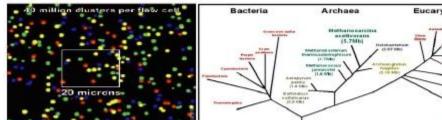
### **Bioinformatics: Introduction and Methods** Le Zhang

#### **Computer Science Department, Southwest University**

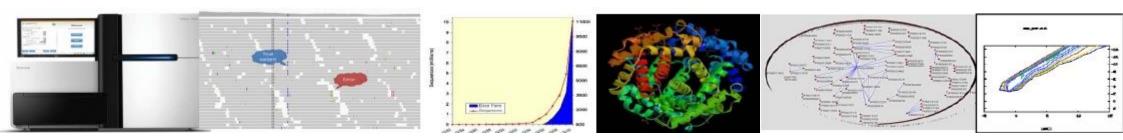




TAACCCTAACCCTAACCCTAACCCTAACCCTA CCTAACCCTAACCCTAACCCTAACCCTAACCC CCCTAACCCCTAACCCTAACCCTAACCCTAAC AACCCTAACCCTAACCCTAACCCTAACCCTA ACCCTAACCCCAACCCCAACCCCAAC CTACCCTAACCCTAACCCTAACCCTAACCCTA ACCCTAACCCTAACCCTAACCCTAACCCTAA

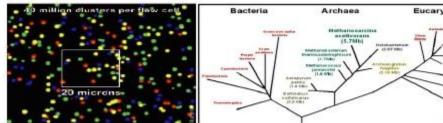


#### Next Generation Sequencing (NGS): Reads Mapping Le Zhang, Ph. D. Computer Science Department Southwest University

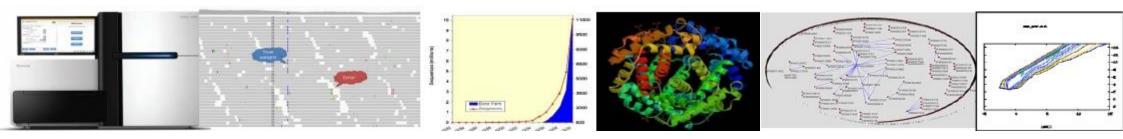




TAACCCTAACCCTAACCCTAACCCTAACCCTA CCTAACCCTAACCCTAACCCTAACCCTAACCC CCCTAACCCCTAACCCTAACCCTAACCCTAAC AACCCTAACCCTAACCCTAACCCCTAACCCTA ACCCTAACCCCAACCCCAACCCCAACCCCAAC CTACCCTAACCCTAACCCTAACCCTAA

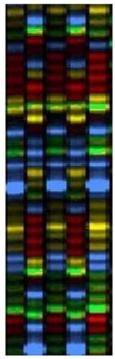


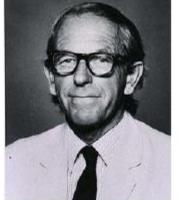
## Unit 1: From Sequencing to NGS Le Zhang, Ph. D. Computer Science Department Southwest University

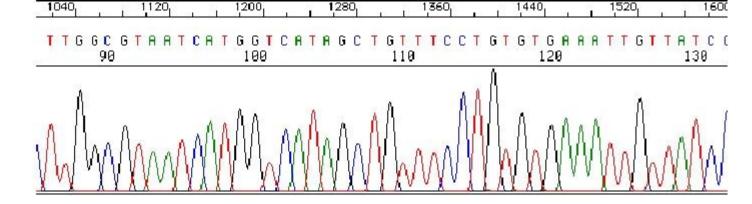


# **Chain Termination Sequencing**

GCGAATGCGTCCACAACGCTACAGGTG GCGARTGCGTCCACACGCTACAGGT н GCGAATGCGTCCACAACGCTACAGG 0 GCGAATGCGTCCACAACGCTACAG CH Z n GCGAATGCGTCCACAACGCTACA 358 GCGAATGCGTCCACAACGCTAC Normal C nucleotides: GCGAATGCGTCCACAACGCTA GCGAATGCGTCCACAACGCT GCGAATGCGTCCACAACGC GCGAATGCGTCCACAACG н GCGAATGCGTCCACAAC 0 GCGAATGCGTCCACAA CHZ GCGAATGCGTCCACA Ō Base Dideoxy Chain Terminators: GCGAATGCGTCCAC GCGAATGCGTCCA GCGAATGCGTCC C GCGAATGCGTC GCGAATGCGT GCGAATGCG GCGAATGC GCGAATG G GCGRAT





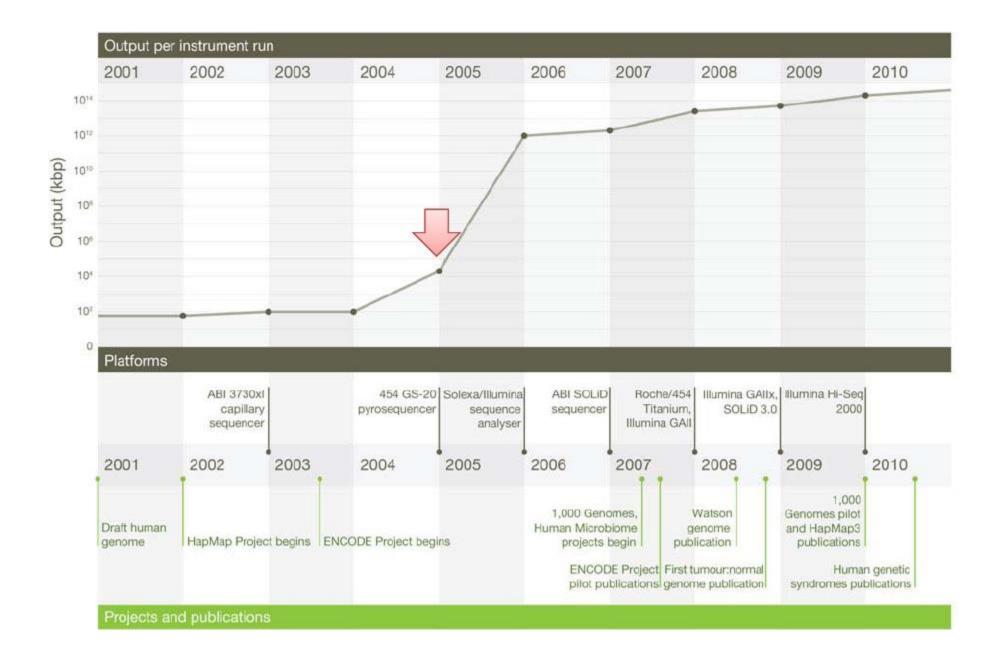


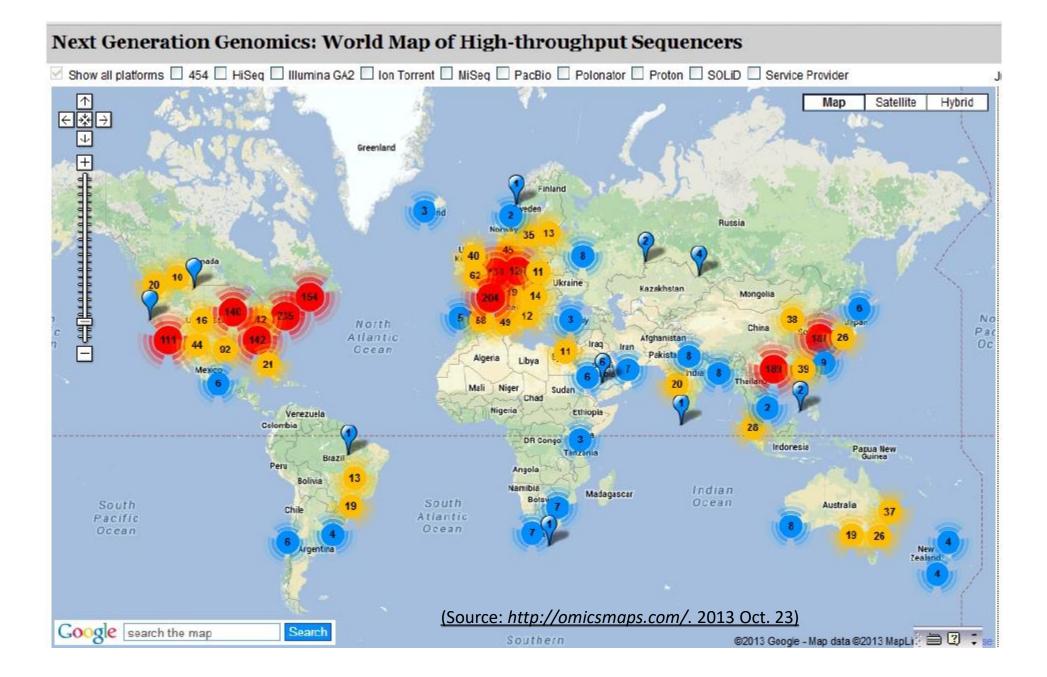






"90% of the three billion base pairs comprising the genome have been read and recorded. The completed work delivers surprises. Perhaps the biggest is that the human genome, estimated at the beginning of the project to contain 80,000 to 100,000 coding genes, appears to possess fewer than 25,000."

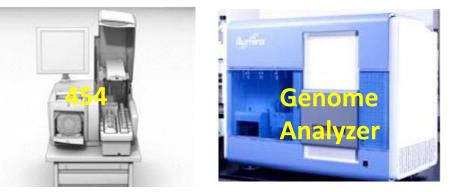




#### Next Generation Sequencing/Deep Sequencing Sanger Sequencing

		,		<b></b>
Sequencer	454 GS FLX	HiSeq 2000	SOLiDv4	Sanger 3730xl
Sequencing mechanism	Pyrosequencing	Sequencing by synthesis	Ligation and two-base coding	Dideoxy chain termination
Read length	700 bp	50SE, 50PE, 101PE	50 + 35 bp or 50 + 50 bp	400~900 bp
Accuracy	99.9%*	98%, (100PE)	99.94% *raw data	99.999%
Reads	1 M	3 G	1200~1400 M	
Output data/run	0.7 Gb	600 Gb	120 Gb	1.9~84 Kb
Time/run	24 Hours	3~10 Days	7 Days for SE 14 Days for PE	20 Mins~3 Hours
Advantage	Read length, fast	High throughput	Accuracy	High quality, long read length
Disadvantage	Error rate with polybase more than 6, high cost, low throughput	Short read assembly	Short read assembly	High cost low throughput









Read: A short DNA fragment which is *read out* by sequencer.

