

## Subsequences and Substrings



<u>Definition</u> A string x' is a **substring** of a string x,

if x = ux'v for some prefix string u and suffix string v

(similarly, 
$$x' = x_i...x_j$$
, for some  $1 \le i \le j \le |x|$ )

A string x' is a **subsequence** of a string x if x' can be obtained from x by deleting 0 or more letters

$$(x' = x_{i1}...x_{ik}, \text{ for some } 1 \le i_1 \le ... \le i_k \le |x|)$$

Note: a substring is always a subsequence

**Example:** x = abracadabra

y = cadabr; substring

z = brcdbr; subseqence, not substring

### Hirschberg's algortihm



Given a set of strings x, y,..., a **common subsequence** is a string u that is a subsequence of all strings x, y, ...

- Longest common subsequence
  - Given strings  $x = x_1 x_2 ... x_M$ ,  $y = y_1 y_2 ... y_N$ ,
  - Find longest common subsequence u = u<sub>1</sub> ... u<sub>k</sub>
- Algorithm:

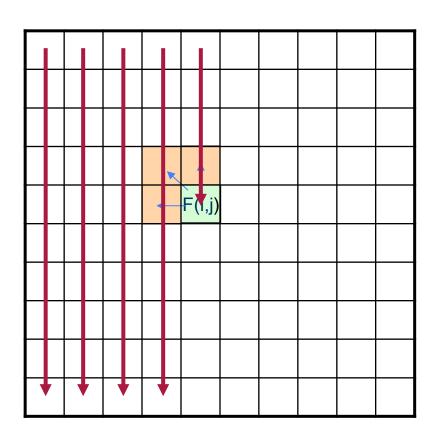
• F(i, j) = max 
$$\begin{cases} F(i-1, j) \\ F(i, j-1) \\ F(i-1, j-1) + [1, if x_i = y_j; 0 \text{ otherwise}] \end{cases}$$

- Ptr(i, j) = (same as in N-W)
- <u>Termination:</u> trace back from Ptr(M, N), and prepend a letter to u whenever
   Ptr(i, j) = DIAG <u>and</u> F(i 1, j 1) < F(i, j)</li>
- Hirschberg's original algorithm solves this in linear space

### Introduction: Compute optimal score



It is easy to compute F(M, N) in linear space



```
Allocate ( column[1] )
Allocate ( column[2] )

For i = 1...M

If i > 1, then:

Free( column[i - 2])

Allocate( column[i])

For j = 1...N

F(i, j) = ...
```



To compute both the optimal score **and** the optimal alignment:

Divide & Conquer approach:

#### **Notation:**

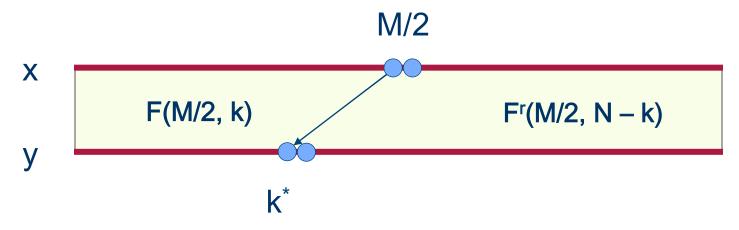
```
x^r, y^r: reverse of x, y
E.g. x = accgg;
x^r = ggcca
```

**F**<sup>r</sup>(**i**, **j**): optimal score of aligning  $x_{1}^{r}...x_{i}^{r}$  &  $y_{1}^{r}...y_{j}^{r}$  same as aligning  $x_{M-i+1}...x_{M}$  &  $y_{N-j+1}...y_{N}$ 



**Lemma:** (assume M is even)

$$F(M, N) = \max_{k=0...N} (F(M/2, k) + F^{r}(M/2, N - k))$$

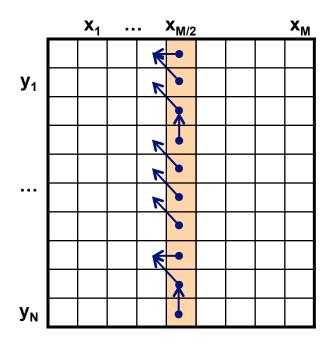


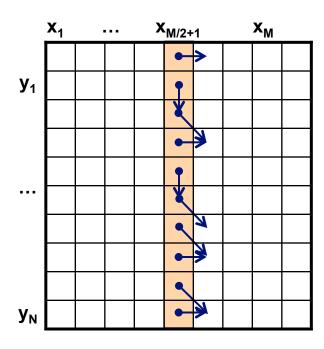
#### **Example:**



 Now, using 2 columns of space, we can compute for k = 1...M, F(M/2, k), F<sup>r</sup>(M/2, N – k)

