pr\{D|H\} &\text{ is the haploid likelihood function} \end{aligned}$$

Variant callers in GATK

- UnifiedGenotyper

Call SNPs and indels separately by considering each variant locus independently

- Accepts any ploidy
- Pooled calling

- HaplotypeCaller

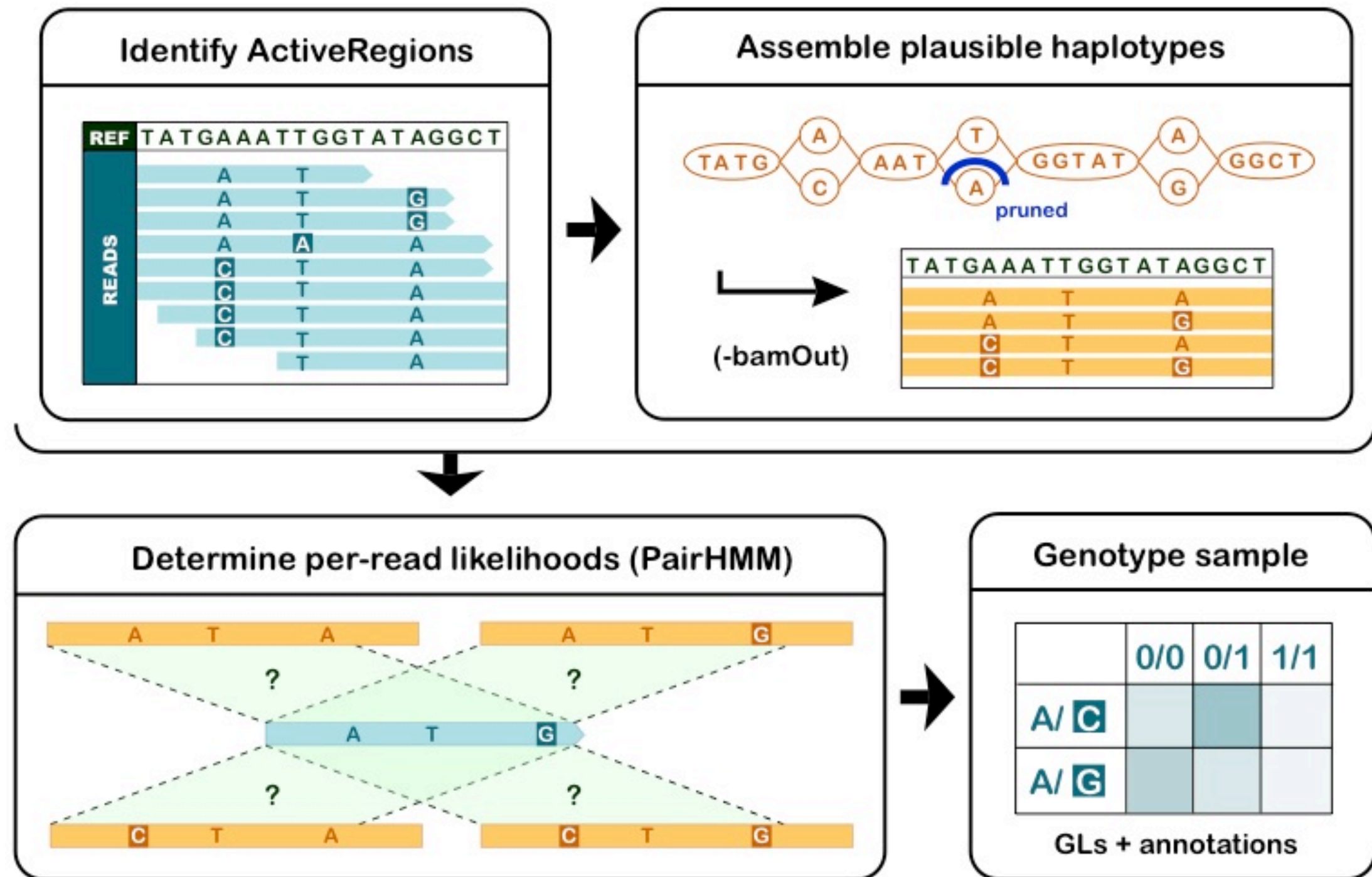
Call SNPs, indels, and some SVs simultaneously by doing local re-assembly and considering haplotypes