- DNA sequence (symbols)
- Quality information

In FASTQ format

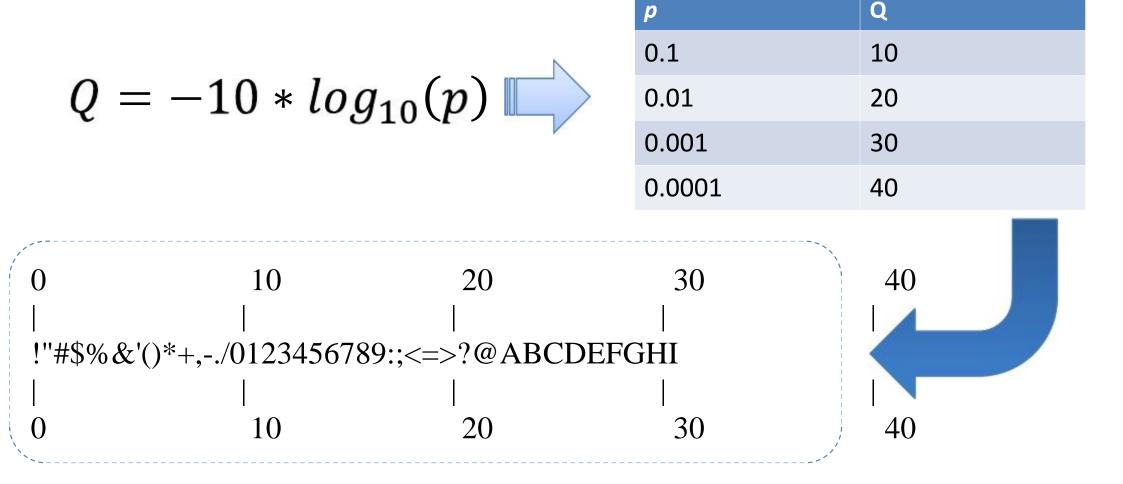
@test\_fastq GATTTGGGGTTCAAAGCAGTATCGATCAAATAGTAA +

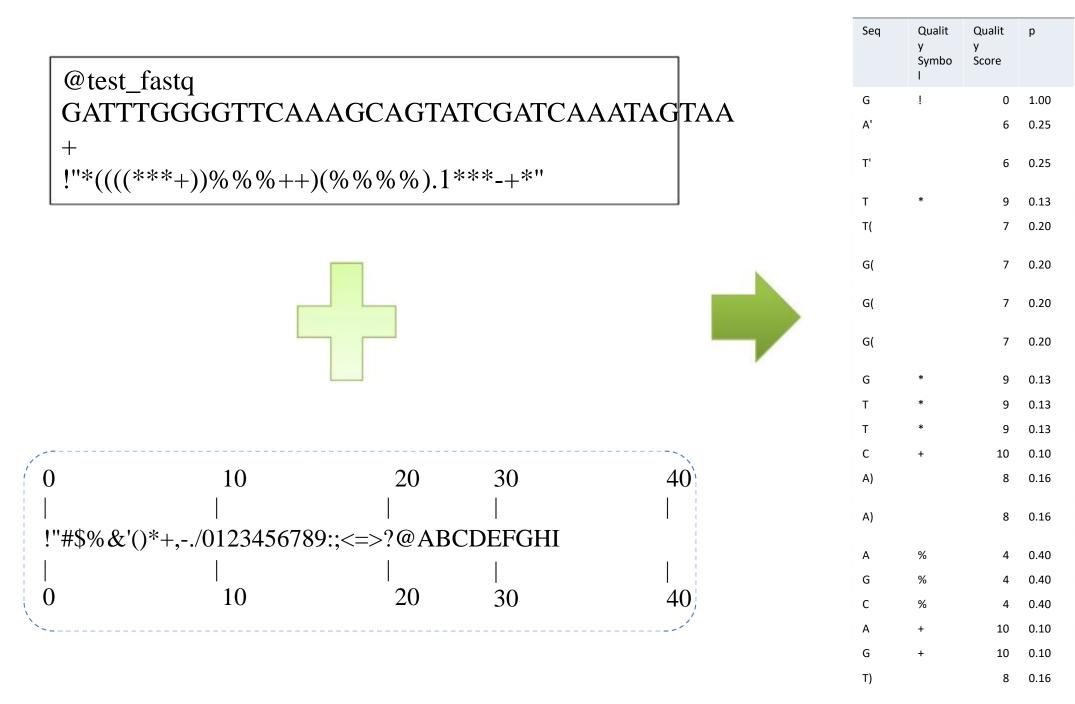
```
!"*((((***+))\%\%\%+)(\%\%\%\%).1***-+*"
```



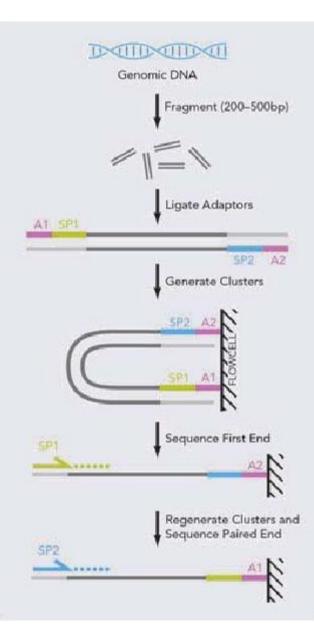
Seq\_ID: test\_fastq Sequence: GATTTGGGGGTTCAAAGCAGTATCGATCAAATAGTAA Quality: !''\*(((((\*\*\*+))%%%++)(%%%%).1\*\*\*-+\*''

# Quality: Given *p* = the probability of a base calling is *wrong*, its Quality Score can be written as





A( 7 0.20



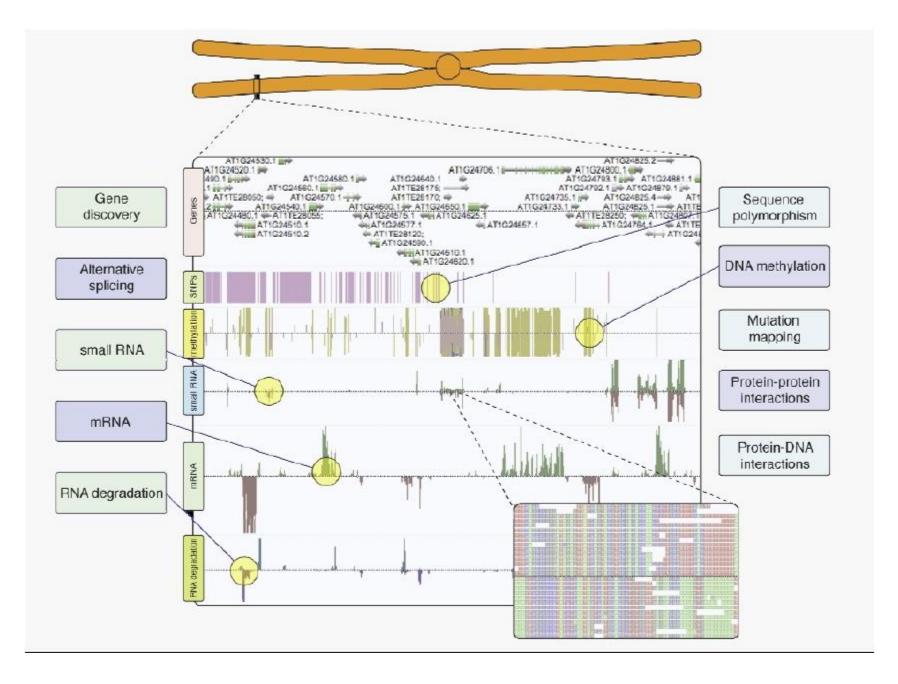
# Paired-End Reads

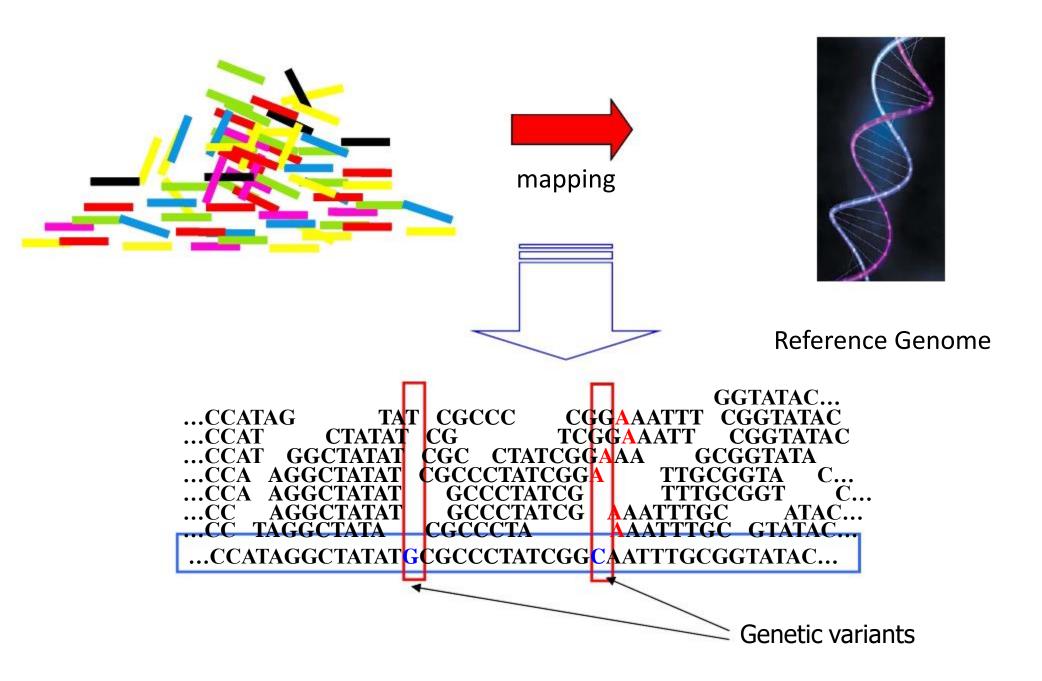
Insertion

@test\_fastq/1 GATTTGGGGTTCAAAGCAGTATCGATCAAATAGTAA +

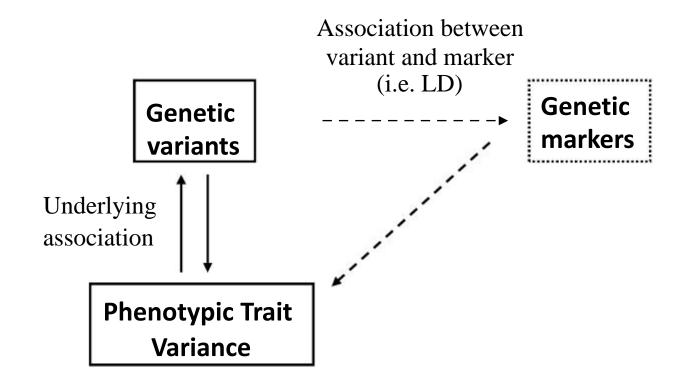
!"\*((((\*\*\*+))%%%+)(%%%%).1\*\*\*-+\*"