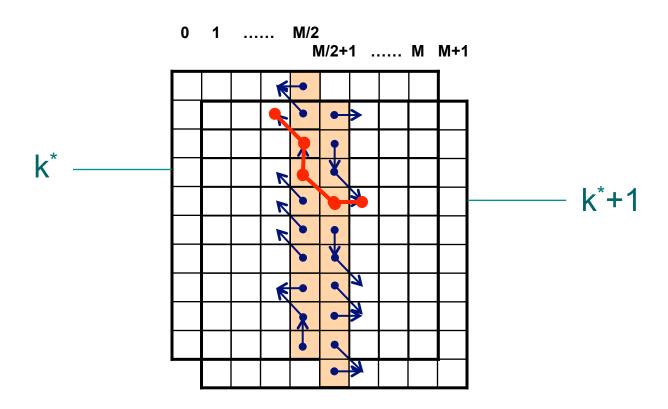
#### PLUS the backpointers





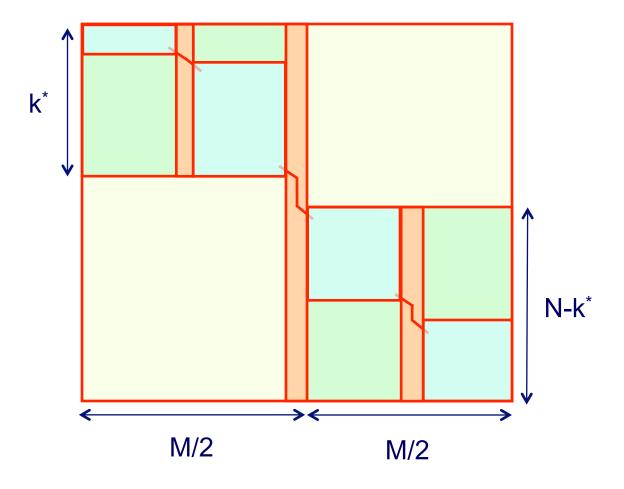


- Now, we can find k\* maximizing F(M/2, k) + Fr(M/2, N-k)
- Also, we can trace the path exiting column M/2 from k\*





Iterate this procedure to the left and right!





#### <u>Hirschberg's Linear-space algorithm:</u>

```
MEMALIGN(I, I', r, r'): (aligns x_1...x_{l'} with y_r...y_{r'})
```

- 1. Let h = [(l'-l)/2]
- Find (in Time O((l' l) × (r' r)), Space O(r' r)) the optimal path, L<sub>h</sub>, entering column h 1, exiting column h Let k<sub>1</sub> = pos'n at column h 2 where L<sub>h</sub> enters k<sub>2</sub> = pos'n at column h + 1 where L<sub>h</sub> exits
- 3. MEMALIGN(I, h 2, r,  $k_1$ )
- 4. Output L<sub>h</sub>
- 5. MEMALIGN(h + 1, l',  $k_2$ , r')

Top level call: MEMALIGN(1, M, 1, N)



#### Time, Space analysis of Hirschberg's algorithm:

To compute optimal path at middle column,

For box of size  $M \times N$ ,

Space: 2N

Time: cMN, for some constant c

Then, left, right calls cost c(  $M/2 \times k^* + M/2 \times (N - k^*)$  ) = cMN/2

All recursive calls cost

**Total Time:** cMN + cMN/2 + cMN/4 + .... = 2cMN = O(MN)

**Total Space:** O(N) for computation,

O(N + M) to store the optimal alignment



# **Heuristic Local Alignerers**

- 1. The basic indexing & extension technique
- Indexing: techniques to improve sensitivity
   Pairs of Words, Patterns
- 3. Systems for local alignment

## Indexing-based local alignment



#### **Dictionary:**

All words of length k (~10)