- More accurate (esp. indels)
- Reference confidence model
- Replaces UG

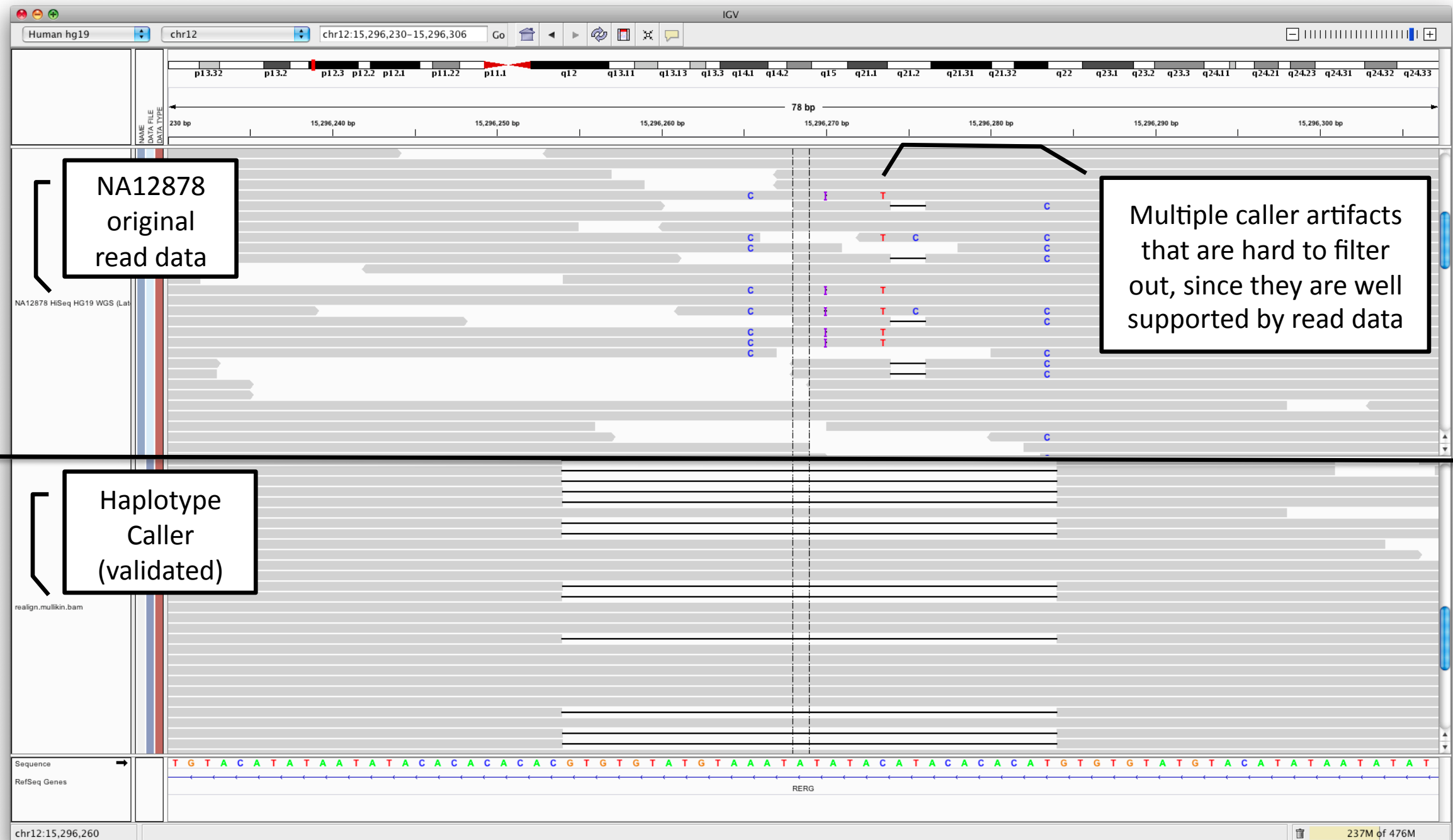
HaplotypeCaller method overview

- Call SNPs, indels, and some SVs simultaneously by doing local re-assembly and considering haplotypes
 - Determine if a region has **potential variation**
 - Make **deBruijn assembly graph** of the region
 - Paths in the graph = **potential haplotypes** to evaluate
 - Calculate **data likelihoods** given the haplotypes (PairHMM)
 - **Identify variants** on most likely haplotypes
 - Compute **allele frequency distribution** to determine most likely allele count, and emit a variant call if appropriate
 - If emitting a variant, **assign genotype** to each sample

HC method illustrated

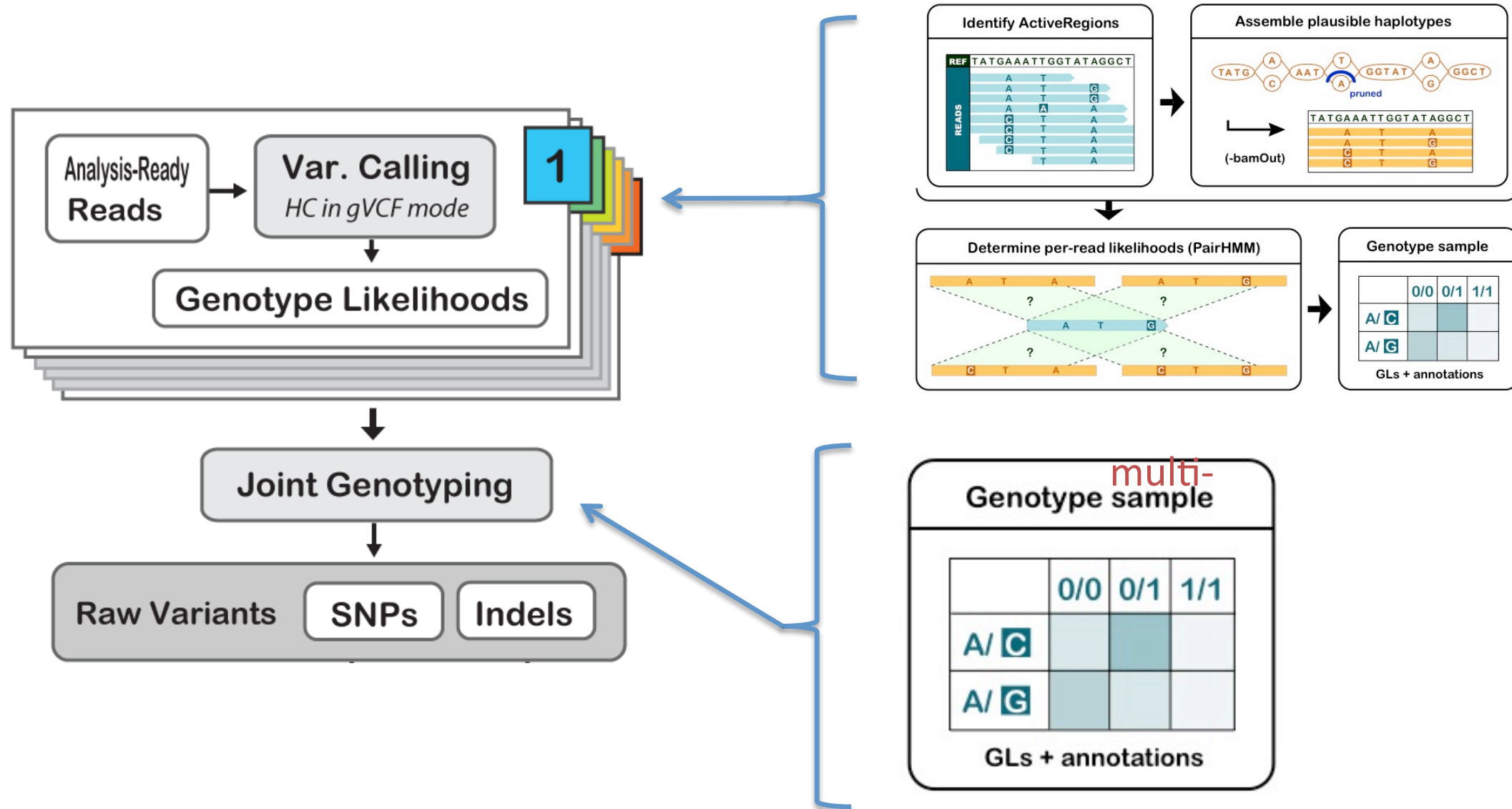


Artifactual SNPs and small indels caused by large indel can be recovered by assembly