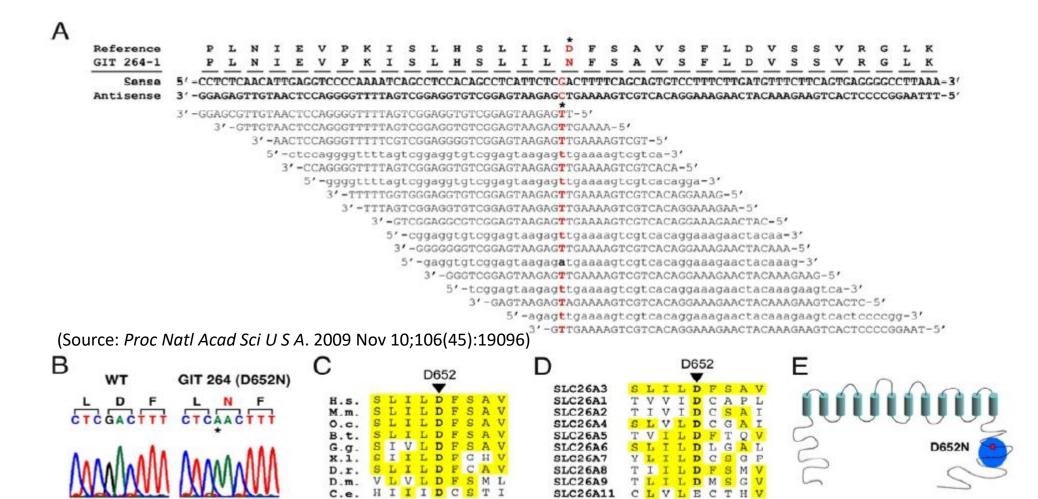
@test\_fastq/2 ACATACTATTACTCATTACTCCTCATANNNNTNCNN + BBB1',9,66<B>9<74<=BB@4=93'!!!!)!'!9





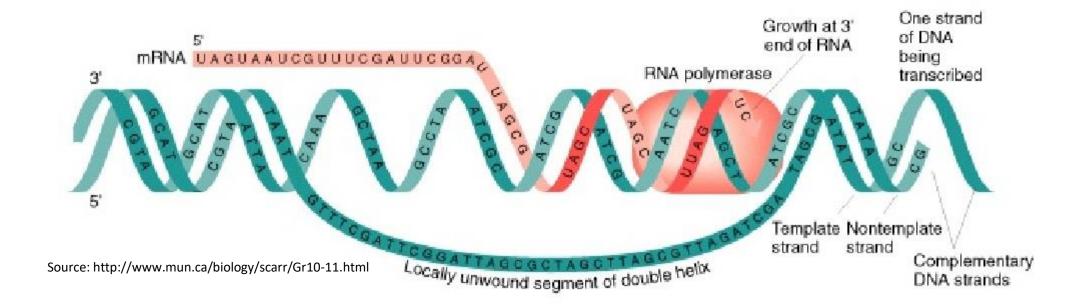
<u>Association Study</u>: for the given phenotypic trait, "functional variants" could be identified by comparing allele frequencies at hundreds of thousands of polymorphic sites, *i.e* allele A is associated with phenotypic trait P if (and only if) people who have P also have A more (or less) often than would be predicted from individual frequencies of A and P in the assessed population.



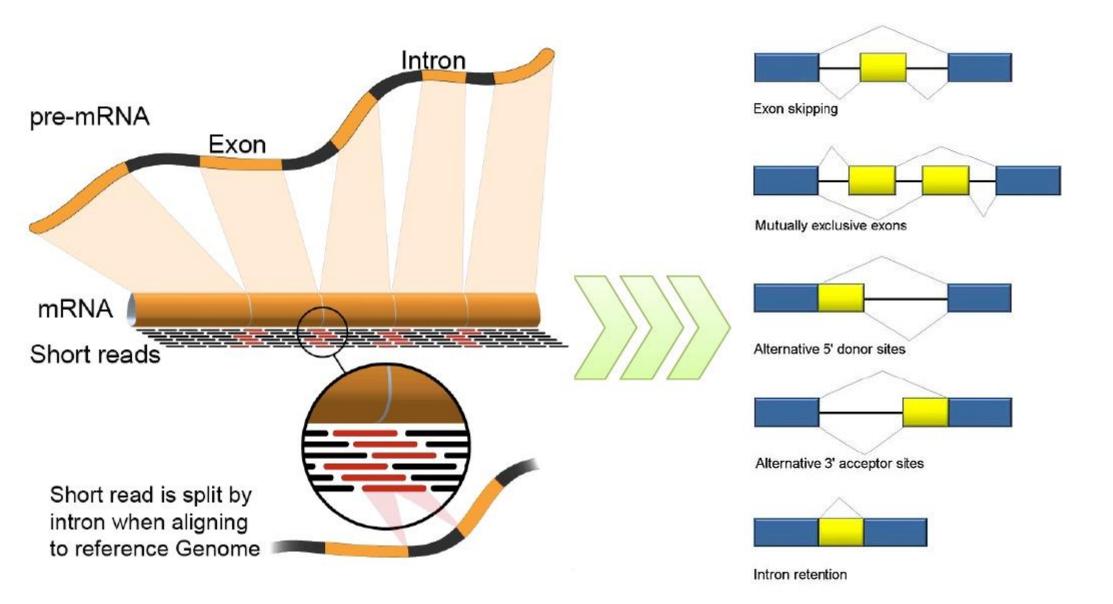


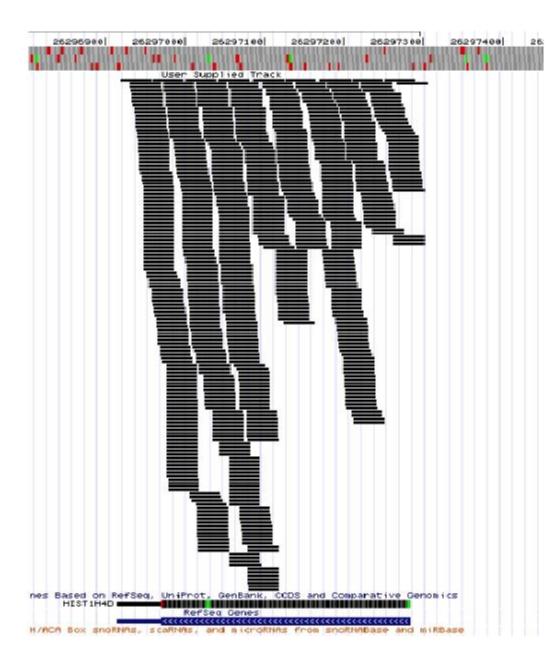
Choi *et al.* used whole-exome sequencing to discover the cause of disease in an individual with an unclear diagnosis. They identified a missense mutations in positions that were highly conserved from invertebrates to humans, in a gene known to cause congenital chloride-losing diarrhoea, consistent with the patient's symptoms.

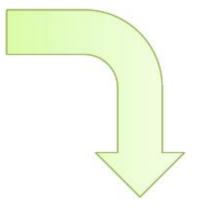
## RNA-Seq: Explore the transcriptome



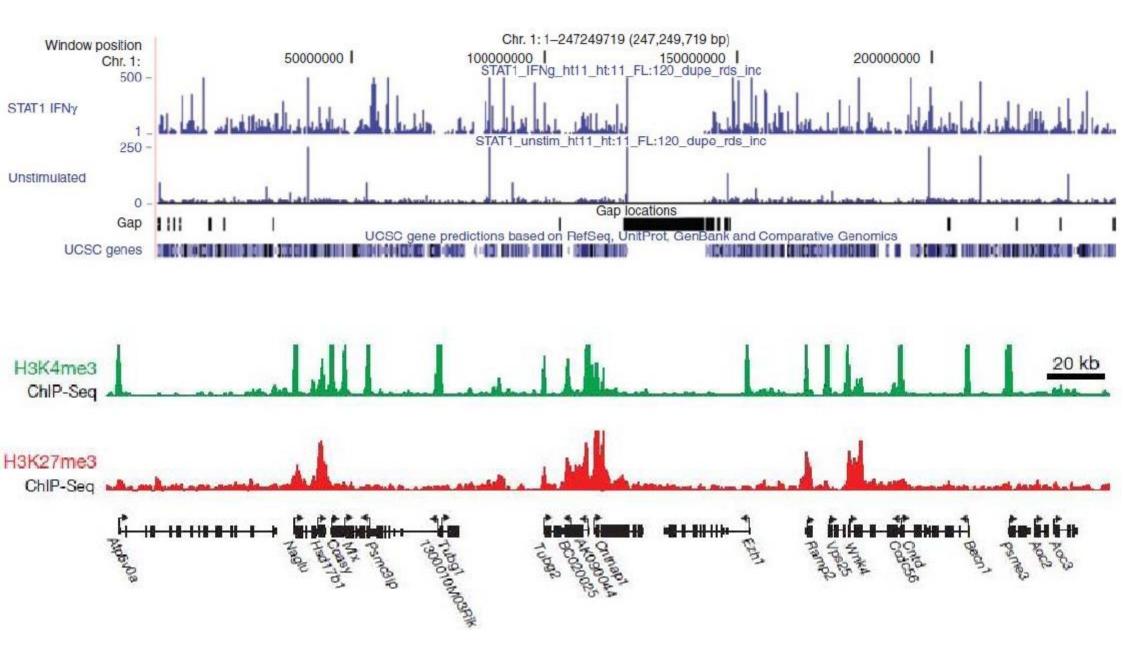
"A transcriptome is a collection of all the transcripts present in a given cell." (NHGRI factsheet, NIH, US)