Alignment initiated between

words of alignment score ≥ T

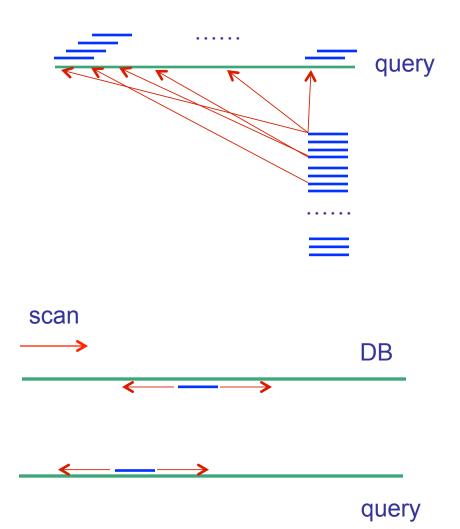
(typically T = k)

#### **Alignment:**

Ungapped extensions until score below statistical threshold

#### **Output:**

All local alignments with score > statistical threshold



## Indexing-based local alignment— Extensions

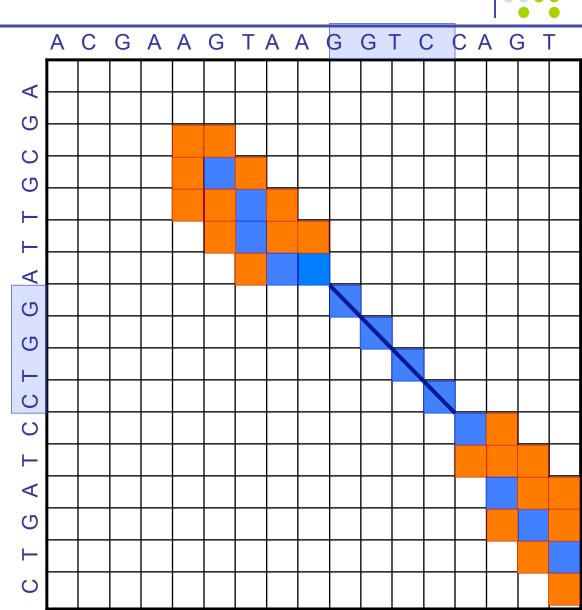


# Gapped extensions until threshold

 Extensions with gaps until score < C below best score so far

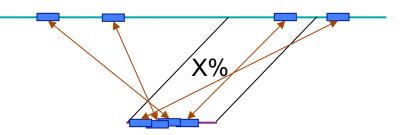
#### **Output:**

GTAAGGTCCAGT GTTAGGTC-AGT



## **Sensitivity-Speed Tradeoff**





Sens.

Speed

	long words (k = 15)	short words (k = 7)
Sensitivity		✓
Speed	✓	

	Table 5.	sensitivity and	a specificity of	single Perfect No	ucieotide K-mer iv	iatties as a sear	Circiterion		
		7	8	9	10	11	12	13	14
	A. 81%	0.974	0.915	0.833	0.726	0.607	0.486	0.373	0.314
	83%	0.988	0.953	0.897	0.815	0.711	0.595	0.478	0.415
Ш	85%	0.996	0.978	0.945	0.888	0.808	0.707	0.594	0.532
	87%	0.999	0.992	0.975	0.942	0.888	0.811	0.714	0.659
	89%	1.000	0.998	0.991	0.976	0.946	0.897	0.824	0.782
	91%	1.000	1.000	0.998	0.993	0.981	0.956	0.912	0.886
	93%	1.000	1.000	1.000	0.999	0.995	0.987	0.968	0.957
	95%	1.000	1.000	1.000	1.000	0.999	0.998	0.994	0.991
	97%	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.999
	В. К	7	8	9	10	11	12	13	14
	F	1.3e+07	2.9e+06	635783	143051	32512	7451	1719	399

Sensitivity and Specificity of Single Perfect Nucleotide Kimer Matches as a Search Offerion

<sup>(</sup>A) Columns are for K sizes of 7–14. Rows represent various percentage identities between the homologous sequences. The table entries show the fraction of homologies detected as calculated from equation 3 assuming a homologous region of 100 bases. The larger the value of K, the fewer homologies are detected.

<sup>(</sup>B) K represents the size of the perfect match. F shows how many perfect matches of this size expected to occur by chance according to equation 4 in a genome of 3 billion bases using a query of 500 bases.

