

### Variant Calling - SNPs and short indels petr.danecek@sanger.ac.uk



### HTS workflow

### Library preparation

- ► DNA extraction
- ► fragmentation
- ► adapter ligation
- ► amplification

### Sequencing

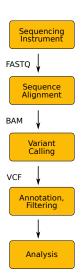
- ▶ base calling
- ► de-multiplexing

#### Data processing

- ► read mapping
- ▶ variant calling
- ► variant filtering

#### Analysis

- ► Variant annotation
- ▶ ...



### Variant types

 $SNPs/SNVs \quad \dots \ Single \ Nucleotide \ Polymorphism/Variation$ 

ACGTTTAGCAT ACGTTCAGCAT

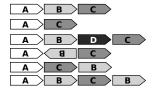
MNPs ... Multi-Nucleotide Polymorphism

ACGTCCAGCAT ACGTTTAGCAT

Indels ... short insertions and deletions

ACGTTTAGCA-TT ACGTT-AGCAGTT

SVs ... Structural Variation



### Some terminology

The goal is to determine the genotype at each position in the genome

#### Genotype

- ▶ in the broad sense ... genetic makeup of an organism
- ▶ in the narrow sense . . . the combination of alleles at a position

#### Reference and alternate alleles - R and A

#### Diploid organism

- two chromosomal copies, three possible genotypes
  - ▶ RR .. homozygous reference genotype
  - ► RA .. heterozygous
  - ► AA .. homozygous alternate

Reference genome:	AGACTTGGCCC	CCTCCCCATTC	AAGGTCTTC
Sequenced genome:		CATCCCCATTC	
	1	<b>†</b>	<b>\</b>
	C/C R R	A/C A R	C/C A A
VCF notation Alternate allele dosage	. 0/0 . 0	1/0 1	1/1 2

### Germline vs somatic mutation

#### Germline mutation

► heritable variation in the germ cells

#### Somatic mutation

 $\,\blacktriangleright\,$  variation in non-germline tissue, tumors. . .

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#### Germline variant calling

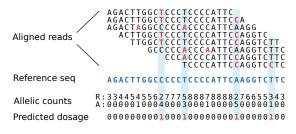
- expect the following fractions of alternate alleles in the pileup:
  - 0.0 for RR genotype (plus sequencing errors)
  - 1.0 for AA (plus sequencing errors)
  - 0.5 for RA (random variation of binomial sampling)

#### Somatic

 any fraction of alt AF possible - subclonal variation, admixture of normal cells in tumor sample

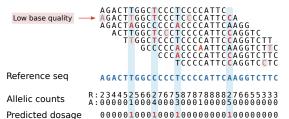


Use fixed allele frequency threshold to determine the genotype



alt AF	genotype		
$   \begin{bmatrix}     0, 0.2 \\     0.2, 0.8 \\     0.8, 1   \end{bmatrix} $	RR homozygous reference RA herezogyous AA homozygous variant		

Use fixed allele frequency threshold to determine the genotype

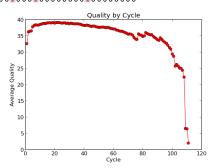


1) Filter base calls by quality e.g. ignore bases Q < 20

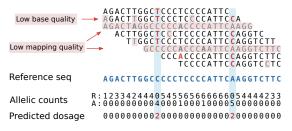
### Phred quality score

 $Q = -10\log_{10}P_{\mathsf{err}}$ 

Quality	Error probability	Accuracy
10 (Q10)	1 in 10	90%
20 (Q20)	1 in 100	99%
30 (Q30)	1 in 1000	99.9%
40 (Q40)	1 in 10000	99.99%



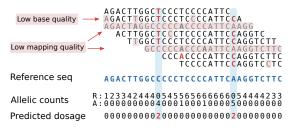
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- 2) Filter reads with low mapping quality

alt AF	genotype	
[0, 0.2) [0.2, 0.8]	RR homozygous reference RA herezogyous	
(0.8, 1]	AA homozygous variant	

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#### Problems:

- ▶ undercalls hets in low-coverage data
- ▶ throws away information due to hard quality thresholds
- gives no measure of confidence

### Real life calling models

More sophisticated models apply a statistical framework

$$P(G|D) = rac{P(D|G)\,P(G)}{P(D)}$$
Posterior

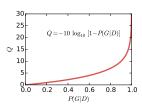
to determine:

1. the most likely genotype  $g \in \{ \mathsf{RR}, \mathsf{RA}, \mathsf{AA} \}$  given the observed data D

$$g = \operatorname*{argmax}_{G} P(G|D)$$

2. and the genotype quality

$$Q = -10\log_{10}[1 - P(G|D)]$$



### Important terms you may encounter

#### Genotype likelihoods

- which of the three genotypes RR, RA, AA is the data most consistent with?
- calculated from the alignments, the basis for calling
- ▶ takes into account:
  - base calling errors
  - mapping errors
  - statistical fluctuations of random sampling
  - local indel realignment (base alignment quality, BAQ)

#### Prior probability

- ▶ how likely it is to encounter a variant base in the genome?
- some assumptions are made
  - ▶ allele frequencies are in Hardy-Weinberg equilibrium

$$P(RA) = 2f(1 - f), P(RR) = (1 - f)^2, P(AA) = f^2$$

▶ can take into account genetic diversity in a population

$$P(G|D) = \frac{P(D|G) P(G)}{P(D)}$$

### Variant calling example

#### Inputs

- ▶ alignment file
- ► reference sequence

#### Outputs

▶ VCF or BCF file

#### Example

```
bcftools mpileup -f ref.fa aln.bam | bcftools call -mv
```

#### Tips

#### bcftools mpileup

- increase/decrease the required number (-m) and the fraction (-F) of supporting reads for indel calling
- the -Q option controls the minimum required base quality (30)
- BAQ realignment is applied by default and can be disabled with -B
- streaming the uncompressed binary BCF (-0u) is much faster than the default text VCF

#### bcftools call

- decrease/increase the prior probability (-P) to decrease/increase sensitivity

#### General advice

- ▶ take time to understand the options
- play with the parameters, see how the calls change

## Factors to consider in calling

### Many calls are not real, a filtering step is necessary

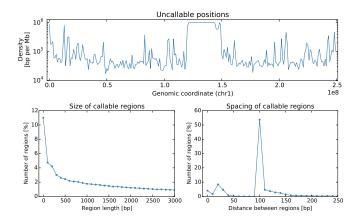
#### False calls can have many causes

- contamination
- ► PCR errors
- sequencing errors
  - ▶ homopolymer runs
- mapping errors
  - repetitive sequence
  - structural variation
- alignment errors
  - ► false SNPs in proximity of indels
  - ► ambiguous indel alignment

### Callable genome

Large parts of the genome are still inaccessible

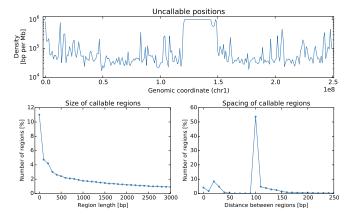
- ▶ the Genome in a Bottle high-confidence regions:
  - ▶ cover 89% of the reference genome
  - ▶ are short intervals scattered across the genome



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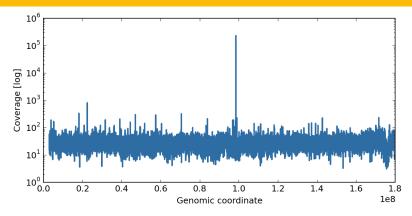
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If possible, include only "nice" regions: for many analyses (e.g. population genetics studies) difficult regions can be ignored

### Maximum depth



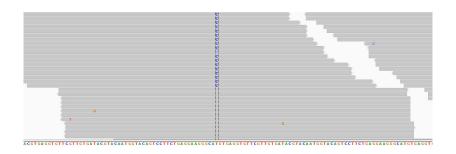
Q: Why is the sequencing depth thousandfold the average in some regions?

## Mapping errors



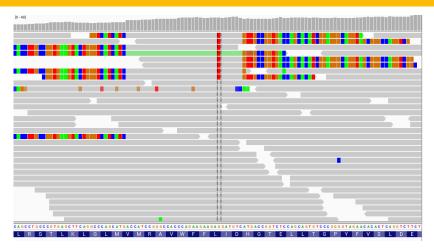
Q: RNA-seq (top) and DNA data (bottom) from the same sample has been mapped onto the reference genome. Can you explain the novel SNVs?

### Strand bias



Q: Is this a valid call?

## Change the display in IGV to reveal artefacts

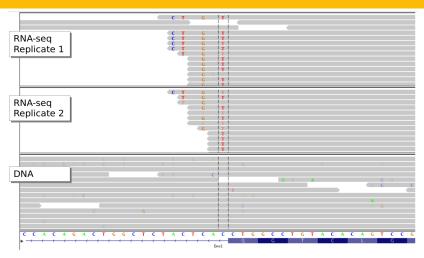


Display soft-clipped bases...