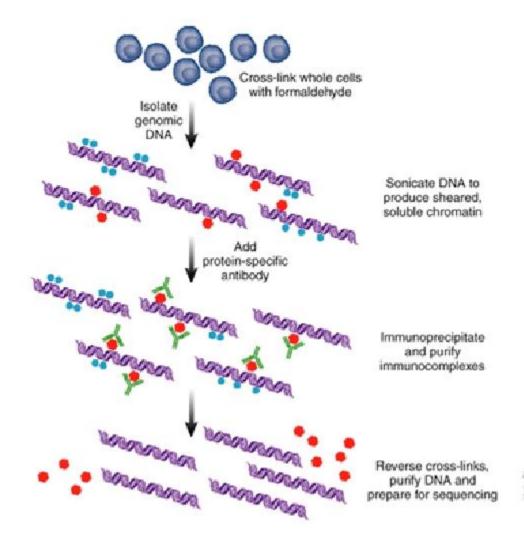






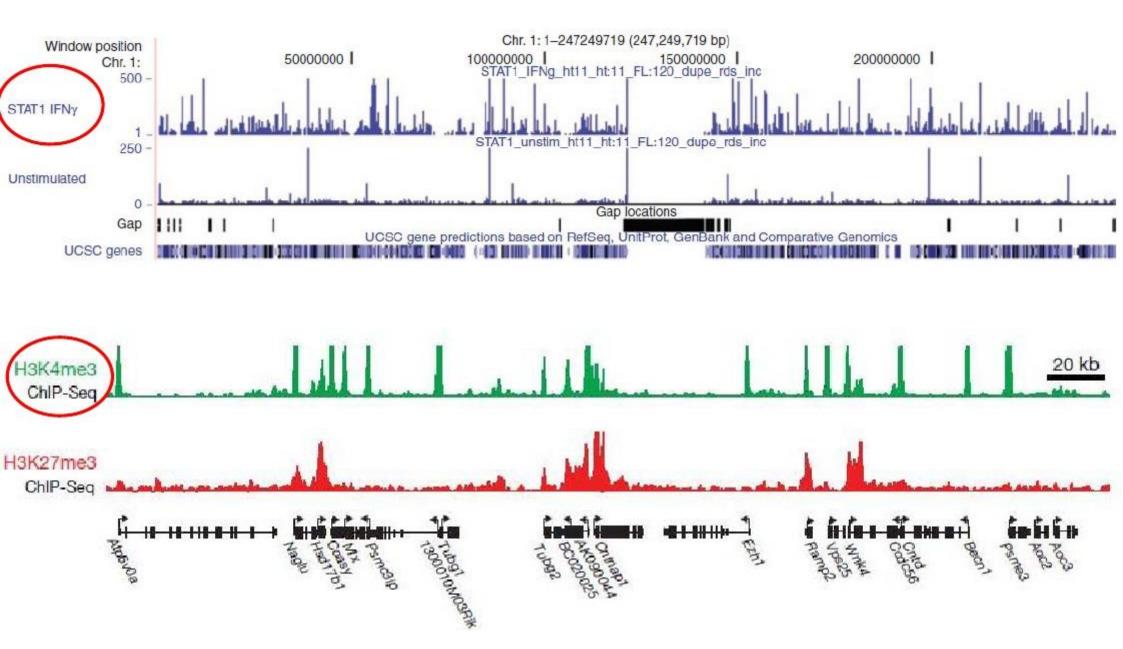
1	В	С	D	E	F
1	gene	nscl	nsc1 SE	nsc2	nsc2 SE
2	brain protein	18. <mark>9</mark> 574	3.79952	21. 5848	3.02241
3	Cluster Incl AW1	11 <mark>0</mark> . 513	7.84625	114.894	7.95669
4	Cluster Incl AI8	235.873	35.6748	210.349	27.612
5	Cluster Incl AV3	47. 4605	3.94976	29.6941	3.6586
6	Cluster Incl AV1	28.4527	3.74512	15. 2986	3.62097
7	Cluster Incl AV1	80.302	6.45368	107.23	8.09591
8	Cluster Incl AV3	40.8113	5. 13418	54. 0835	3. 18591
9	Cluster Incl AI1	53. 1437	3. 63392	58.635	5. 50994





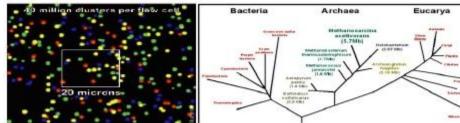
# <u>Chromatin</u> <u>ImmunoPrecipita-</u> <u>tion Sequencing</u> (ChIP-Seq):

# Profile Protein-DNA interaction

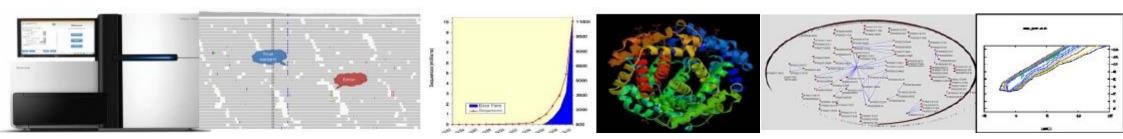




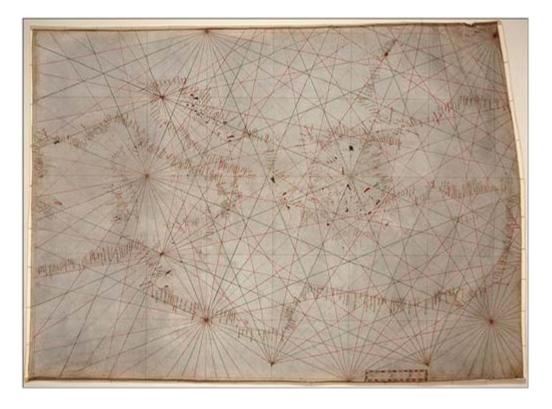
TAACCCTAACCCTAACCCTAACCCTAACCCTA CCTAACCCTAACCCTAACCCTAACCCTAACCC CCCTAACCCCTAACCCTAACCCTAACCCTAAC AACCCTAACCCTAACCCTAACCCTAACCCTA ACCCTAACCCCAACCCCAACCCCAAC CTACCCTAACCCTAACCCTAACCCTA ACCCTAACCCTAACCCTAACCCTAA



### Unit 2: NGS: Reads Mapping Le Zhang, Ph. D. Computer Science Department Southwest University

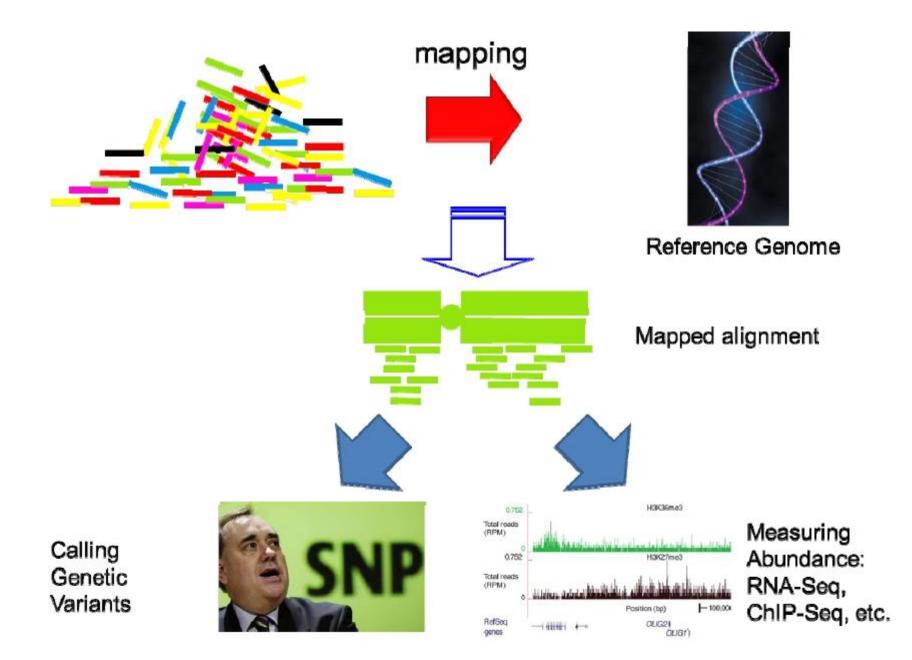


# **Reads Mapping**



Map-Making / Cartography: Establish relationship between locations Technological: Reads is usual too short to be used/assembled *de novo* 

Scientific: Taking full usage of existing annotation/knowledge



# Mapping: Input Data

- Reference Genome
  - Nucleotide

Length: Hundreds of Mb per chromosome

~3 Gb in total (for human genome)



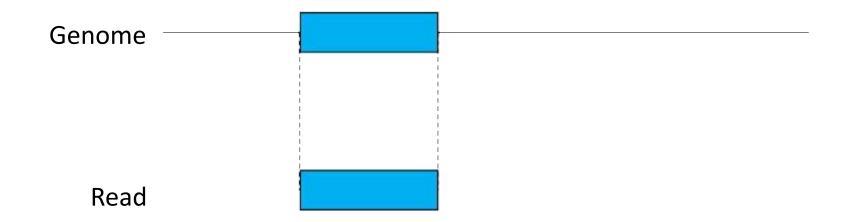
mapping

Reference Genome

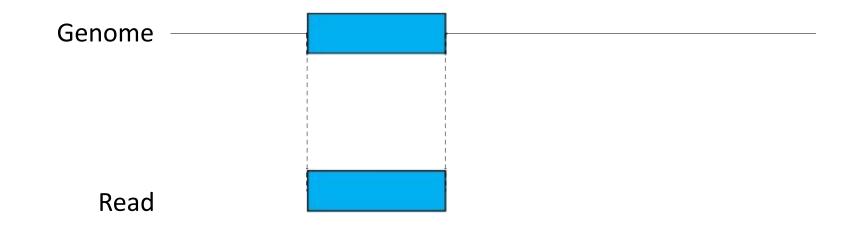
- Reads
  - Nucleotide, with various qualities (relatively high error rate: 1e-2 ~ 1e-5)

Length: 36~80 bp per read
Hundreds of Gbs per run

# "Embedded" Alignment

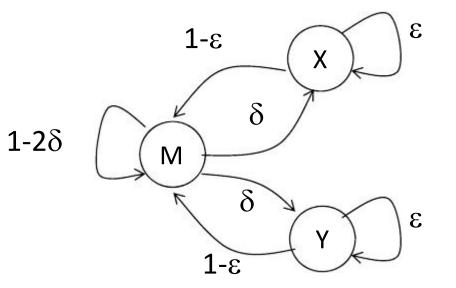


# One sequence is "*embedded*" in the other sequence (NGS Reads, PCR primer, *etc.*)



What we need here is actually a hybrid "global-local" alignment

- ✓ "Global" for short sequence (i.e. NGS Read)
- ✓ But "Local" for long sequence (i.e. Reference Genome)
- ✓ In particular, the surrounding "overhang" gaps should be not penalized.



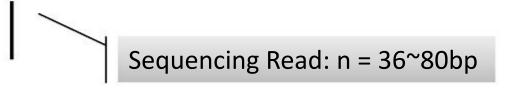
Μ	Match
---	-------

- X Insertat sequence X (delete at sequence Y)
- Y Insertat sequenceY (delete at sequence X)

δ	Gap open
3	Gap Extension

	Μ	Х	Y
Μ	1-2δ	δ	δ
Х	1-ε	3	0
Y	1-ε	0	0

Genomic chromosome: m = hundreds of Mb



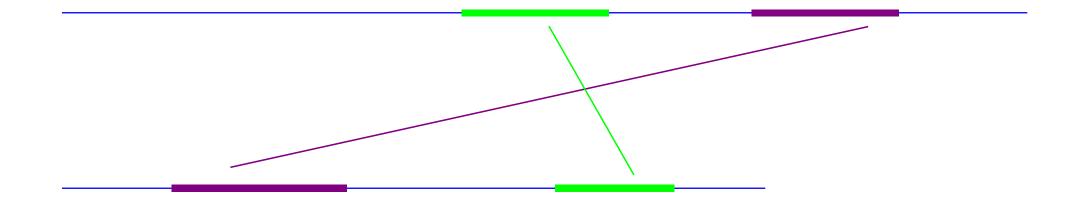
#### Most of paths will just fail eventually!

