## Variant Calling

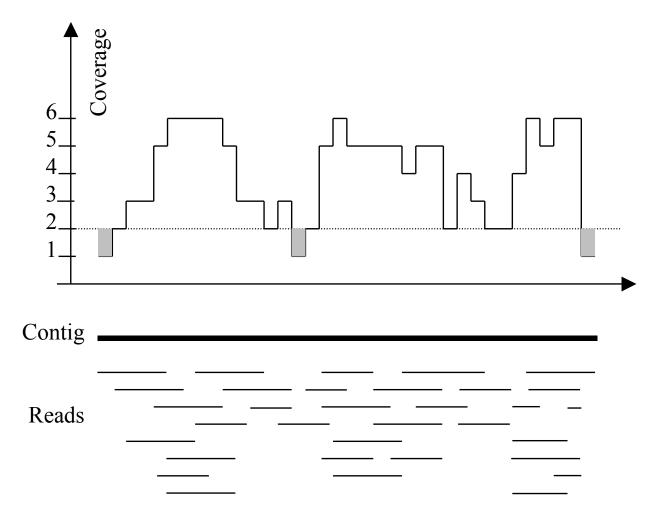
Michael Schatz

October 23 – Lecture 15 EN.601.452 Computational Biomedical Research AS.020.415 Advanced Biomedical Research





### Typical sequencing coverage

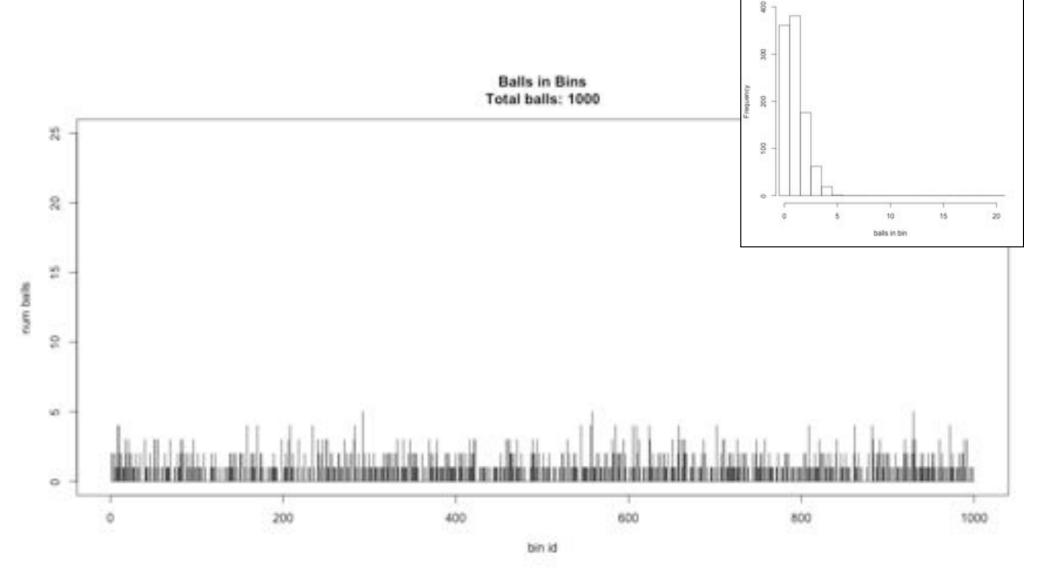


Imagine raindrops on a sidewalk
We want to cover the entire sidewalk but each drop costs \$1

If the genome is 100 Mbp, should we sequence 1M 100bp reads?