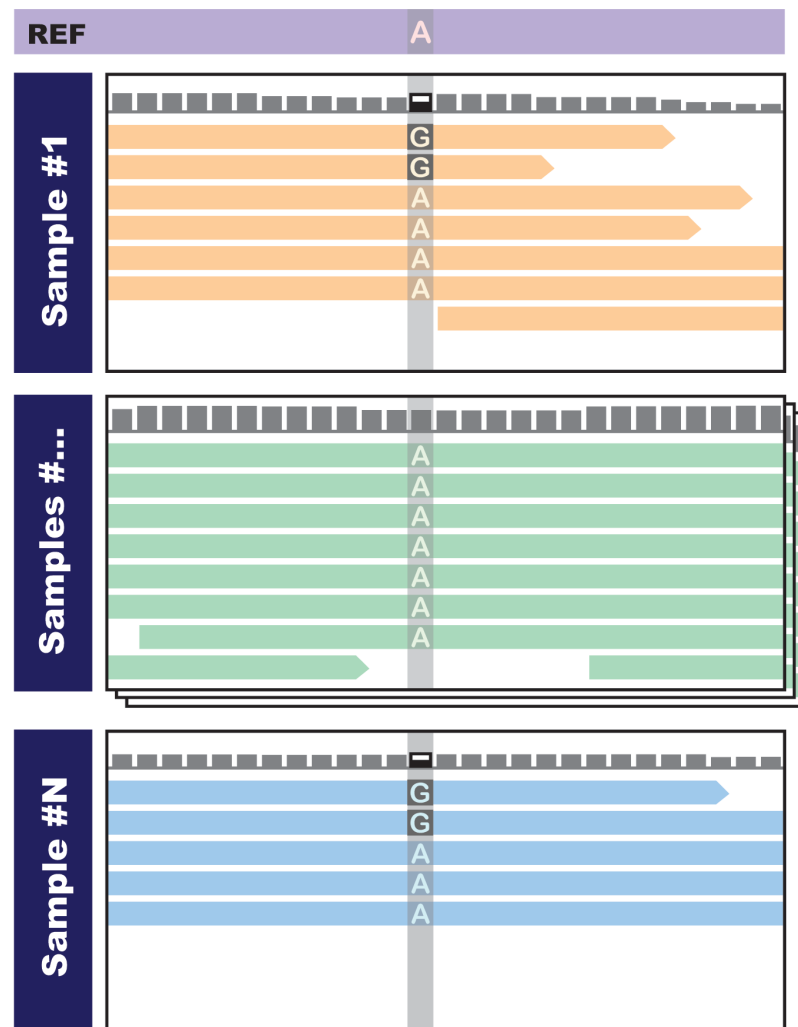


Joint Genotyping

Add a joint analysis step to take advantage of cohort / pop genetics data



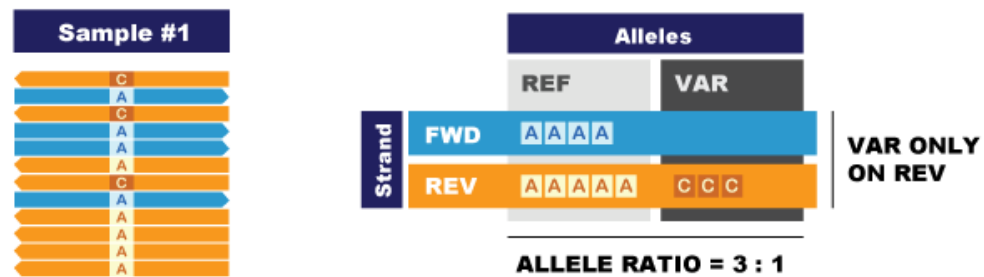
Joint discovery empowers discovery at difficult sites



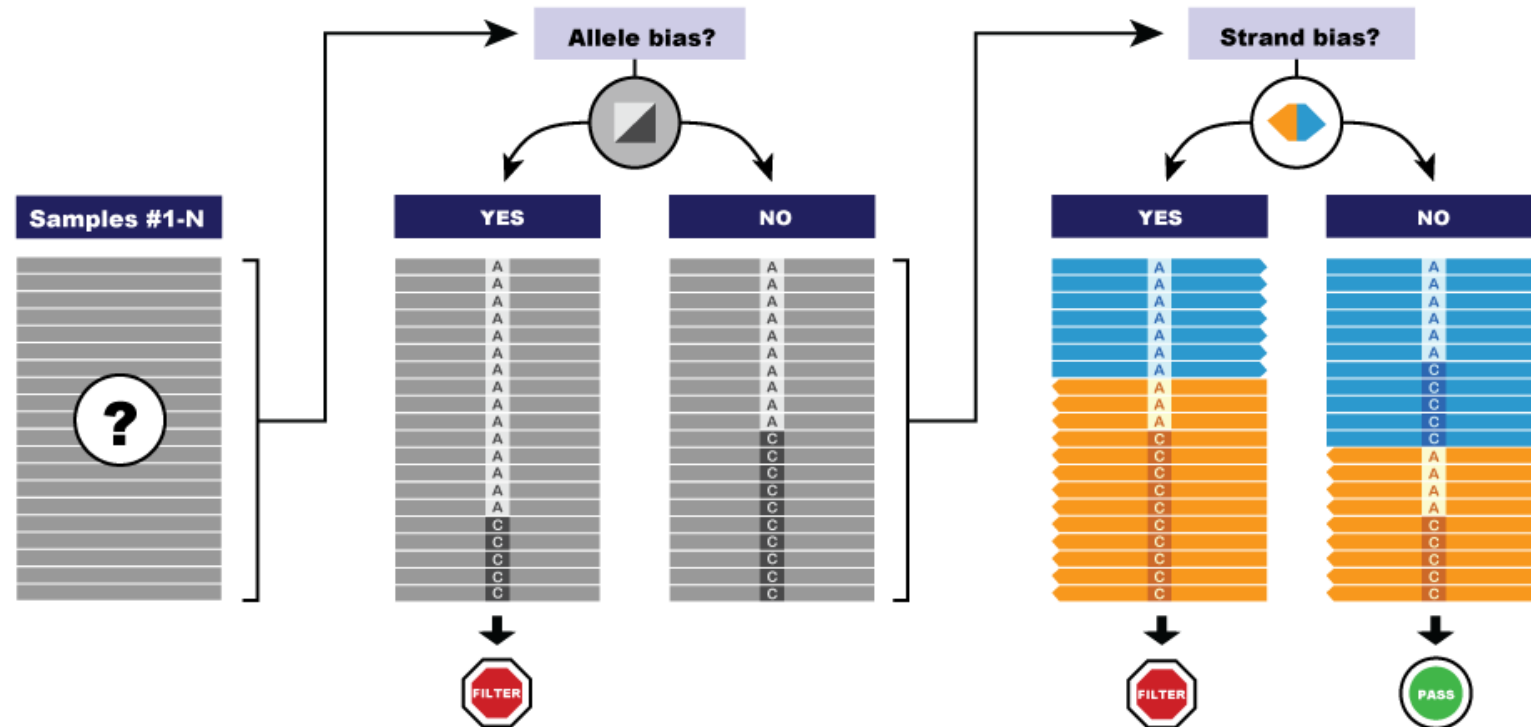
- If we analyze Sample #1 or Sample #N alone we are not confident that the variant is real
- If we see both samples then we are more confident that there is real variation at this site in the cohort