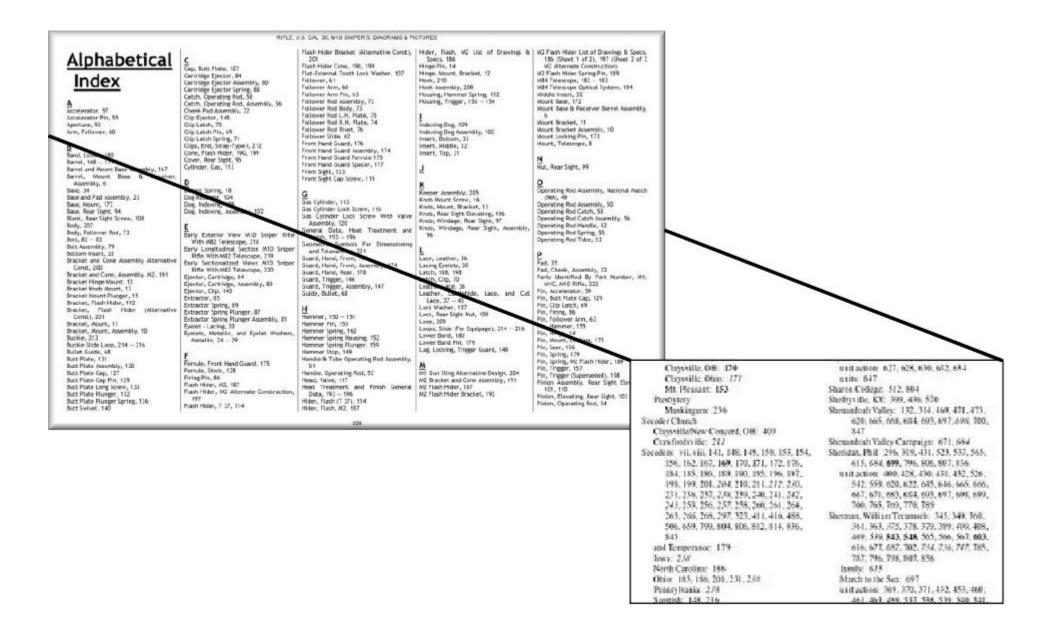


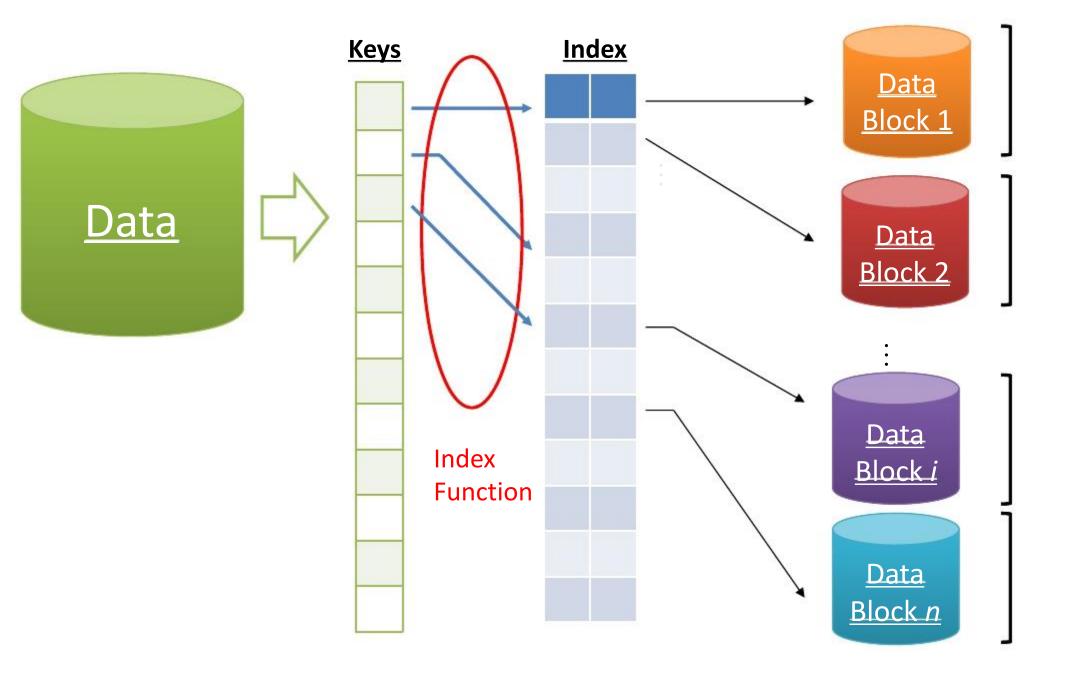
In real world, the speed will be a BIG problem!

# **BLAST Ideas: Seeding-and-extending**

- 1. Find matches (seed) between the query and subject
- 2. Extend seed into High Scoring Segment Pairs (HSPs)
  - Run Smith-Waterman algorithm on the specified region only.
- 3. Assess the reliability of the alignment.

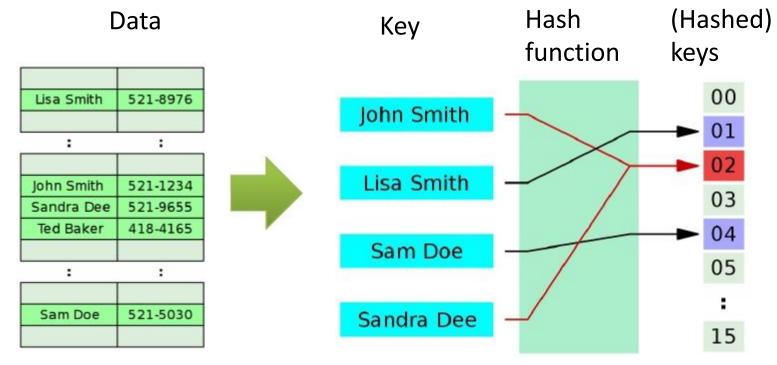


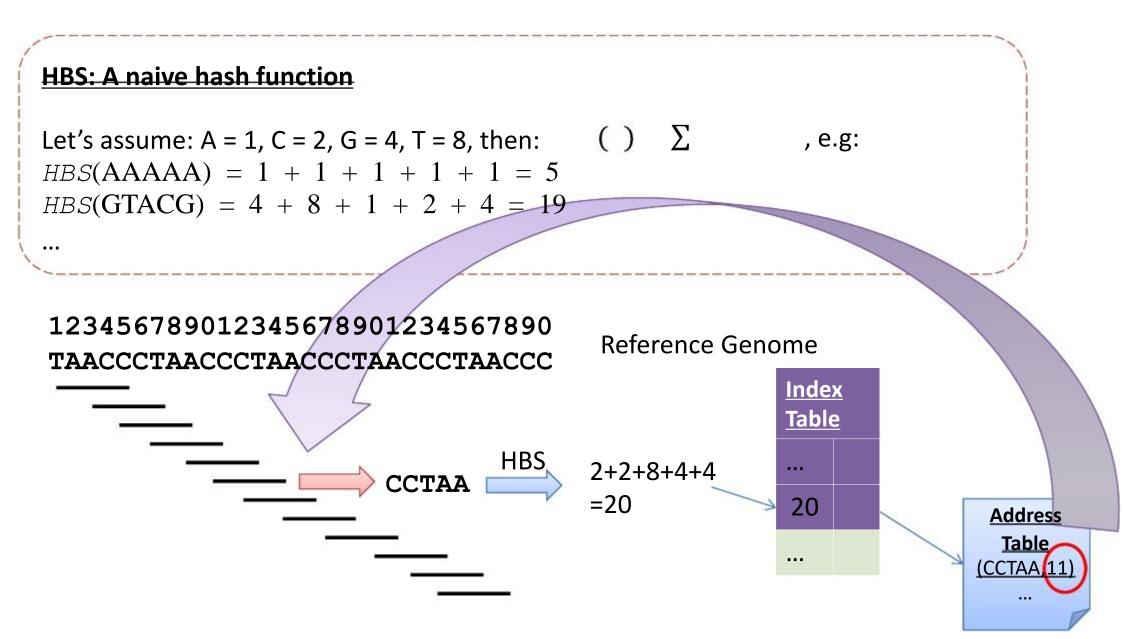




# Hash #

Hash function maps (partial) data into (hashed) keys for following-up indexing





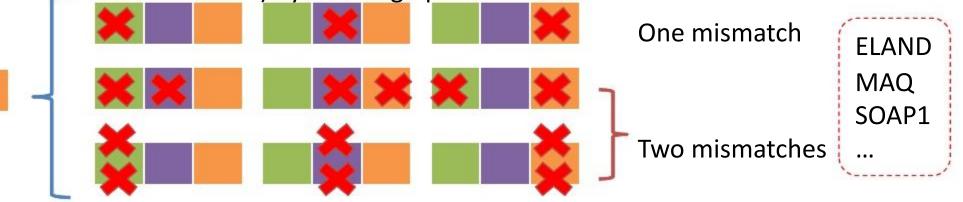
#### Pigeonhole principle (抽屉原理)

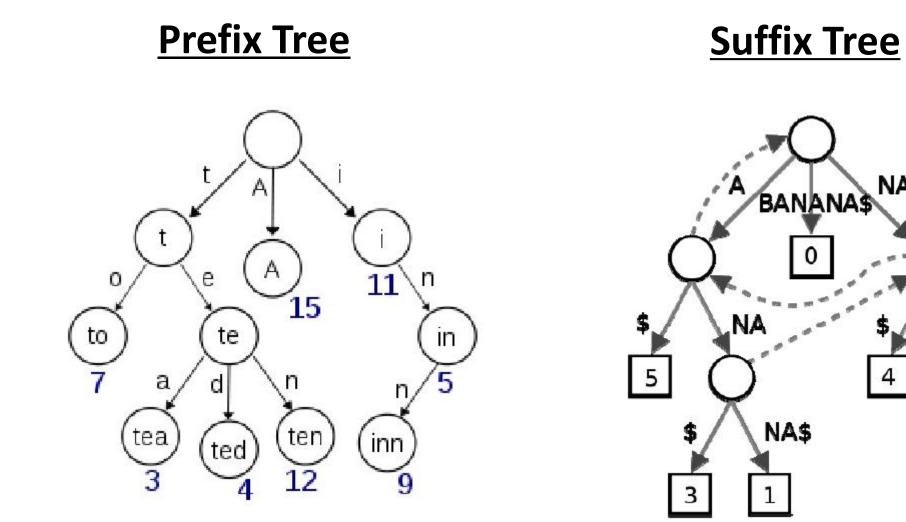
"In mathematics, the pigeonhole principle states that if n items are put into m pigeonholes with n > m, then at least one pigeonhole must contain more than one item."



http://en.wikipedia.org/wiki/Pigeonhole\_principle

After splitting the read into *n* (non-overlapped) blocks, there will be at least *n-m* perfectly-matched blocks (i.e. without any mismatch with in the block) by allowing up-to-*m* mismatches.