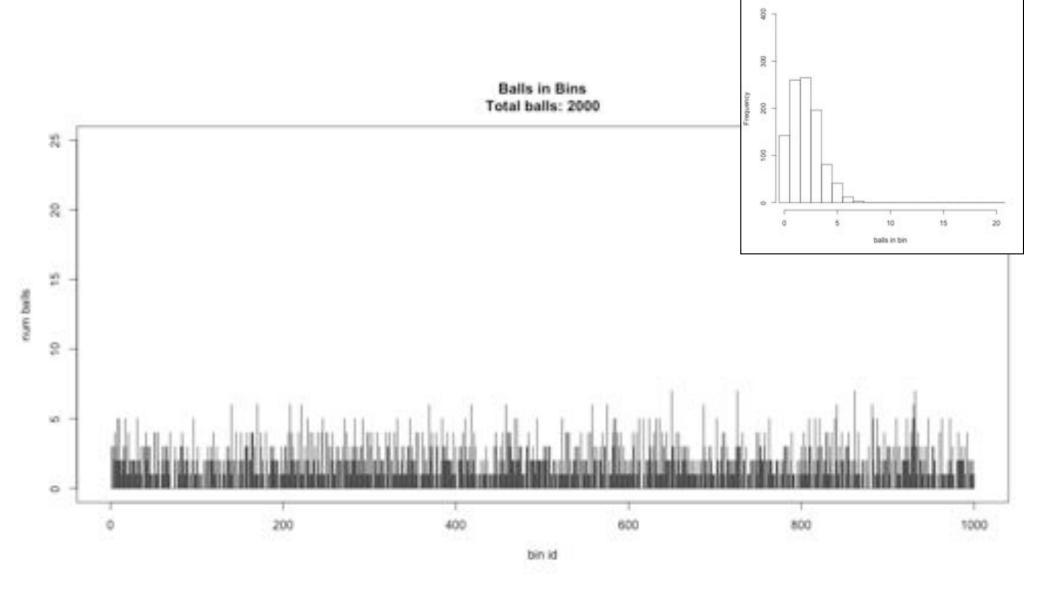
### Ix sequencing

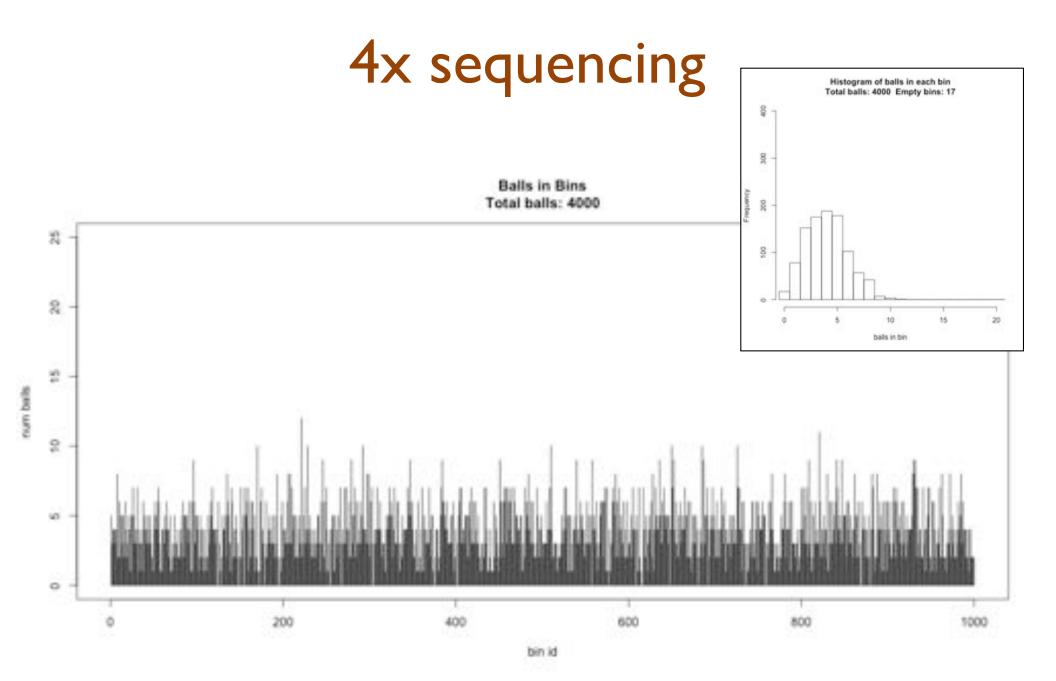
Histogram of balls in each bin Total balls: 1000 Empty bins: 361

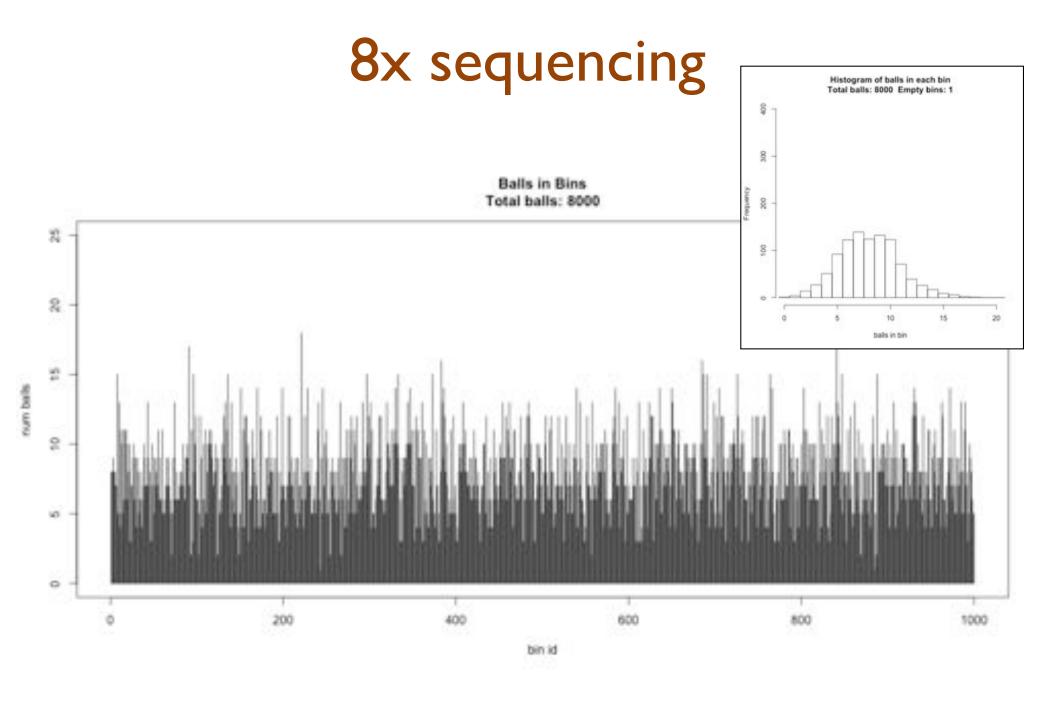


## 2x sequencing

Histogram of balls in each bin Total balls: 2000 Empty bins: 142







#### Poisson Distribution

The probability of a given number of events occurring in a fixed interval of time and/or space if these events occur with a known average rate and independently of the time since the last event.

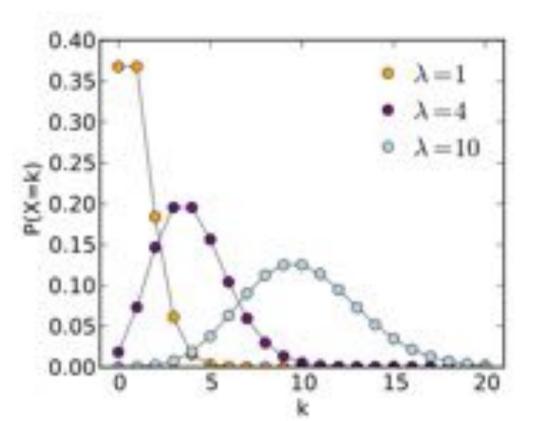
Formulation comes from the limit of the binomial equation

Resembles a normal distribution, but over the positive values, and with only a single parameter.