Joint discovery helps resolve bias issues

A. Single sample showing strand and allelic biases

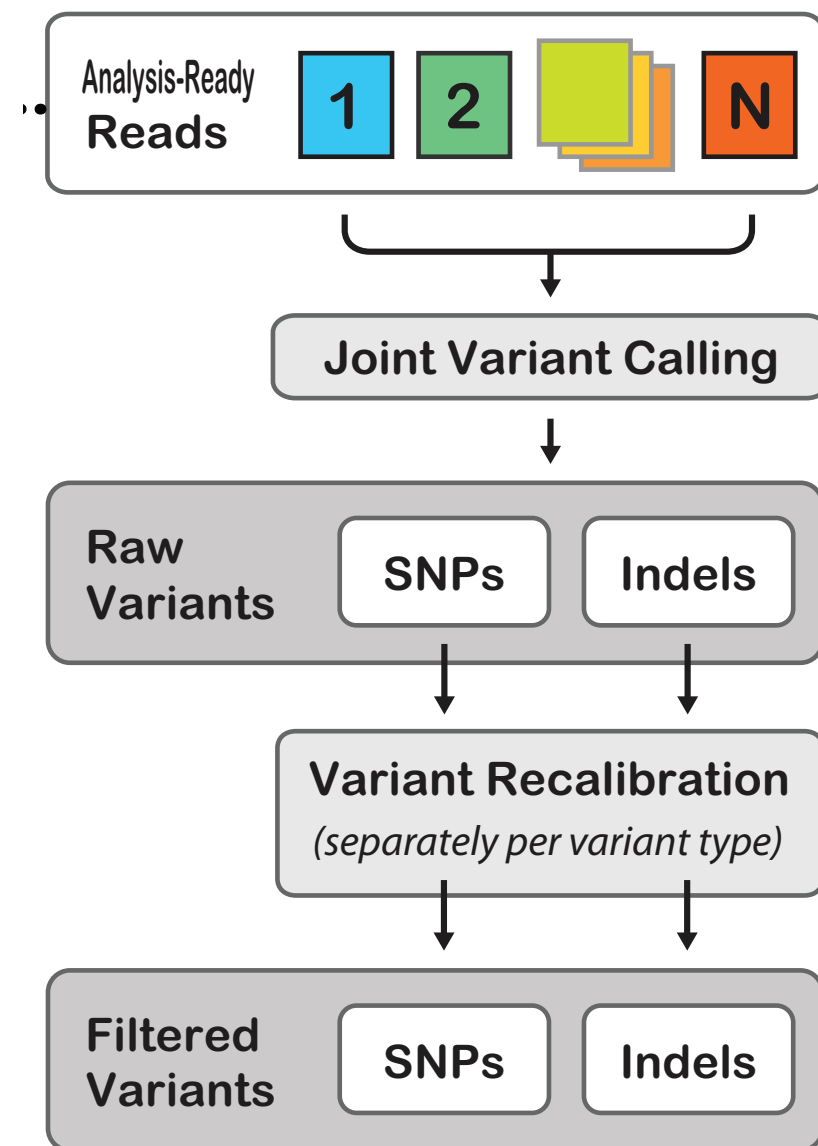


B. Decision process using evidence from multiple samples to filter out sites showing systematic biases



Classic approach to multi-sample variant discovery

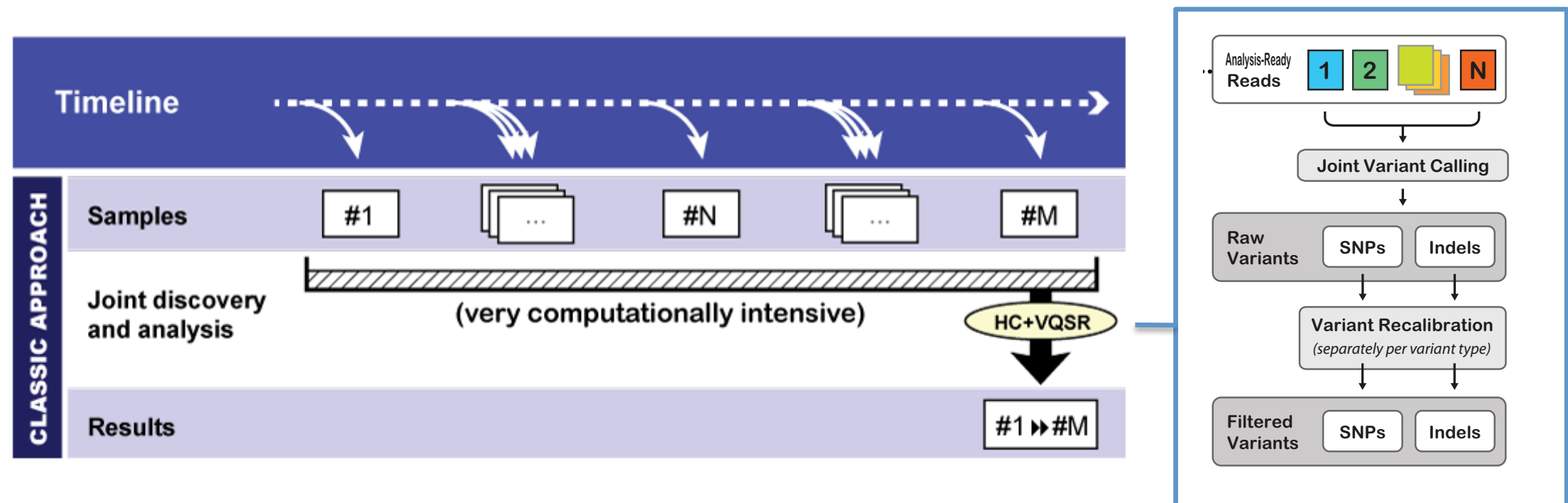
- Call variants jointly on all sample data
 - **Scales badly** -> limitations in amount of data that can be processed
 - Slow with **UnifiedGenotyper** (per-locus calculations)
 - *Impossibly* slow with **HaplotypeCaller** (so much extra work!)

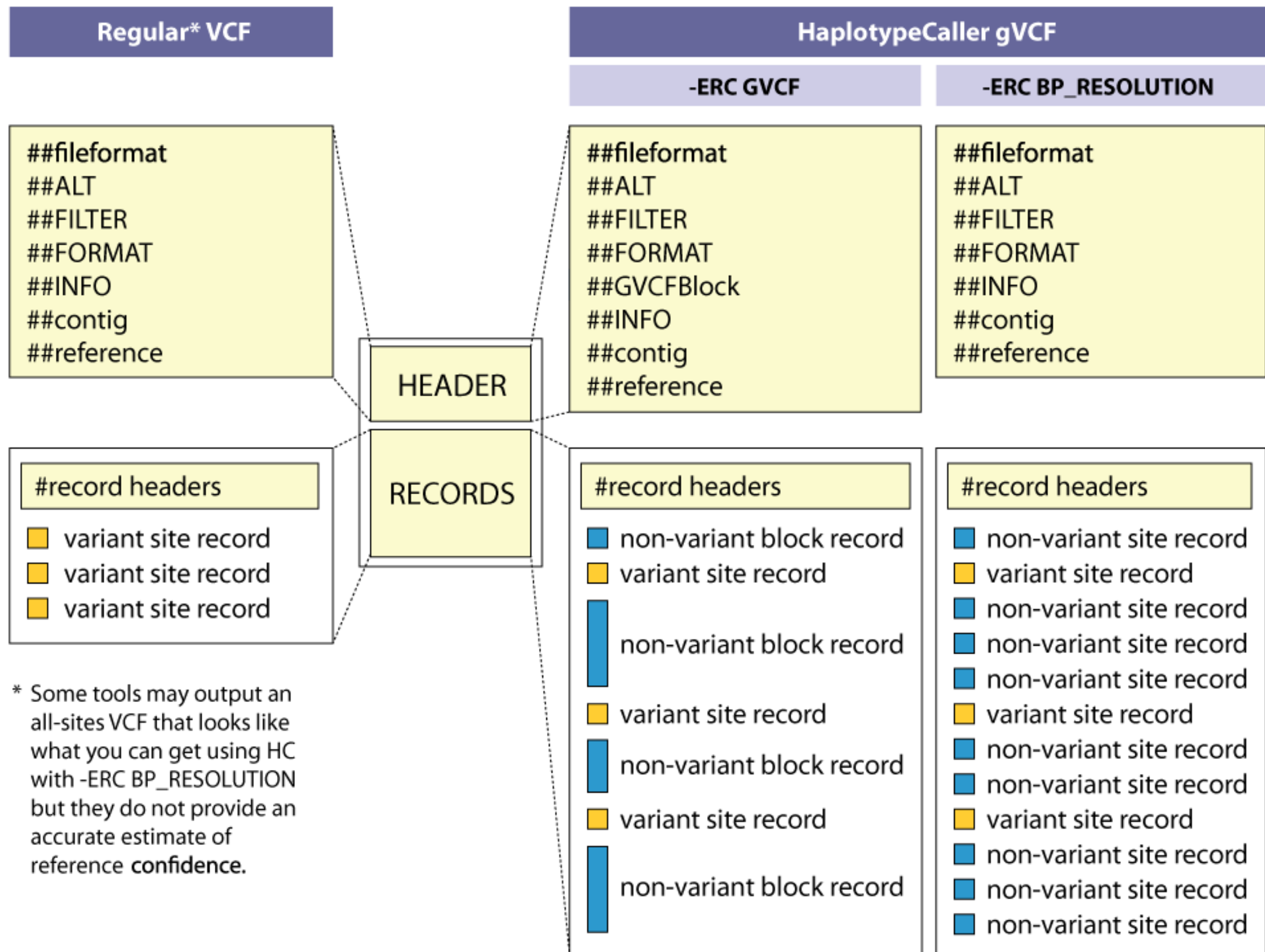


But we want to use HaplotypeCaller because it is so much better!