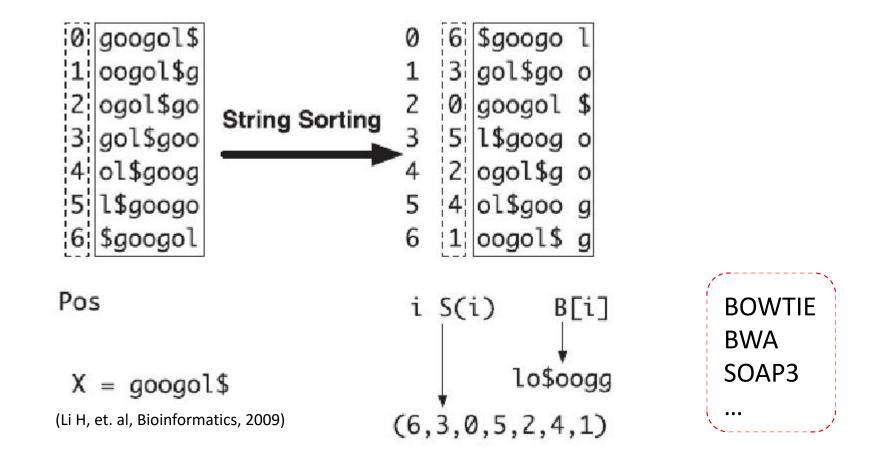
NA

4

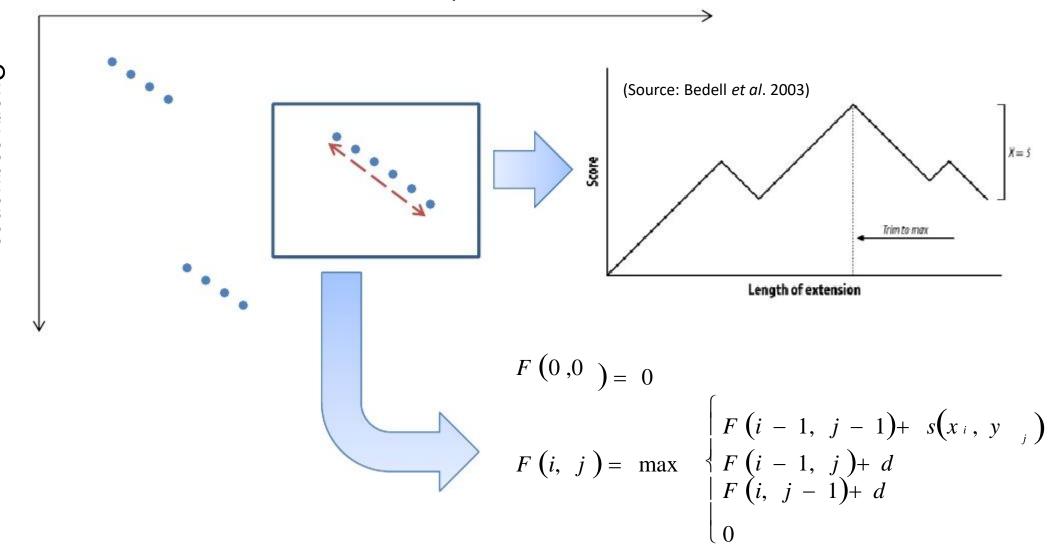
NA\$

2

# Burrows–Wheeler transform (BWT)

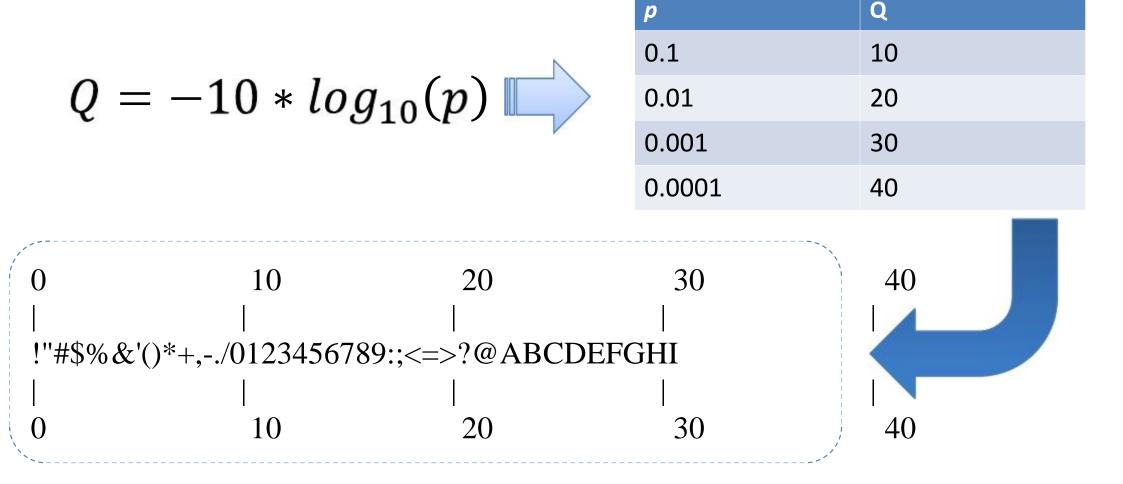


One of candidate sequence



Query sequence

# Quality: Given *p* = the probability of a base calling is *wrong*, its Quality Score can be written as



#### **Mapping Quality**

Given reference sequence z (length L), a read sequence x (length I), u is the alignment position of x on z, the probability that z actually coming from the position u is  $p(z \mid x, u)$ (Genome Res. 2008 Nov;18(11):1851.)

$$p(z \mid x, u) = \prod_{mismatch} p(z_i) \qquad SQ(u) = \log(p(z \mid x, u)) = \sum_{mismatch} p(z_i) = \sum_{mismatch} Q(z_i)$$

Read: ACGT (Quality: 30 30 25 20) Ref: ACGTACGGA

AC

A

GT	0+ 0+ 0+ 0	SQ(0)
CGT	30+30+25+20	SQ(1)
ACGT	30+30+25+20	SQ(2)
ACGT	30+30+25+20	SQ(3)
ACGT	0+ 0+ 0+20	SQ(4)
ACGT	30+30+ 0+20	SQ(5)

#### **Mapping Quality**

If we assume that a uniform NULL model, i.e. the read can randomly come from all possible positions with equal probability, then the error of mapping to a specified position u could be written as GO(u) = GO(u)(Genome Res. 2008 Nov;18(11):1851.)

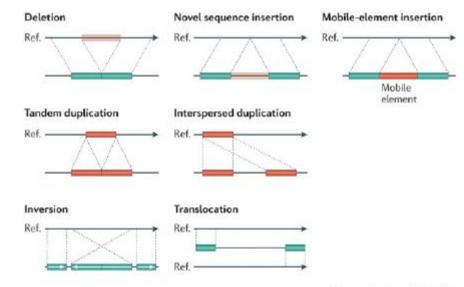
$$E(u) = \frac{SQ(u)}{\sum_{i} SQ(i)}$$

(Quality: 30 30 25 20) ACGT Read: Ref: ACGTACGGA SQ(u)E(u)CT 0+ 0+ 0/  $\mathbf{0+}$ ACGT 105/415 30+30+25+20ACGT 105/415 30+30+25+20ACGT 105/415 30+30+25+20ACGT 0+ 0+ 0+2020/415 80/415 30+30+ 0+20 ACGT

## **Genetic Variants**

SNV: Single Nucleotide Variant – Substitution (SNP) – Indel: insertion/deletion

- Structural Variation (SV)
  - Large-scale insertion/deletion
  - Inversion
  - Translocation
  - Copy Number Variation (CNV)

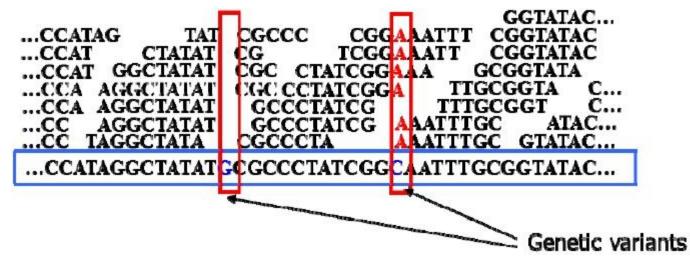


Nature Reviews | Genetics

# SNP Calling is NOT Genotyping

- "SNP calling aims to determine in which positions there are polymorphisms or in which positions at least one of the bases differs from a reference sequence"
- "Genotype calling is the process of determining the genotype for each individual and is typically only done for positions in which a SNP or a 'variant' has already been called."

#### Counting: an intuitive (and naïve) approach

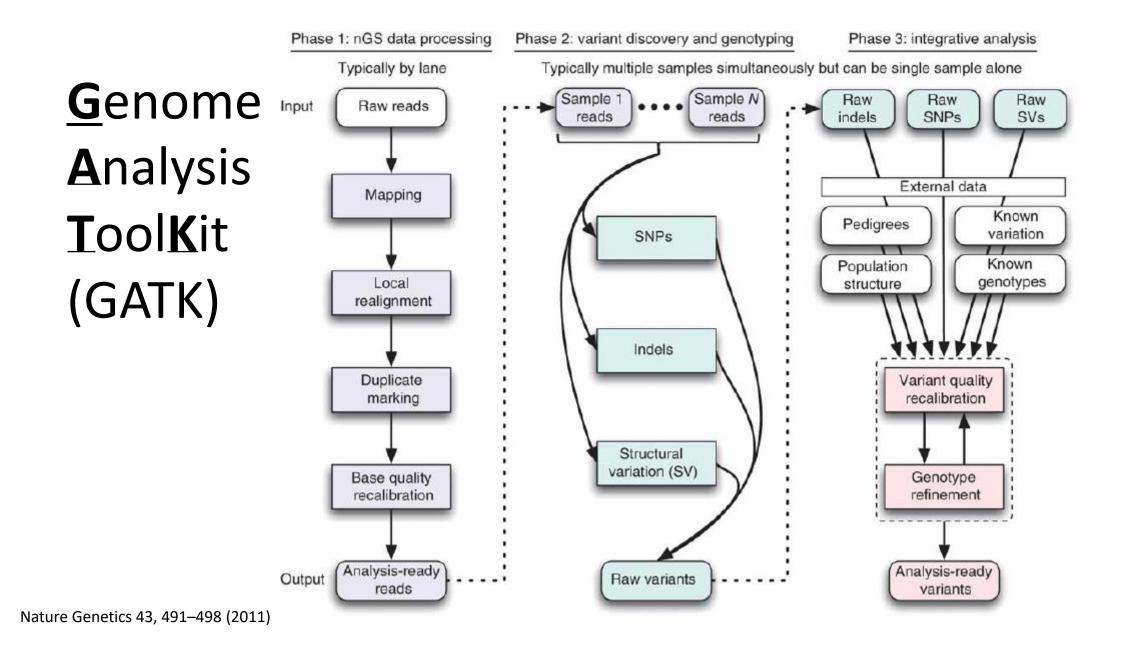


- Counting high-confident , non-reference allele (i.e. Quality >= 20)
  - Freq <20% or > 80%: homozygous genotype
  - Otherwise: heterozygous
- Works well for "deeply sequenced regions" (DSR), i.e. <u>depth > 25x</u>
  - But suffer from under-calling of heterozygous genotypes for low-coverage regions
  - And can't give an objective measurement for reliability