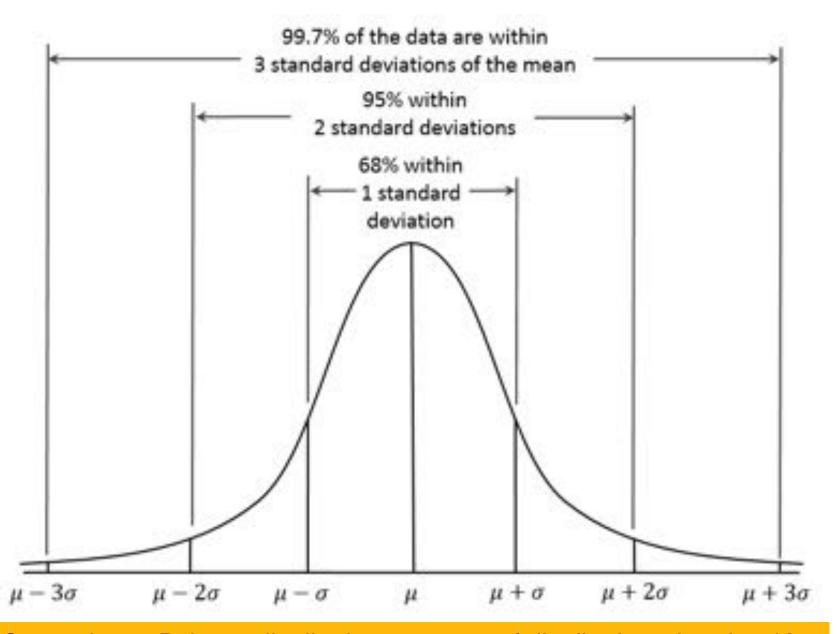
#### Key properties:

- The standard deviation is the square root of the mean.
- For mean > 5, well approximated by a normal distribution

$$P(k) = \frac{\lambda^k}{k!} e^{-\lambda}$$



## Normal Approximation



Can estimate Poisson distribution as a normal distribution when  $\lambda > 10$ 

#### Pop Quiz!

I want to sequence a 10Mbp genome to 24x coverage. How many 150bp reads do I need?

I need I 0Mbp x 24x = 240Mbp of data 240Mbp / 150bp / read = 1.6M reads

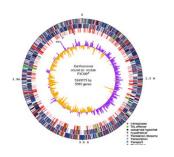
I want to sequence a 10Mbp genome so that >97.5% of the genome has at least 24x coverage. How many 150bp reads do I need?

Find X such that X-2\*sqrt(X) = 24

36-2\*sqrt(36) = 24

I need I0Mbp  $\times$  36x = 360Mbp of data 360Mbp / I50bp / read = 2.4M reads

#### **Assembly Summary**

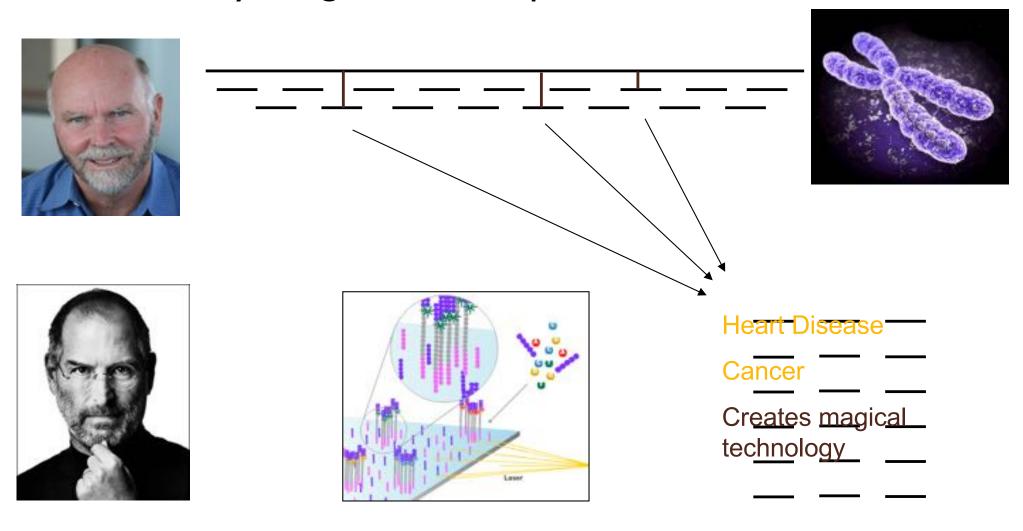


#### Assembly quality depends on

- 1. Coverage: low coverage is mathematically hopeless
- 2. Repeat composition: high repeat content is challenging
- 3. Read length: longer reads help resolve repeats
- 4. Error rate: errors reduce coverage, obscure true overlaps
- Assembly is a hierarchical, starting from individual reads, build high confidence contigs/unitigs, incorporate the mates to build scaffolds
  - Extensive error correction is the key to getting the best assembly possible from a given data set
- Watch out for collapsed repeats & other misassemblies
  - Globally/Locally reassemble data from scratch with better parameters & stitch the 2 assemblies together