## **Sensitivity-Speed Tradeoff**

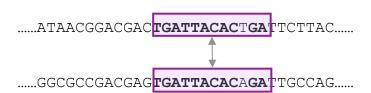


### Methods to improve sensitivity/speed

1. Using pairs of words



2. Using inexact words



3. Patterns—non consecutive positions



### Messurad improvement

Table 7. Sensitivity and Specificity of Multiple (2 and 3) Perfect Nucleotide K-mer Matches as a Search Criterion

	2,8	2,9	2,10	2,11	2,12	3,8	3,9	3,10	3,11	3,12
A. 81%	0.681	0.508	0.348	0.220	0.129	0.389	0.221	0.112	0.051	0.021
83%	0.790	0.638	0.475	0.326	0.208	0.529	0.339	0.193	0.099	0.045
85%	0.879	0.762	0.615	0.460	0.318	0.676	0.487	0.313	0.180	0.093
87%	0.942	0.866	0.752	0.611	0.461	0.809	0.649	0.470	0.305	0.177
89%	0.978	0.940	0.868	0.761	0.625	0.910	0.801	0.648	0.476	0.314
91%	0.994	0.980	0.947	0.884	0.787	0.969	0.914	0.815	0.673	0.505
93%	0.999	0.996	0.986	0.962	0.912	0.993	0.976	0.933	0.851	0.722
95%	1.000	1.000	0.998	0.993	0.979	0.999	0.997	0.987	0.961	0.902
97%	1.000	1.000	1.000	1.000	0.999	1.000	1.000	0.999	0.997	0.987
B. N,K	2,8	2,9	2,10	2,11	2,12	3,8	3,9	3,10	3,11	3,12
F	524	27	1.4	0.1	0.0	0.1	0.0	0.0	0.0	0.0

<sup>(</sup>A) Columns are for N sizes of 2 and 3 and K sizes of 8–12. Rows represent various percentage identities between the homologous sequences. The table entries show the fraction of homologies detected as calculated by equation 10. (B) N and K represent the number and size of the near-perfect matches, respectively. F shows how many perfect clustered matches expected to occur by chance according to equation 14 in a translated genome of 3 billion bases using a guery of 167 amino acids.

**Table 5.** Sensitivity and Specificity of Single Near-Perfect (One Mismatch Allowed) Nucleotide K-mer Matches as a Search Criterion

	12	13	14	15	16	17	18	19	20	21	22
A. 81%	0.945	0.880	0.831	0.721	0.657	0.526	0.465	0.408	0.356	0.255	0.218
83%	0.975	0.936	0.904	0.820	0.770	0.649	0.591	0.535	0.480	0.361	0.318
85%	0.991	0.971	0.954	0.900	0.865	0.767	0.719	0.669	0.619	0.490	0.445
87%	0.997	0.990	0.983	0.954	0.935	0.867	0.833	0.796	0.757	0.634	0.591
89%	1.000	0.997	0.995	0.984	0.976	0.939	0.920	0.897	0.872	0.775	0.741
91%	1.000	1.000	0.999	0.996	0.994	0.979	0.971	0.962	0.950	0.890	0.869
93%	1.000	1.000	1.000	0.999	0.999	0.996	0.994	0.991	0.988	0.963	0.954
95%	1.000	1.000	1.000	1.000	1.000	1.000	0.999	0.999	0.999	0.994	0.992
97%	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
B. K	12	13	14	15	16	17	18	19	20	21	22
F	275671	68775	17163	4284	1070	267	67	17	4.2	1.0	0.3

(A) Columns are for K sizes of 12–22. Rows represent various percentage identities between the homologous sequences. The table entries show the fraction of homologies detected as calculated by equation 6 assuming a homologous region of 100 bases. (B) K represents the size of the near-perfect match. F shows how many perfect matches of this size expected to occur by chance according Genome Research 2002 billion bases using a query of 500 bases.



### Non-consecutive words—Patterns

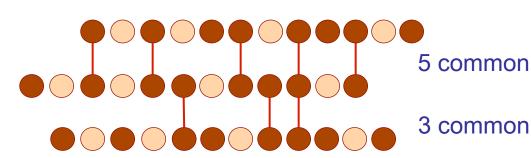


Patterns increase the likelihood of at least one match within a long conserved region

**Consecutive Positions** 

6 common
7 common

Non-Consecutive Positions



On a 100-long 70% conserved region:

<u>Consecutive</u>

Expected # hits: 1.07

Prob[at least one hit]: 0.30

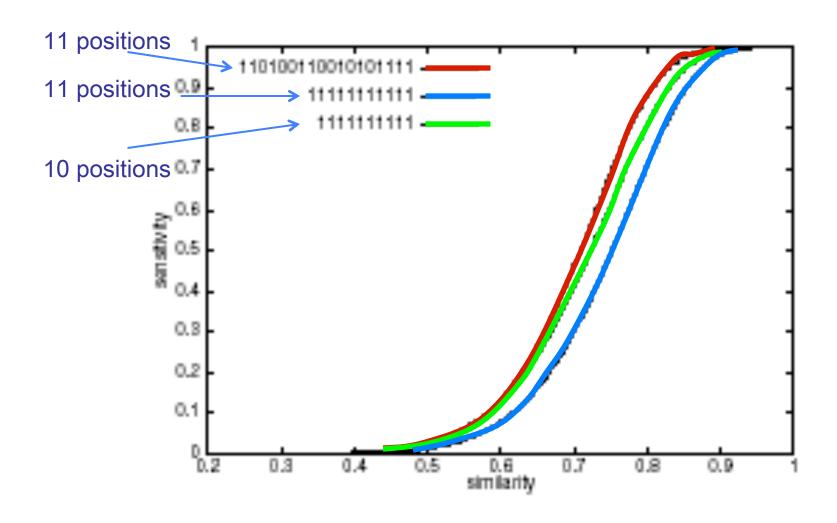
Non-consecutive

0.97

0.47

## **Advantage of Patterns**





### Multiple patterns





T G TT CAC G

T G T C CAG

TTGATT A G

How long does it take to search the query?

Seed	Pattern	Pr[detection]	Alignments Found	Time (s)
$\pi_c$	$\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10\}$	0.600	66419	15802
$\pi_{c10}$	$\{0, 1, 2, 3, 4, 5, 6, 7, 8, 9\}$	0.707	73539	24129
$\pi_{ph}$	$\{0, 1, 2, 4, 7, 9, 12, 13, 15, 16, 17\}$	0.691	75518	16717
$\pi_{N_0}$	$\{0, 1, 2, 4, 7, 8, 11, 13, 16, 17, 18\}$	0.683	75231	16225
$\pi_{N_5}$	$\{0, 1, 2, 3, 5, 6, 7, 10, 12, 13, 14\}$	0.709	75547	16817
$\pi_1 + \pi_2$	$\{0, 1, 2, 4, 5, 9, 14, 16, 17, 18, 19, 20\}+$	0.744	77211	22033
	$\{0, 1, 2, 3, 4, 6, 7, 8, 10, 11, 12, 13\}$			

Buhler et al. RECOMB 2003 Sun & Buhler RECOMB 2004

## **Human Genome Resequencing**



Which human did we sequence?

Answer one:

Answer two: "it doesn't matter"



Polymorphism rate: number of letter changes between two different members of a species

Humans: ~1/1,000



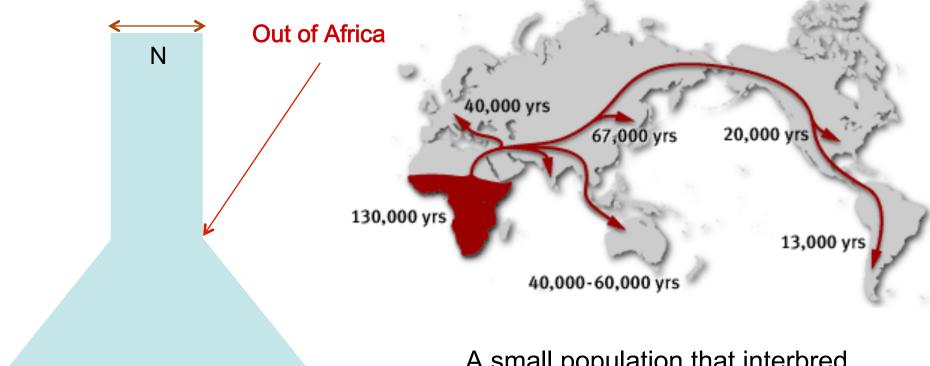
Other organisms have much higher polymorphism rates

Population size!