Reviews Genetics 12, 443-451)

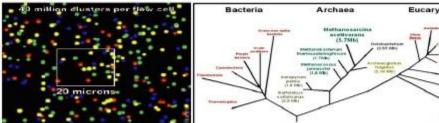
#### A Simple Probabilistic Model for Genotyping

- 1. For a diploid genome, there will be at most two different alleles (A and a) observed at a given site:
  - 3 possible genotypes: <A,A>, <A,a>, <a,a>
  - Number of A: k; Number of a: n-k
- 2. Then, the probability for each genotypes is
  - P(D|<A,A>) = the probability that we have (n-k) sequencing errors at this site  $\prod$
  - Similarly, we can see the  $P(D|<a,a>) = \prod$
  - P(D|<A,a>) = 1 (P(D|<A,A>) + P(D|<a,a>))
- 3. Bayes Formula can be further employed to calculate posterior probabilities, i.e. P(<A,A>|D), P(<a,a>|D), and P(<A,a>|D) if we can estimate the prior probabilities P(<A,A>), P(<a,a>) and P(<A,a>)

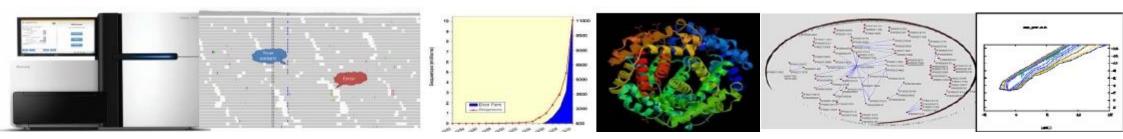








#### Unit 3: BWA & BWT algorithm Le Zhang, Ph. D. Computer Science Department Southwest University



# Outline

- BWA & BWT algorithm
- Variant caller
  - $-\operatorname{samtools}$
  - $-\operatorname{GATK}$

# BWA / BWT algorithm

- The compression algorithm used in BWA
- Lossless compression
- Sort and transform the char matrix with string rotation
- Reverse-char method was utilized for match
- Cannot handle gap

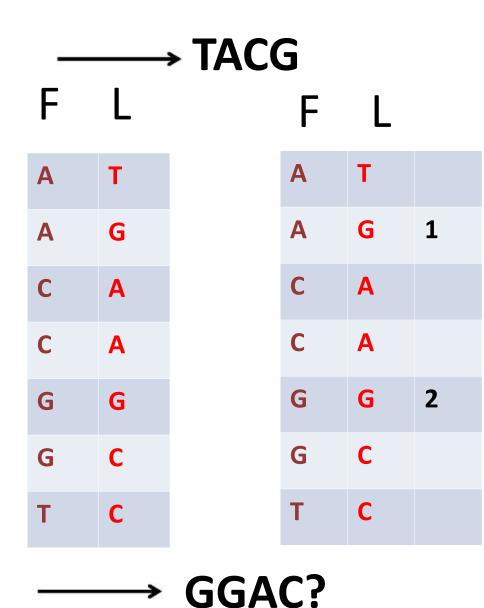
#### ACTACGG

Α	С	т	Α	С	G	G		Α	С	G	G	Α	С	т
С	Т	Α	С	G	G	Α		Α	С	т	Α	С	G	G
т	Α	С	G	G	Α	С	sort	С	G	G	Α	С	т	Α
Α	С	G	G	Α	С	т	$\rightarrow$	С	Т	Α	С	G	G	Α
C	G	G	Α	С	т	Α		G	Α	С	т	Α	С	G
G	G	Α	С	т	Α	С		G	G	Α	С	т	Α	C
G	Α	С	Т	Α	С	G		т	Α	С	G	G	Α	С

TGAAGCC I=2

TGAAGCC											
L	F	F			=	2		L	F	L	
т	Α	Α	С	G	G	Α	С	Т	Α	т	5
G	Α	Α	С	т	Α	С	G	G	Α	G	1
A	sort	С	G	G	Α	С	Т	Α	С	Α	4
A	С	С	Т	Α	С	G	G	Α	С	Α	7
G	G	G	Α	С	Т	Α	С	G	G	G	2
С	G	G	G	Α	С	т	Α	С	G	С	3
С	т	т	Α	С	G	G	Α	С	т	С	6

ACTACGG



L F Α Т 4 Α G С Α 3 С Α G G 1 С 2 G Т С

ACTACGG

ACTACGG | | || AC GG

# ACTACGG $\longrightarrow$ ACTACGG\$ F L



F	L	
\$	G	
Α	Т	
Α	\$	3
С	Α	
С	Α	2
G	G	
G	С	
т	С	1

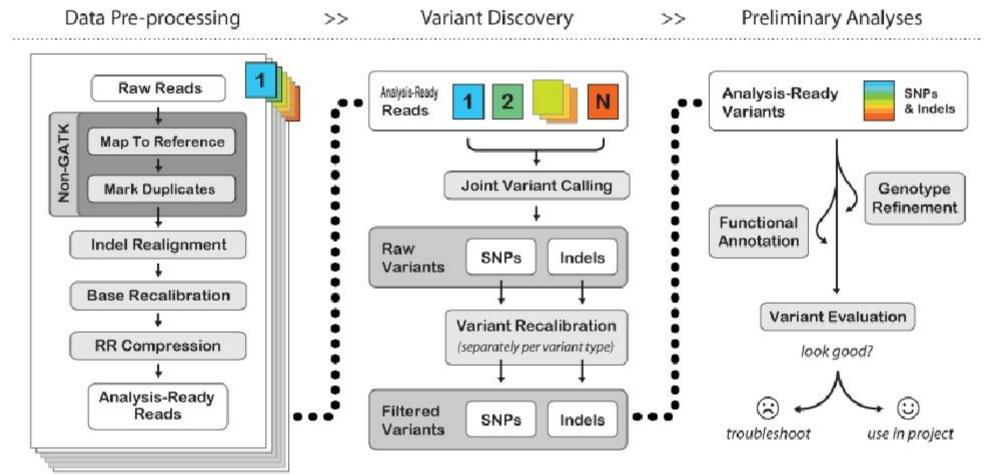
# Variant caller

samtools

– mpileup + bcftools

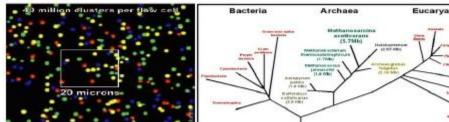
- GATK
  - UnifiedGenotyper
  - HaplotypeCaller

# GATK

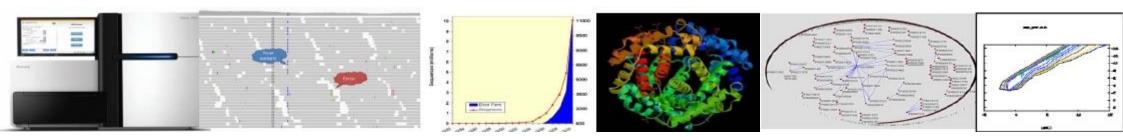




TAACCCTAACCCTAACCCTAACCCTAACCCTA CCTAACCCTAACCCTAACCCTAACCCTAACCC CCCTAACCCCTAACCCTAACCCTAACCCTAAC AACCCTAACCCTAACCCTAACCCCTAACCCTA ACCCTAACCCCAACCCCAACCCCAACCCCAAC CTACCCTAACCCTAACCCTAACCCTAA



#### Unit 4: Likelihood and Bayesian approach Le Zhang, Ph. D. Computer Science Department Southwest University



# Outline

- Introduction of Likelihood and Bayesian approach
- Genotyper of MAQ and SNVMix

# Likelihood & Bayesian

Likelihood function

- a function of the parameters of a statistical model  $- L(\theta) = P(Data | \theta)$ 

- Bayesian approach
   P(θ|Data) ∝ P(θ)\* P(Data|θ)
  - posterior  $\propto$  prior \* likelihood

# **A Simple Demostration**

- Toss a biased coin, let  $\theta$  = P(Head) in one trial
- Probability for seeing HTHH?

 $L(\theta) = P(Data|\theta) = P(HTHH|\theta)$ Bernoulli distribution  $= \theta \cdot (1 - \theta) \cdot \theta \cdot \theta = \theta^3 (1 - \theta)$ 

 Probability for seeing 3 Heads in 4 trials?  $L(\theta) = P(Data|\theta) = P(3H \text{ in } 4|\theta)$ binomial distribution  $= \binom{4}{3} \theta^3 (1-\theta)$ 

### Models for SNP Calling and Genotyping

- MAQ
  - Li, H., Ruan, J., and Durbin, R. (2008). Mapping short DNA sequencing reads and calling variants using mapping quality scores. Genome Research 18, 1851–1858.
- samtools
  - Li, H. (2011). A statistical framework for SNP calling, mutation discovery, association mapping and population genetical parameter estimation from sequencing data. Bioinformatics 27, 2987–2993.
- GATK
  - McKenna, A., Hanna, M., Banks, E., Sivachenko, A., Cibulskis, K., Kernytsky, A., Garimella, K., Altshuler, D., Gabriel, S., Daly, M., et al. (2010). The Genome Analysis Toolkit: A MapReduce framework for analyzing next-generation DNA sequencing data. Genome Research 20, 1297–1303.
  - DePristo, M.A., Banks, E., Poplin, R., Garimella, K.V., Maguire, J.R., Hartl, C., Philippakis, A.A., del Angel, G., Rivas, M.A., Hanna, M., et al. (2011). A framework for variation discovery and genotyping using next-generation DNA sequencing data. Nature Genetics 43, 491–498.
- SNVMix

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 Goya, R., Sun, M.G.F., Morin, R.D., Leung, G., Ha, G., Wiegand, K.C., Senz, J., Crisan, A., Marra, M.A., Hirst, M., et al. (2010). SNVMix: predicting single nucleotide variants from next-generation sequencing of tumors. Bioinformatics 26, 730–736.