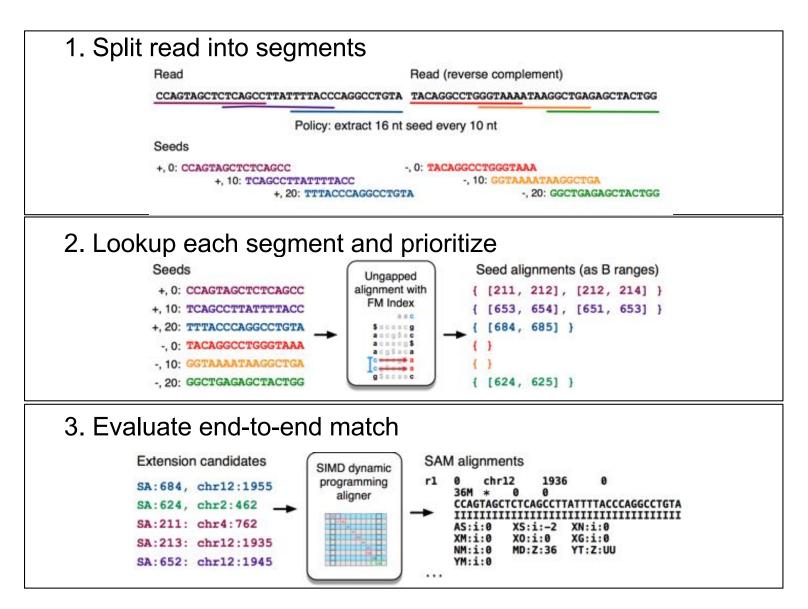
#### Personal Genomics

How does your genome compare to the reference?



### Variant Calling Overview

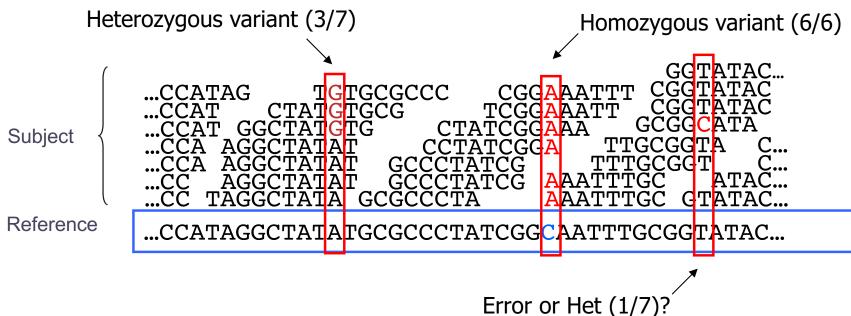
## Read Mapping Overview



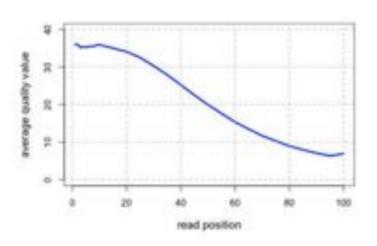
#### Fast gapped-read alignment with Bowtie 2

Langmead & Salzberg (2012) Nature Methods. doi:10.1038/nmeth.1923

#### Genotyping Theory



- If there were no sequencing errors, identifying SNPs would be very easy: any time a read disagrees with the reference, it must be a variant!
- Sequencing instruments make mistakes
  - Quality of read decreases over the read length
- A single read differing from the reference is probably just an error, but it becomes more likely to be real as we see it multiple times



# The Binomial Distribution: Adventures in Coin Flipping

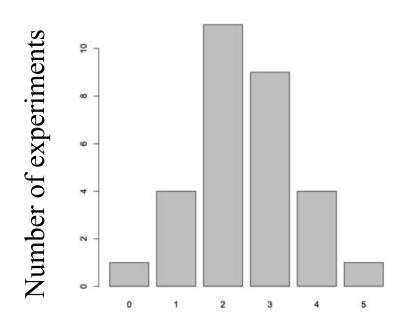


P(heads) = 0.5



P(tails) = 0.5

# What is the distribution of tails (alternate alleles) do we expect to see after 5 tosses (sequence reads)?



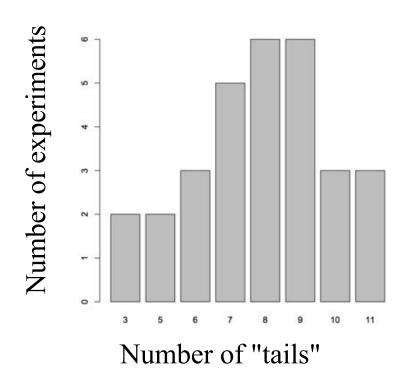
Number of "tails"

#### R code:

barplot(table(rbinom(30, 5, 0.5)))

30 experiments (students tossing coins)
5 tosses each
Probability of Tails

# What is the distribution of tails (alternate alleles) do we expect to see after 15 tosses (sequence reads)?



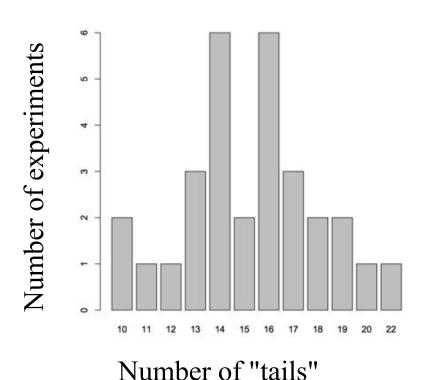
#### R code:

barplot(table(rbinom(30, 15, 0.5)))

30 experiments (students tossing coins) 15 tosses each

Probability of Tails

# What is the distribution of tails (alternate alleles) do we expect to see after 30 tosses (sequence reads)?

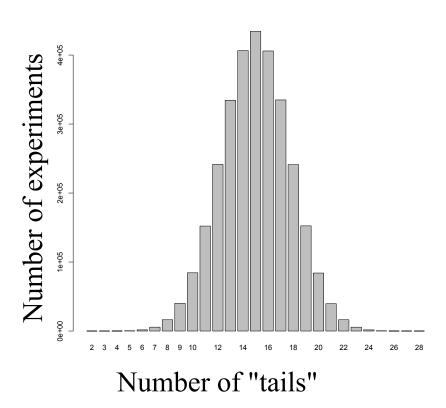


#### R code:

barplot(table(rbinom(30, 30, 0.5)))