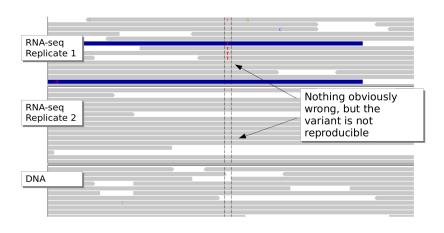
Too many soft-clipped reads in a region suggest mapping errors, beware!

### Variant distance bias



Q: Can you explain what happened here?

## Reproducibility





Mind the biological variability. If possible, validate and replicate.

## False SNPs caused by incorrect alignment

Pairwise alignemnt artefacts can lead to false SNPs

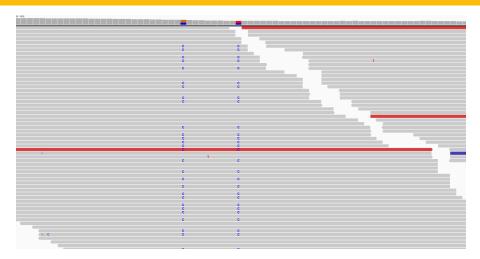
- ▶ multiple sequence alignment is better, but very expensive
- ▶ instead: base alignment quality (BAQ) to lower quality of misaligned bases

```
Aligned reads

aggttttataaaac----aaataa
ggttttataaaac----aaataat
ttataaaacaaataattaagtctaca
caaat----aattaagtctacagagcaac
aat----aattaagtctacagagcaact
t----aattaagtctacagagcaact
aggtttataaaac----aattaagtctacagagcaacta
```

Q: How many SNPs are real?

# What good SNPs look like?



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## What good SNPs look like?

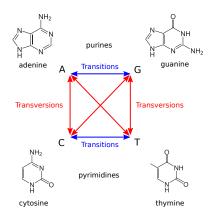


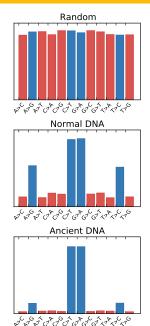
Q: Is this call real? There are many reads with MQ=0.

### How to estimate the quality of called SNPs?

#### Transitions vs transversions ratio, known as ts/tv

▶ transitions are 2-3× more likely than transversions





### Indel calling challenges

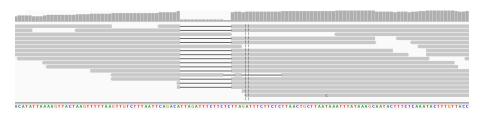
The sequencing error rate is elevated in microsatellites

Low reproducibility across callers

➤ 37.1% agreement between HapCaller, SOAPindel and Scalpel Narzisi et al. (2014) Nat Methods, 11(10):1033

Reads with indels are more difficult to map and align

- ▶ the aligner can prefer multiple mismatches rather than a gap
- ▶ indel representation can be ambiguous



```
CTTTAATTCAGACATTAGATTTCTTCTC
CTTTAATTCAGACATTAGATTTCTTCTCTTA
CTTTAATTCAGACA------TTAGATTTCTTCTCTTAACTGCTT
CTTTAATTCAGACATTAGATTTCTTC---TA------TTAACTGCTT
```

## Future of variant calling

#### Current approaches

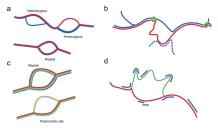
- rely heavily on the supplied alignment, but aligners see one read at a time
- ▶ largely site based, do not examine local haplotype and linked sites

#### Local de novo assembly based variant callers

- ► call SNPs, indels, MNPs and small SV simultaneously
- ► can remove alignment artefacts
- ▶ eg GATK haplotype caller, Scalpel, Octopus

#### Variation graphs

▶ align to a graph rather than a linear sequence



Iqbal et al. (2012) Nat Gen 44(2):226

#### **Functional annotation**

VCF can store arbitrary INFO tags (per site) and FORMAT tags (per sample)

- ► describe genomic context of the variant (e.g. coding, intronic, UTR)
- ▶ predict functional consequence (e.g. synonymous, missense, start lost)

#### Several tools for annotating a VCF, only few are haplotype-aware

 $\mathsf{BCFtools/csq} \qquad \qquad \mathsf{http://github.com/samtools/bcftools}$ 

 $VEP\ Haplosaurus \quad {\tt http://github.com/willmclaren/ensembl-vep}$ 

A)		COTEAGE COLO	B)	<b>*</b>	CÉTICÉ CICÉTIC ÉTICÉ GICÂGITÉTICAT   LO COROTIC CTICOTIC T GICAGITETICATI
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C)		GATIS GALACCICA GICCTIGGG			A HATTITE A IGATITE GICT A IA EA
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