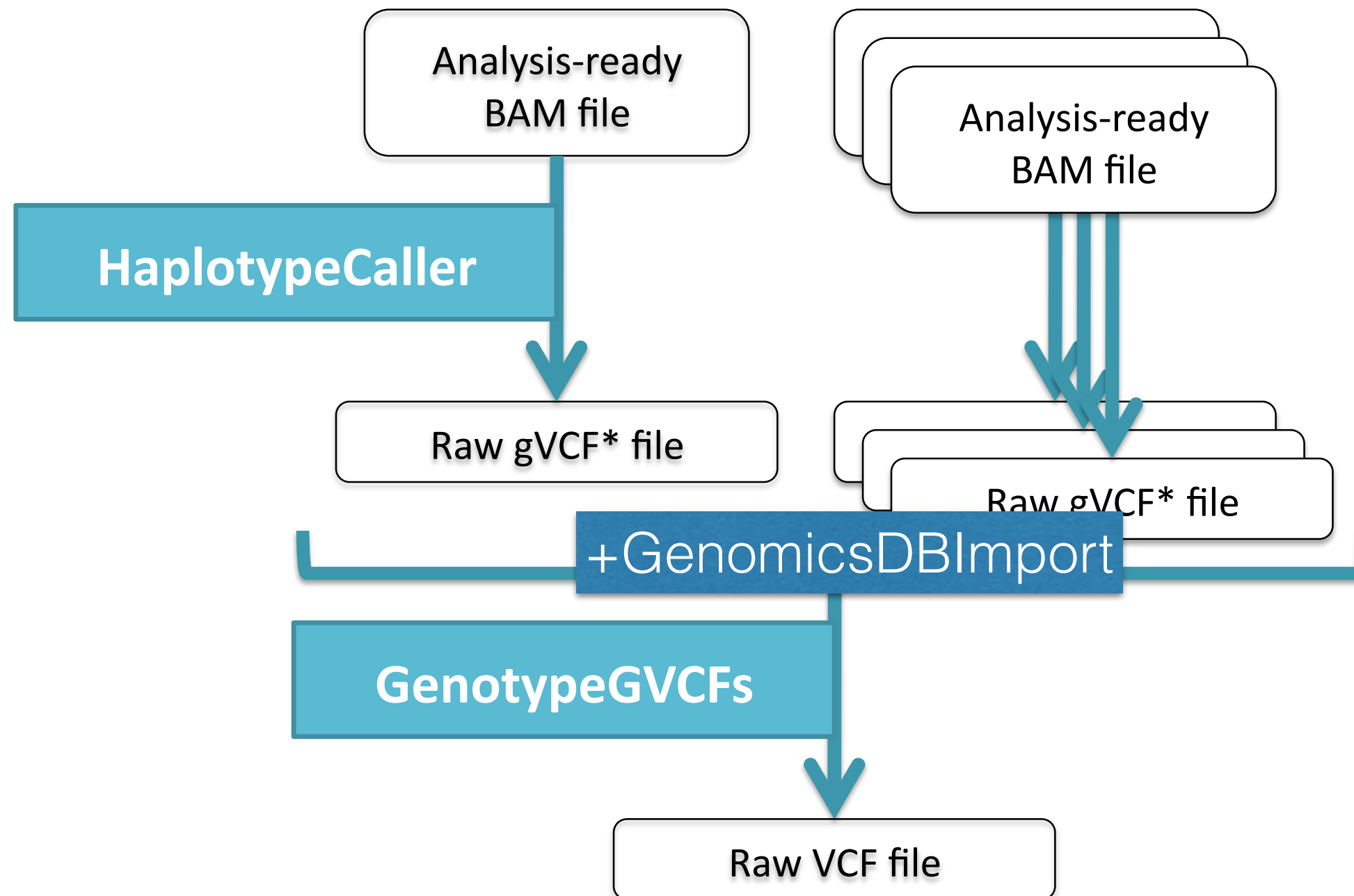
Problems with the “all together” approach

- Computing costs
- The “N+1 problem”





Variant calling + joint genotyping workflow



Variant annotations provide key information to identify and remove artifacts!

VCF record for an A/G SNP at 22:49582364

22	49582364	.	A	G	198.96	.
AC=3; AF=0.50; AN=6; DP=87; MLEAC=3; MLEAF=0.50; MQ=71.31; MQ0=22; QD=2.29; SB=-31.76 GT:DP:GQ		INFO field	AC	No. chromosomes carrying alt allele	MLEAF	Max likelihood AF
			AN	Total no. of chromosomes	MQ	RMS MAPQ of all reads
			AF	Allele frequency	MQ0	No. of MAPQ 0 reads at locus
			DP	Depth of coverage	QD	QUAL score over depth
			MLEAC	Max likelihood AC	SB	Estimated strand bias score
		0/1:12:99.00	0/1:11:89.43		0/1:28:37.78	

VCF Files store variant information

```
##fileformat=VCFv4.1
##reference=1000GenomesPilot-NCBI36
##INFO=<ID=DP,Number=1,Type=Integer,Description="Total Depth">
##INFO=<ID=AF,Number=A,Type=Float,Description="Allele Frequency">
##INFO=<ID=DB,Number=0,Type=Flag,Description="dbSNP membership, build 129">
##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">
#CHROM POS ID REF ALT QUAL FILTER INFO
FORMAT NA00001 NA00002 NA00003

20 14370 rs6054257 G A 29 PASS DP=14;AF=0.5;DB
GT:GQ:DP 0|0:48:1 1|0:48:8 1/1:43:5
20 1110696 rs6040355 A G,T 67 PASS DP=10;AF=0.333,0.667;DB
GT:GQ:DP 1|2:21:6 2|1:2:0 2/2:35:4
20 1230237 . T . 47 PASS DP=13
GT:GQ:DP 0|0:54:7 0|0:48:4 0/0:61:2
20 1234567 microsat1 GTCT G,GTACT 50 PASS DP=9
GT:GQ:DP 0/1:35:4 0/2:17:2 1/1:40:3
```

Header

Variant records

Official specification in

[www.1000genomes.org/wiki/Analysis/Variant Call Format/vcf-variant-call-format-version-41](http://www.1000genomes.org/wiki/Analysis/Variant%20Call%20Format/vcf-variant-call-format-version-41)

Variant Filtering

- By default, GATK is very permissive. It will output false positive sites!
- Two ways of filtering:
 - Hard filters
 - Variant recalibration