30 experiments (students tossing coins) 30 tosses each Probability of Tails

# What is the distribution of tails (alternate alleles) do we expect to see after 30 tosses (sequence reads)?

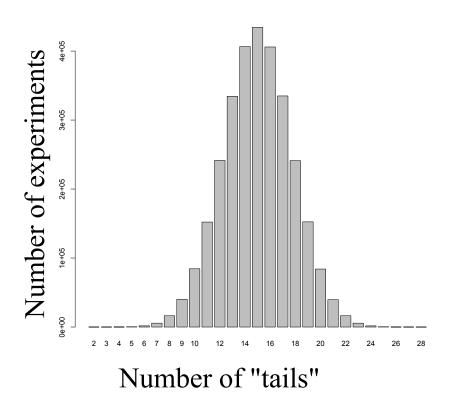


#### R code:

barplot(table(rbinom(3e6, 30, 0.5)))

3M experiments (students tossing coins) 30 tosses each Probability of Tails

# So, with 30 tosses (reads), we are much more likely to see an even mix of alternate and reference alleles at a heterozygous locus in a genome

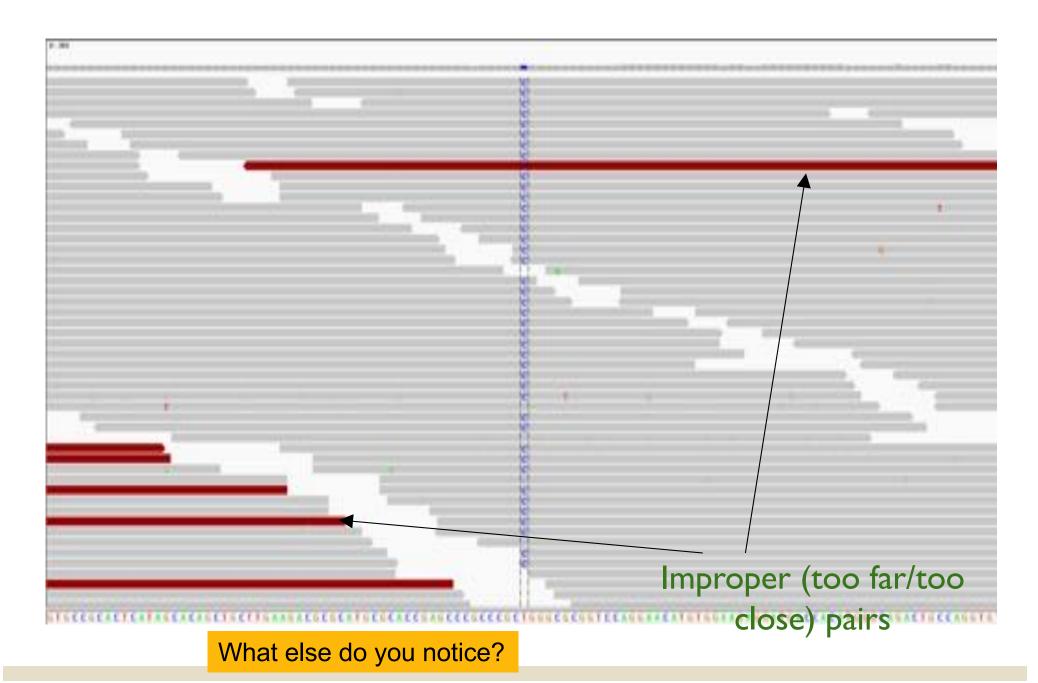


This is why at least a "30X" (30 fold sequence coverage) genome is recommended: it confers sufficient power to distinguish heterozygous alleles and from mere sequencing errors

P(3/30 het) <?> P(3/30 err)