- Data: a pile of bases, with baseQ
  - k nucleotide b and (n-k) nucleotide b' with error rate  $\epsilon_1 \leq \cdots \leq \epsilon_k \quad \epsilon_{k+1} \leq \cdots \leq \epsilon_r$
- Goal: call genotype <b,b>, <b,b'>, <b',b'>

• For G=, 
$$\Pr{Data|G=} \approx \frac{1}{2^n} {n \choose k}$$

• For G=<b,b>,

 $\alpha_{nk} = \Pr\{\text{exactly } k \text{ errors in } n \text{ bases}\}$ 

$$\bar{\alpha}_{nk}(\bar{\epsilon}) = \binom{n}{k} \bar{\epsilon}^k (1-\bar{\epsilon})^{n-k}$$

 $\alpha_{nk} = \Pr\{\text{exactly } k \text{ errors in } n \text{ bases}\}$ 

 $\beta_{nk} = \begin{cases} \Pr\{\text{more than } k \text{ errors} | \text{more than } k - 1 \text{ errors in } n \text{ bases} \} & (k > 0) \\ \Pr\{\text{more than } 0 \text{ error in } n \text{ bases} \} & (k = 0) \end{cases}$ 

$$\alpha_{nk} = (1 - \beta_{nk})\beta_{n(k-1)} \cdots \beta_{n2}\beta_{n1} = (1 - \beta_{nk})\prod_{i=0}^{k-1}\beta_{ni} \qquad \sum_{k=0}^{n}\alpha_{nk} = 1$$
$$\beta_{nk} = \frac{\sum_{i=k+1}^{n}\alpha_{ni}}{\sum_{i=k}^{n}\alpha_{ni}} = \frac{1 - \sum_{i=0}^{k}\alpha_{ni}}{1 - \sum_{i=0}^{k-1}\alpha_{ni}} \qquad \beta_{nn} = 0$$

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$$\bar{\alpha}_{nk}(\bar{\epsilon}) = \binom{n}{k} \bar{\epsilon}^{k} (1-\bar{\epsilon})^{n-k} \qquad \bar{\beta}_{nk}(\bar{\epsilon}) = \frac{1-\sum_{i=0}^{k} \bar{\alpha}_{ni}}{1-\sum_{i=0}^{k-1} \bar{\alpha}_{ni}}$$

$$\beta_{nk}(\bar{\epsilon}) = \bar{\beta}_{nk}^{f_k}(\bar{\epsilon}) \qquad 0 < f_k \le 1$$

$$\alpha_{nk}(\bar{\epsilon}) = (1-\bar{\beta}_{nk}^{f_k}) \prod_{i=0}^{k-1} \bar{\beta}_{mi}^{f_i} = (1-\bar{\beta}_{nk}^{f_k}) \prod_{i=0}^{k-1} \left(\frac{\bar{\beta}_{ni}}{\bar{\epsilon}}\right)^{f_i} \cdot \bar{\epsilon}^{f_i} = c_{nk}(\bar{\epsilon}) \cdot \prod_{i=0}^{k-1} \bar{\epsilon}^{f_i}$$

$$c_{nk}(\bar{\epsilon}) = (1-\bar{\beta}_{nk}^{f_k}) \prod_{i=0}^{k-1} \left(\frac{\bar{\beta}_{ni}}{\bar{\epsilon}}\right)^{f_i}$$

$$\alpha_{nk}(\epsilon_{1},\cdots,\epsilon_{k};\epsilon_{k+1},\cdots,\epsilon_{n}) \approx c_{nk}(\bar{\epsilon}) \cdot \prod_{i=0}^{k-1} \epsilon_{i+1}^{f_{i}}$$
$$\log \bar{\epsilon} = \frac{\sum_{i=0}^{k-1} f_{i} \log \epsilon_{i+1}}{\sum_{i=0}^{k-1} f_{i}} \qquad \prod_{i=0}^{k-1} \bar{\epsilon}_{i}^{f_{i}} = \prod_{i=0}^{k-1} \epsilon_{i+1}^{f_{i}}$$
$$f_{k} = 0.85^{k}$$
$$\alpha_{nk}(\epsilon_{1},\cdots,\epsilon_{k};\tilde{\epsilon}_{1},\cdots,\tilde{\epsilon}_{k};\epsilon_{k+1},\cdots,\epsilon_{n};\tilde{\epsilon}_{k+1},\cdots,\tilde{\epsilon}_{n}) \approx c_{nk}(\bar{\epsilon}) \prod_{i=0}^{k-1} \epsilon_{i+1}^{f_{i}} \cdot c_{n\bar{k}}(\bar{\epsilon}) \prod_{i=0}^{\bar{k}-1} \tilde{\epsilon}_{i+1}^{f_{i}}$$

- For G=<b,b>,  $\Pr{Data|G=<b,b>} = \alpha_{nk}(\epsilon_1,\cdots,\epsilon_k;\epsilon_{k+1},\cdots,\epsilon_n)$
- For G=<b,b'>,  $\Pr{Data|G=<b,b'>} \approx \frac{1}{2^n} {n \choose k}$
- For G=<b',b'>,  $\Pr{Data|G=<b',b'>} = \alpha_{n,n-k}(\epsilon_{k+1},\cdots,\epsilon_n;\epsilon_1,\cdots,\epsilon_k)$

# Genotyping Model used in MAQ $Pr{G|Data} \propto Pr{G} \cdot Pr{Data|G}$

• For G=  
b, b>|Data} =  

$$\Pr\{G = < b, b>\} \cdot \Pr\{Data | G = < b, b>\}$$
  
 $\Pr\{G = < b, b>\} \cdot \Pr\{Data | G = < b, b>\}$   
 $\Pr\{G = < b, b>\} \cdot \Pr\{Data | G = < b, b>\} + \Pr\{G = < b, b'>\} \cdot \Pr\{Data | G = < b, b'>\} + \Pr\{G = < b, b'>\} + \Pr\{G = < b, b'>\}$ 

$$\Pr\{G = \langle b, b' \rangle | Data\} = \langle b, b' \rangle,$$

$$\Pr\{G = \langle b, b' \rangle | Data|G = \langle b, b' \rangle | Pr\{G = \langle b, b' \rangle\} \cdot \Pr\{Data|G = \langle b, b' \rangle\}$$

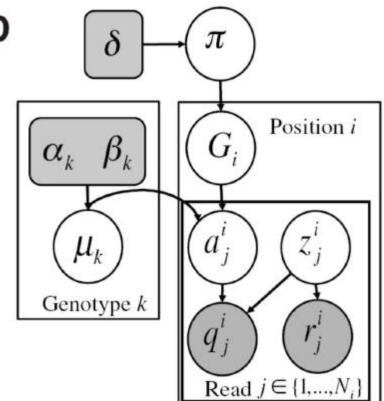
$$\Pr\{G = \langle b, b \rangle | Data\} = \langle b', b' \rangle,$$

$$\Pr\{G = \langle b', b' \rangle | Data|G = \langle b', b' \rangle\} \cdot \Pr\{Data|G = \langle b', b' \rangle\}$$

 $\Pr\{G = \langle b, b \rangle\} \cdot \Pr\{Data | G = \langle b, b \rangle\} + \Pr\{G = \langle b, b' \rangle\} \cdot \Pr\{Data | G = \langle b, b' \rangle\} + \Pr\{G = \langle b', b' \rangle\} \cdot \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b, b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b' \rangle\} + \Pr\{Data | G = \langle b', b$ 

# Genotyping Model used in SNVMix

- Probabilistic Graphical Model
  - position i, read j, genotype k
  - Gi: genotype
  - aji: match reference allele or not?
  - q<sub>ji</sub>: prob. of correct base calling
  - z<sub>ji</sub>: alignment correct or not?
  - r<sub>ji</sub>: prob. of correct mapping
  - $-~\mu{\bf k}$ : parameter of binomial for genotype k



SNVMix2 model

Goya, R., et al. (2010). SNVMix: predicting single nucleotide variants from

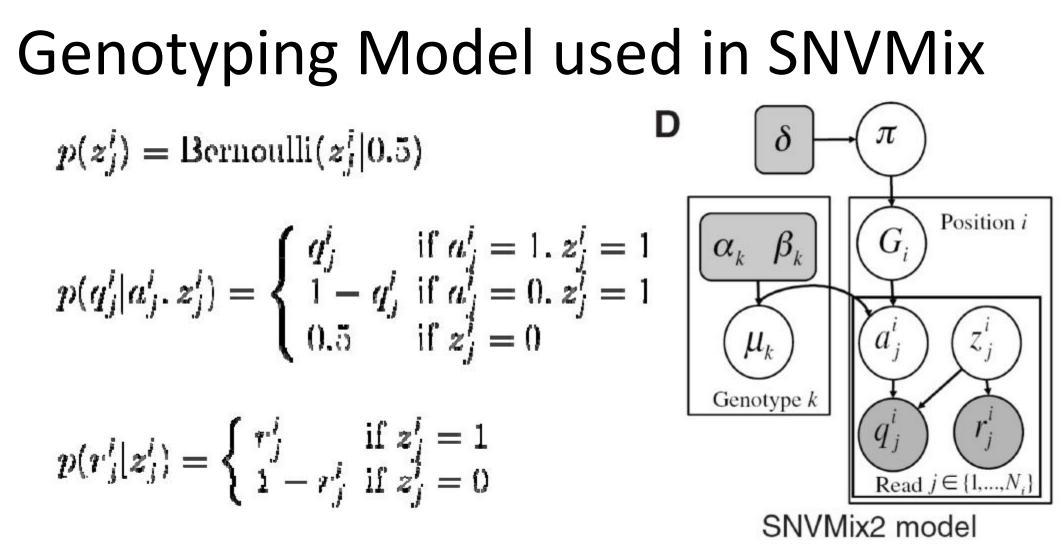
# Genotyping Model used in SNVMix $p(G_i|\pi) = \text{Multinomial}(G_i|\pi, 1)$ $p(\pi|\delta) = \text{Dirichlet}(\pi|\delta)$ $p(a_i^i|G_i = k, \mu_k) = \text{Bernoulli}(a_i^i|\mu_k)$ $(a_i^j, (z_j^i))$

 $p(\mu_k | \alpha_k, \beta_k) = \text{Gamma}(\mu_k | \alpha_k, \beta_k)$ 

SNVMix2 model

Goya, R., et al. (2010). SNVMix: predicting single nucleotide variants from 14

Genotype k



Goya, R., et al. (2010). SNVMix: predicting single nucleotide variants from 15

#### **Bioinformatics: Introduction and Methods**

**Computer Science Department, Southwest University** 

### Thank you