Hard Filters

- User defined thresholds for each site. Hard to know where to make cut offs?
 - Mapping quality high enough
 - Depth above a minimum but not too high
 - Minor allele frequency above a minimum
 - Heterozygosity not too high

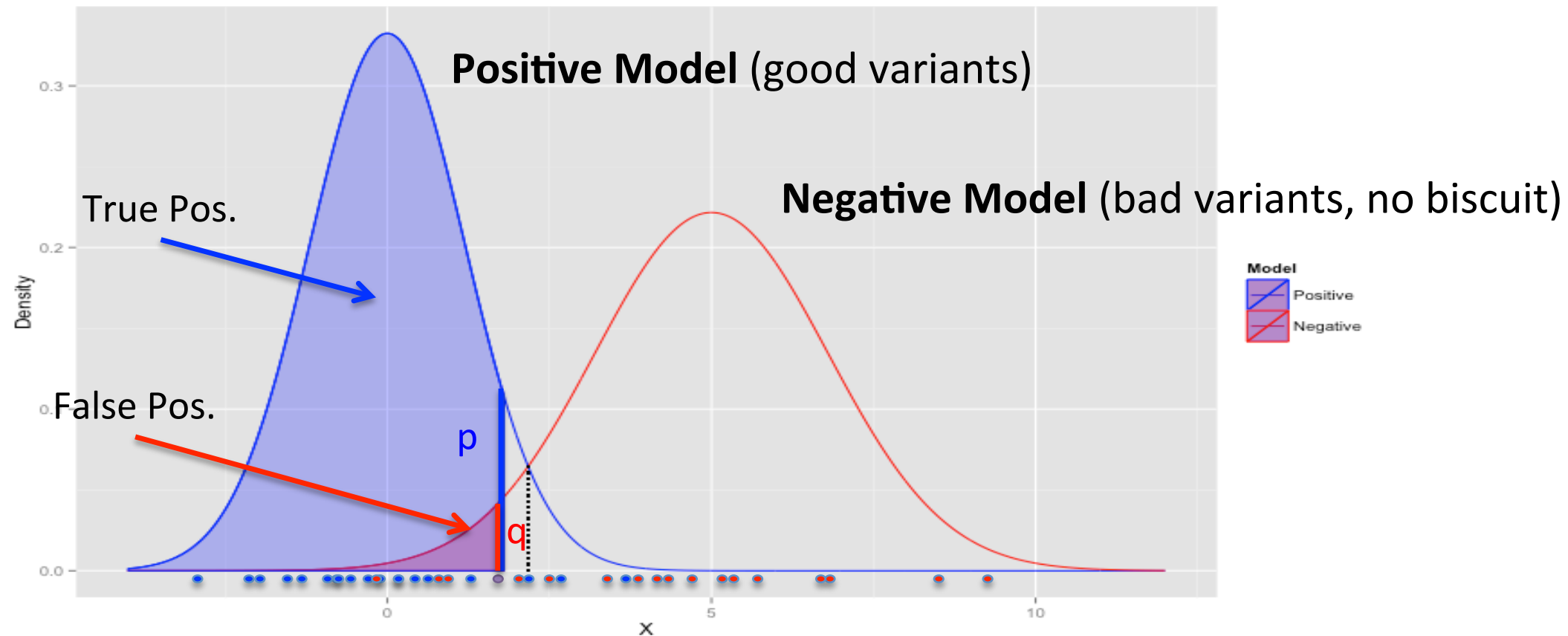
How variant recalibration works



Train on high-confidence known sites to determine the probability that other sites are true or false

- Assume annotations tend to form **Gaussian clusters**
- Build a “Gaussian mixture model” from annotations of **known variants** in our dataset
- Score **all variants** by where their annotations lie relative to these clusters
- Filter base on **sensitivity to truth set**

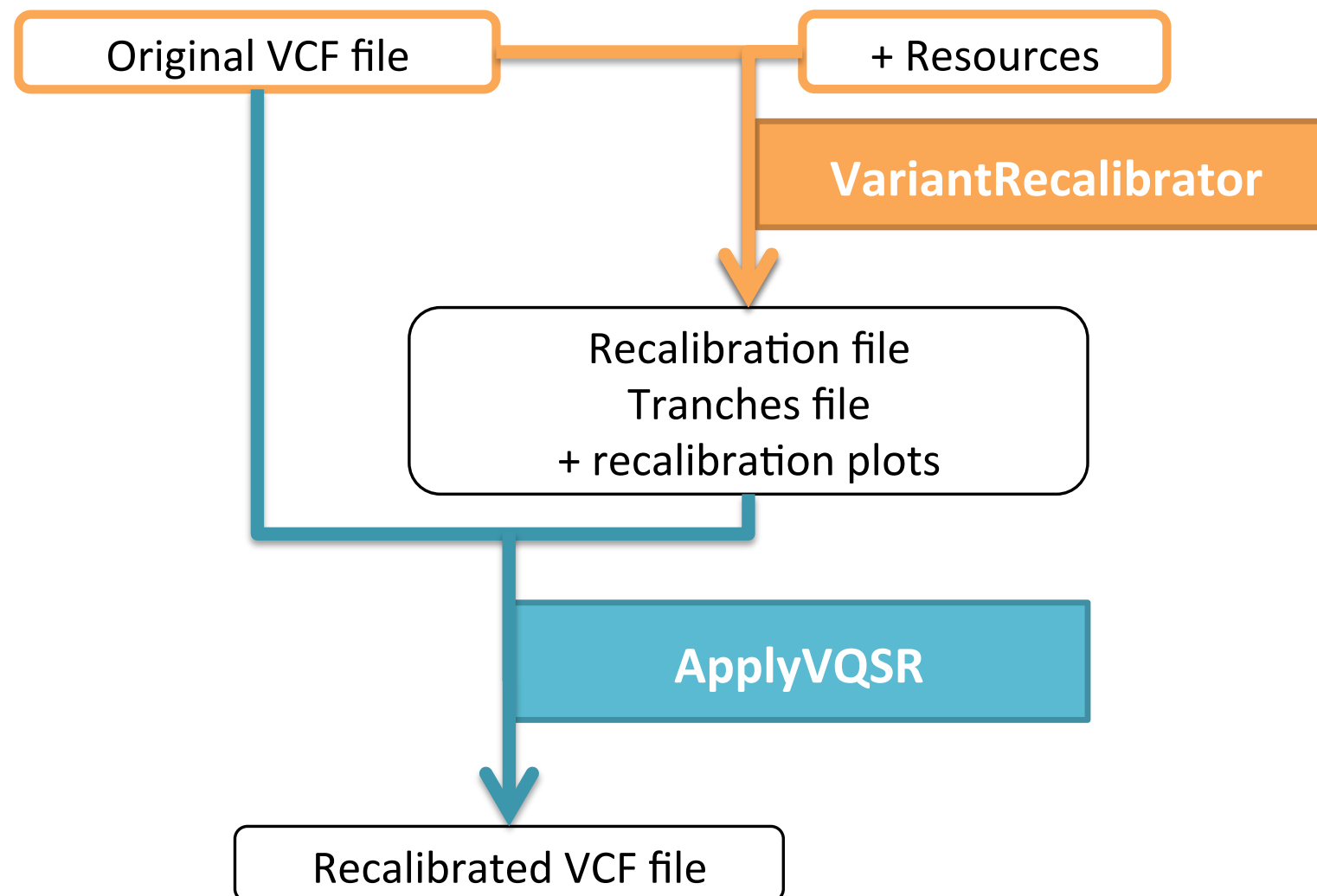
Actually two models: positive and negative