#### Some real examples of SNPs in IGV

#### Homozygous for the "C" allele

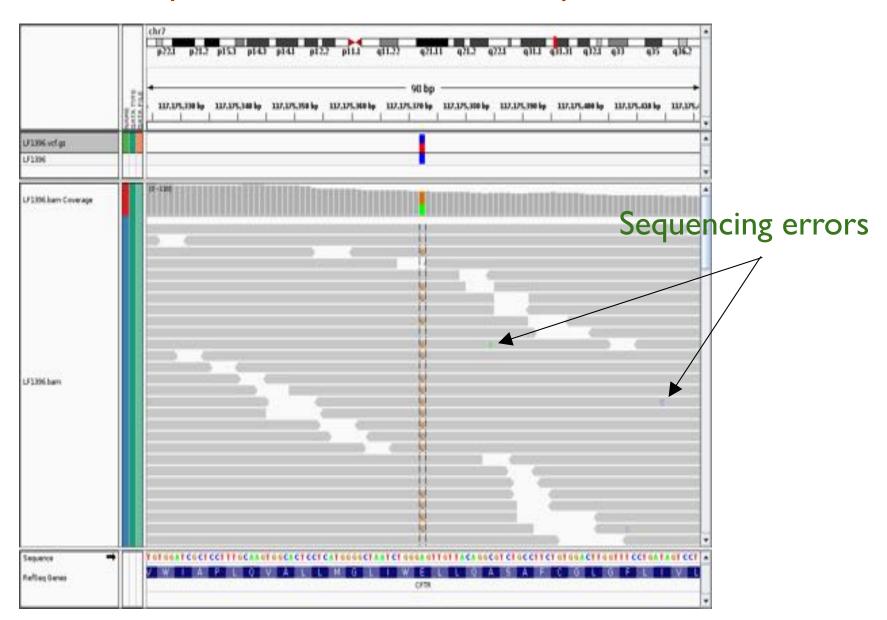


#### Heterozygous for the alternate allele



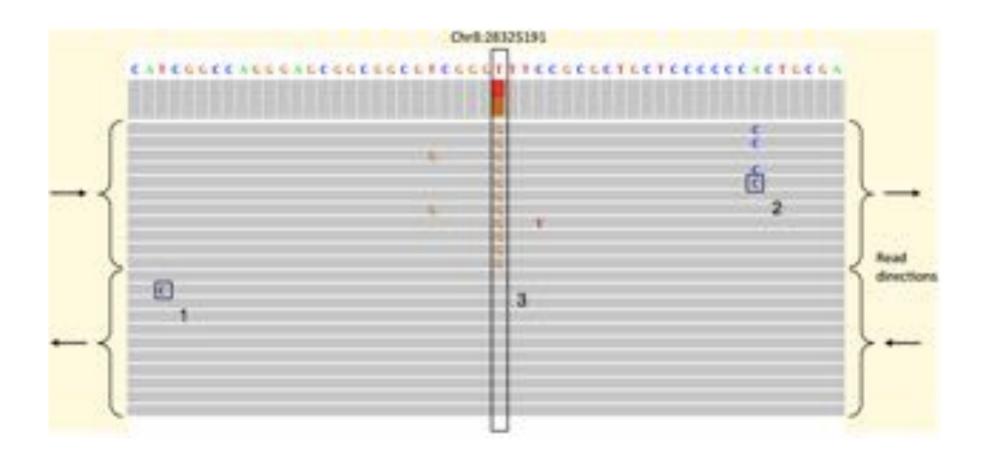
Which genotype prediction do you have more confidence in?

# Sequencing errors fall out as noise (most of the time)



It is not always so easy ③

#### Beware of Systematic Errors

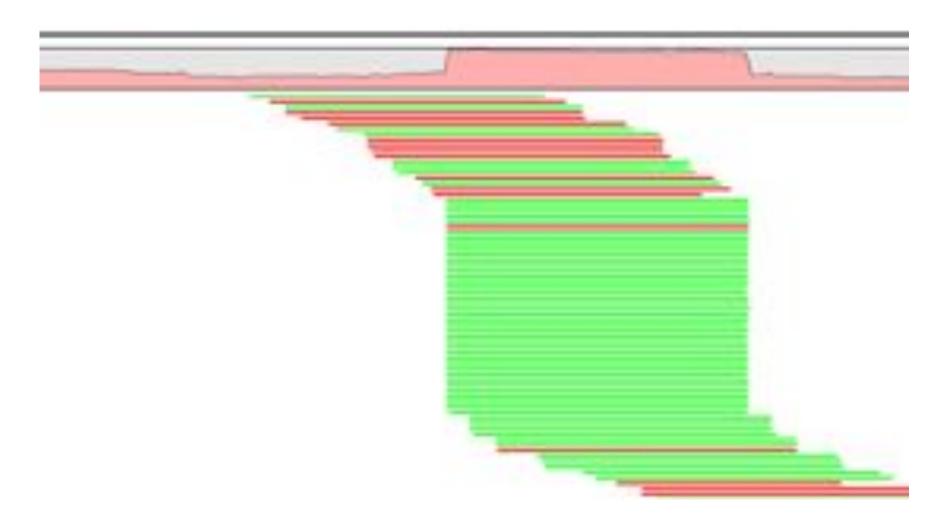


Identification and correction of systematic error in high-throughput sequence data Meacham et al. (2011) *BMC Bioinformatics*. 12:451

#### A closer look at RNA editing.

Lior Pachter (2012) Nature Biotechnology. 30:246-247

#### Beware of Duplicate Reads

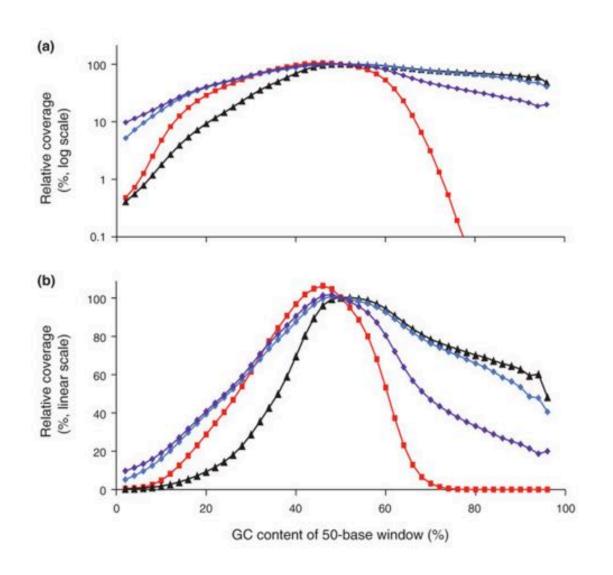


The Sequence alignment/map (SAM) format and SAMtools.

Li et al. (2009) Bioinformatics. 25:2078-9

Picard: <a href="http://picard.sourceforge.net">http://picard.sourceforge.net</a>

#### Beware of GC Biases



## Illumina sequencing does not produce uniform coverage over the genome

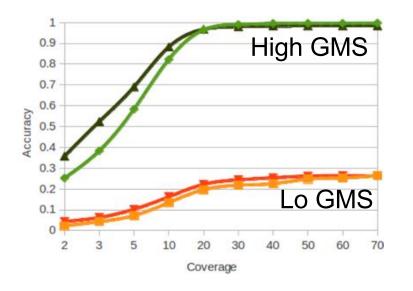
- Coverage of extremely high or extremely low GC content will have reduced coverage in Illumina sequencing
- Biases primarily introduced during PCR; lower temperatures, slower heating, and fewer rounds minimize biases
- This makes it very difficult to identify variants (SNPs, CNVs, etc) in certain regions of the genome

Analyzing and minimizing PCR amplification bias in Illumina sequencing libraries. Aird et al. (2011) *Genome Biology.* 12:R18.

## Beware of Mapping Errors

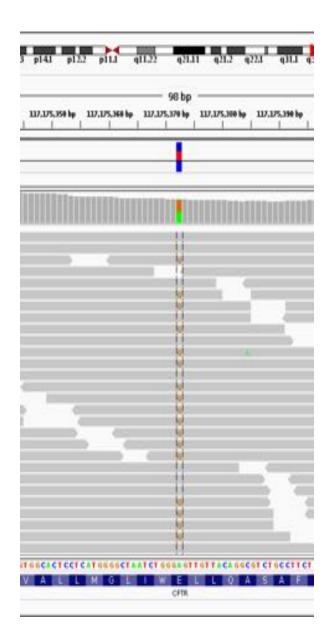
- Short read mapping is a essential for identifying mutations in the genome
  - Not every base of the genome can mapped equally well, especially because of repeats
- Introduced a new probabilistic metric the Genome Mappability Score - that quantifies how reliably reads can be mapped to every position in the genome
  - We have little power to measure 11-13% of the human genome, including of known clinically relevant variations
  - Errors in variation discovery are dominated by errors in low GMS regions

Species (build)	size	paired/single	whole (%)	transcription (%)
yeast (sc2)	12 Mbp	paired	94.85	95.04
	1.5	single	94.25	94.62
fly (dm3)	130 Mbp	paired	90.52	96.14
		single	89.70	95.94
mouse (mm9)	2.7 Gbp	paired	89.39	96.03
		single	87.47	94.75
human (hg19)	3.0 Gbp	paired	89.02	97.40
	153	single	87.79	96.38



Genomic Dark Matter: The reliability of short read mapping illustrated by the GMS. Lee and Schatz (2012) *Bioinformatics*. doi: 10.1093/bioinformatics/bts330

# What information is needed to decide if a variant exists?



- Depth of coverage at the locus
- Bases observed at the locus
- The base qualities of each allele
- The strand composition
- Mapping qualities
- Proper pairs?
- Expected polymorphism rate

# PolyBayes: The first statistically rigorous variant detection tool.

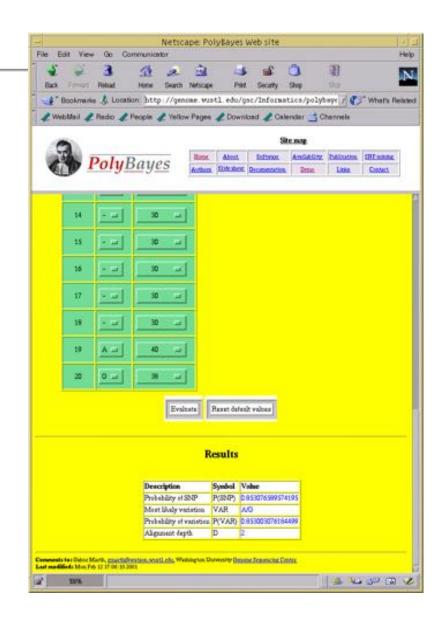


\$\$ \$ 1999 Nature America Inc. • http://genetics.nature.com

#### A general approach to single-nucleotide polymorphism discovery

Gabor T. Marth<sup>1</sup>, Ian Korf<sup>1</sup>, Mark D. Yandell<sup>1</sup>, Raymond T. Yeh<sup>1</sup>, Zhijie Gu<sup>2</sup>, Hamideh Zakeri<sup>2</sup>, Nathan O. Stitziel<sup>1</sup>, LaDeana Hillier<sup>1</sup>, Pui-Yan Kwok<sup>2</sup> & Warren R. Gish<sup>1</sup>

## Its main innovation was the use of Bayes's theorem



## Bayes theorem

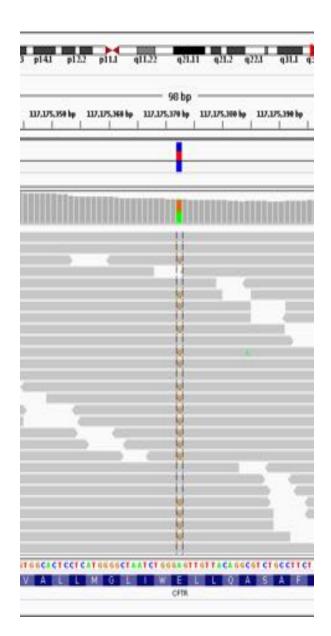
$$P(A|B) = P(B|A) * P(A)$$

$$\uparrow P(B)$$

Conditional probability.

That is, the probability of A occurring, given that B has occurred.