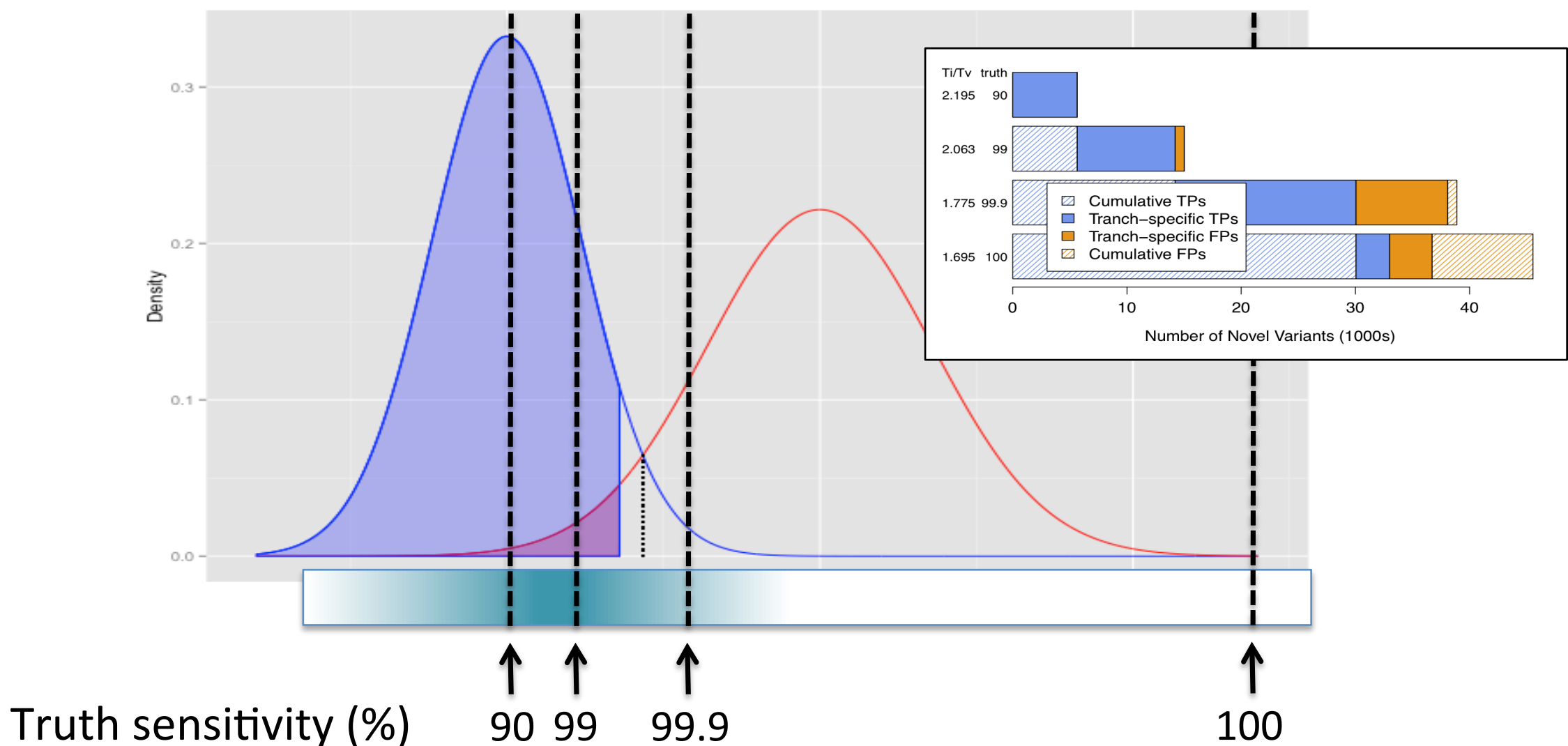
$$\text{VQSLOD}(x) = \text{Log}(\textcolor{blue}{p}(\textcolor{blue}{x})/\textcolor{red}{q}(\textcolor{red}{x}))$$

Done for each annotation X
then integrated into single overall VQSLOD

Step 1: VariantRecalibrator



Tranches : slices of sensitivity threshold values



Lower tranche = More stringent filtering

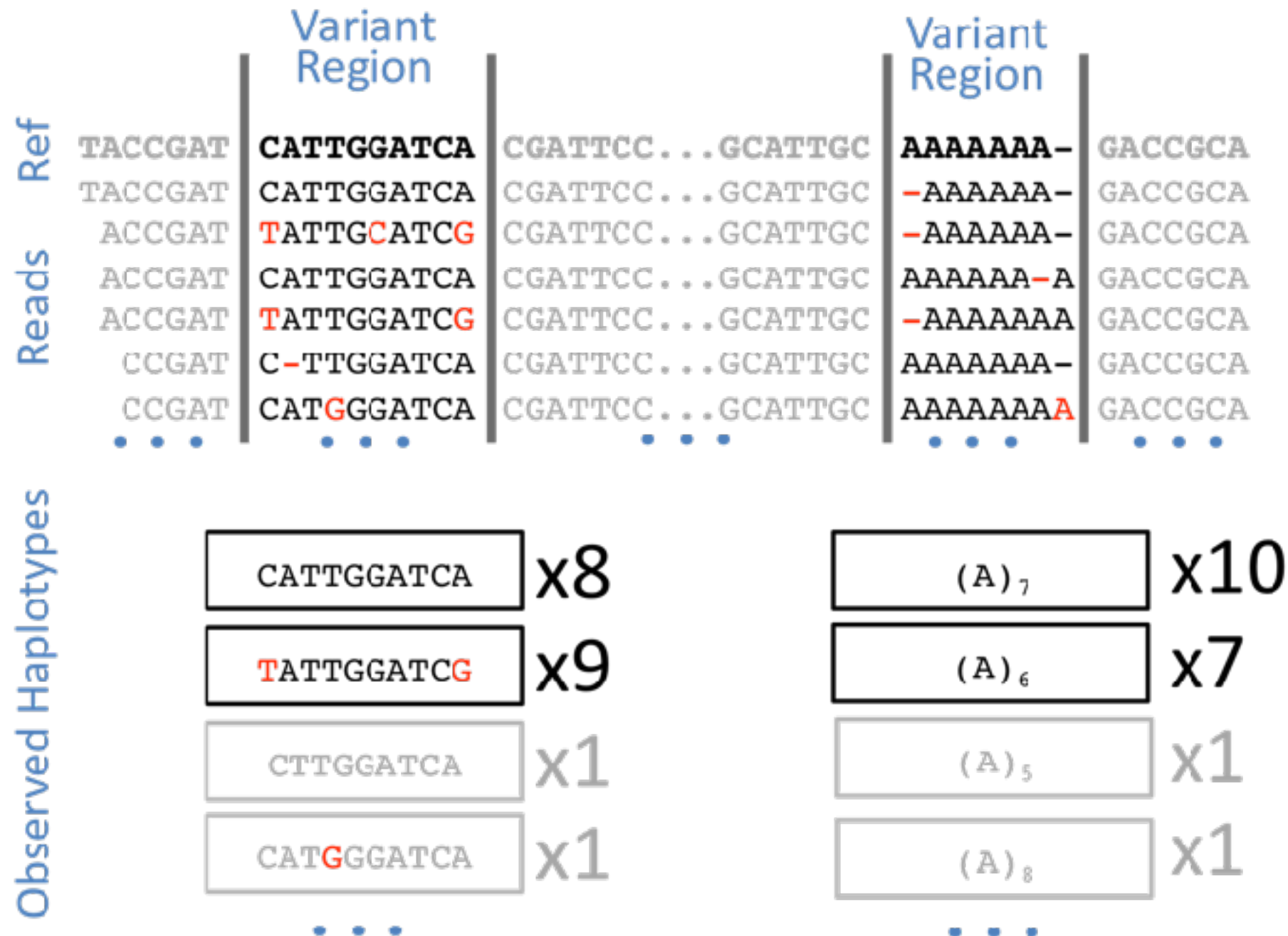
Where to get truth set?