### Bayesian SNP calling



 $P(SNP|Data) = P(\underline{Data|SNP}) * P(SNP)$  P(Data)

- Depth of coverage at the locus
- Bases observed at the locus
- The base qualities of each all ele
- Transition or Transversion? Which type?
- The strand composition
- Mapping qualities
- Proper pairs?
- Expected polymorphism rate

# PolyBayes: The first statistically rigorous variant detection tool.



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Bayesian posterior probability

Base call +

Base quality  $P(S_1|R_1) \cdot P(S_N|R_N)$   $P_{Prior}(S_1) \cdot P_{Prior}(S_N)$   $P_{Prior}(S_1,...,S_N)$ 

Probability of observed base composition (should model sequencing error rate)

## PolyBayes: The first statistically rigorous variant detection tool.

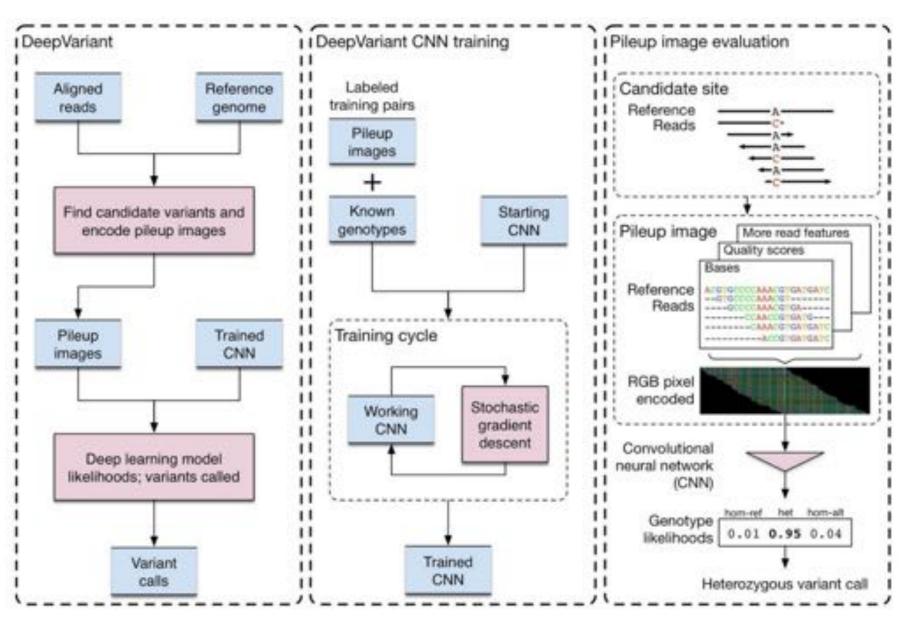
letter ≈ 1999 Nature America Inc. - http://genetics.nature.com

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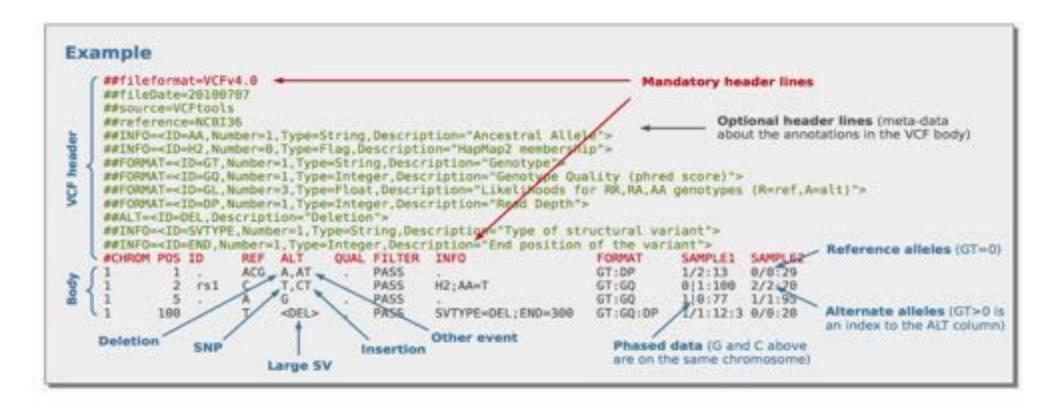
This Bayesian statistical framework has been adopted by other modern SNP/INDEL callers such as FreeBayes, GATK, and samtools

## Deep Variant

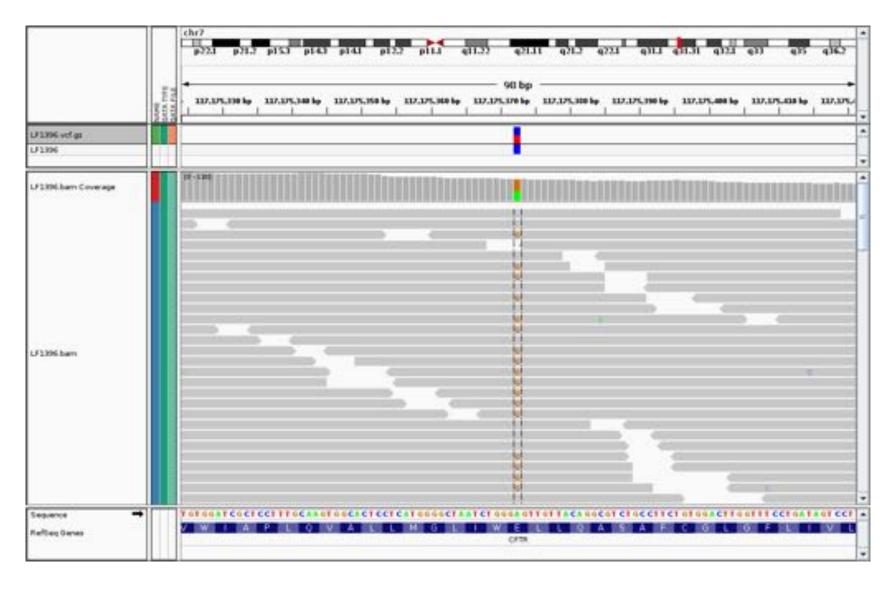


Creating a universal SNP and small indel variant caller with deep neural networks Poplin et al. (2016) bioRxiv. doi: https://doi.org/10.1101/092890

#### **VCF** Format



#### **VCF** Format



#CHROM POS ID REF ALT QUAL FILTER INFO FORMAT LF1396 chr7 117175373 . A G 90 PASS AF=0.5 GT