- Reference sets (e.g. 1000 genomes)
- Take your dataset, call SNPs, hard filter heavily, then use those as a truth set for recalibrating the unfiltered dataset.

Alternative Filtering

- Call SNPs using multiple programs and look for variants called in multiple programs, or combine the information in each.
- e.g. BAYSIC

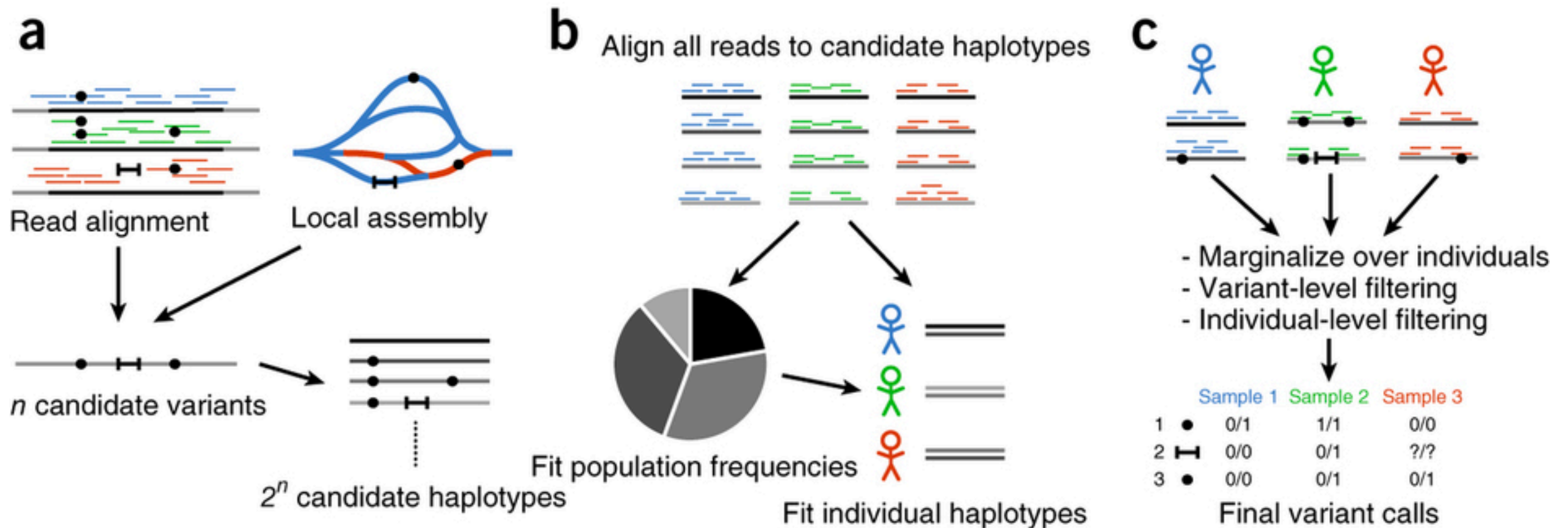
FreeBayes



FreeBayes

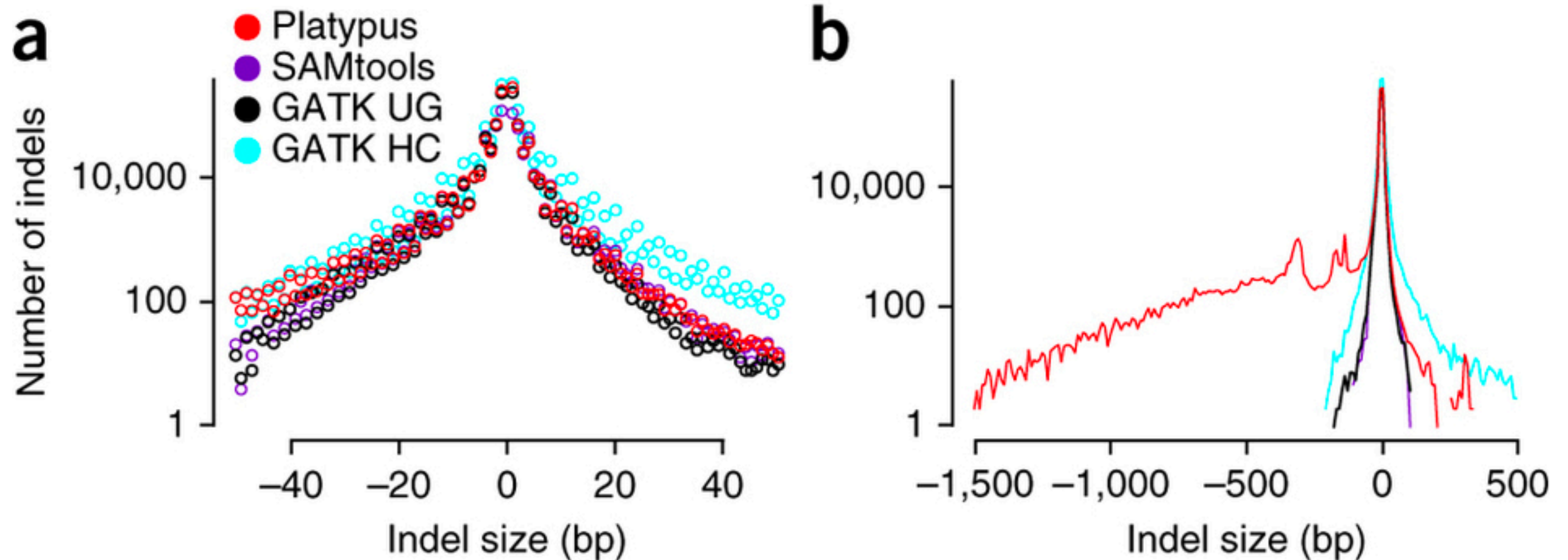
- Free and open source.
- Uses literal sequences of bases and haplotypes to call SNPs so is less affected by local alignment issues.
- Does not have “gvcf” n+1 method, although complicated work around exists.
- Generally faster than GATK, although RAM intensive.

Platypus



Includes local assembly, better for large indels

Platypus



Includes local assembly, better for large indels

ANGSD

- Calls SNPs based on reads per site, no realignment.
- Outputs genotype likelihoods.
- Links with algorithms that use likelihood.
- Questionable with high diversity systems.