## Why humans are so similar





Heterozygosity: H H = 4Nu/(1 + 4Nu)u ~  $10^{-8}$ , N ~  $10^{4}$  $\Rightarrow$  H ~  $4 \times 10^{-4}$  A small population that interbred reduced the genetic variation

Out of Africa ~ 40,000 years ago

## **DNA Sequencing**



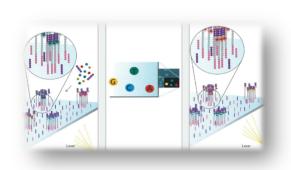
#### Goal:

Find the complete sequence of A, C, G, T's in DNA

#### **Challenge:**

There is no machine that takes long DNA as an input, and gives the complete sequence as output

Can only sequence ~150 letters at a time

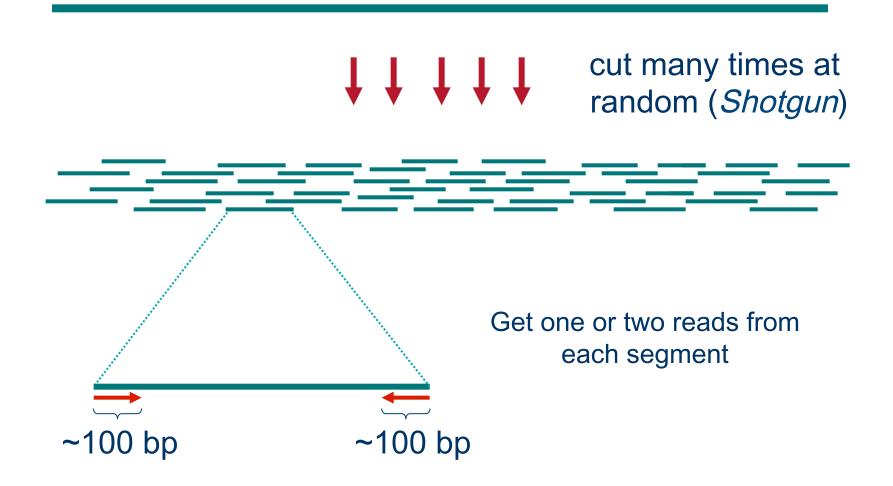




## Method to sequence longer regions

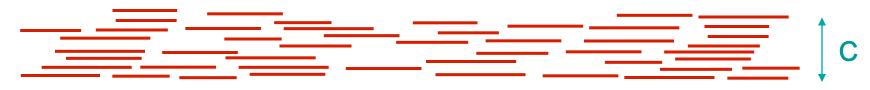


### genomic segment



## **Definition of Coverage**





Length of genomic segment: G

Number of reads: N

Length of each read:

**Definition:** Coverage C = N L / G

How much coverage is enough?

Lander-Waterman model: Prob[ not covered bp ] = e-C

Assuming uniform distribution of reads, C=10 results in 1 gapped region /1,000,000 nucleotides

### Repeats



Bacterial genomes: 5%
Mammals: 50%

#### **Repeat types:**

Low-Complexity DNA (e.g. ATATATACATA...)

 Microsatellite repeats (a<sub>1</sub>...a<sub>k</sub>)<sup>N</sup> where k ~ 3-6 (e.g. CAGCAGTAGCAGCACCAG)

Transposons

SINE (Short Interspersed Nuclear Elements)

e.g., ALU: ~300-long, 10<sup>6</sup> copies

LINE (Long Interspersed Nuclear Elements)

~4000-long, 200,000 copies

LTR retroposons (Long Terminal Repeats (~700 bp) at each end)

cousins of HIV

Gene Families genes duplicate & then diverge (paralogs)

Recent duplications ~100,000-long, very similar copies

### Two main assembly problems



De Novo Assembly



Resequencing



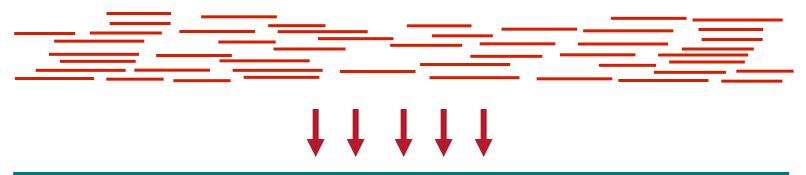
### **Human Genome Variation**



SNP	TGCTGAGA TGCCGAGA	Novel Sequence	TGC <b>TCG</b> GAGA TGC GAGA
Inversion	$\Rightarrow \Leftrightarrow \Rightarrow$	Mobile Element or Pseudogene Insertion	<b>→</b>
Translocation		Tandem Duplication	<b>→</b>
Microdeletion	TGC AGA TGCCGAGA	Transposition	$\Rightarrow \rightarrow \Rightarrow$
Large Deletion	<b>→</b>	Novel Sequence at Breakpoint	TGC >

### **Read Mapping**





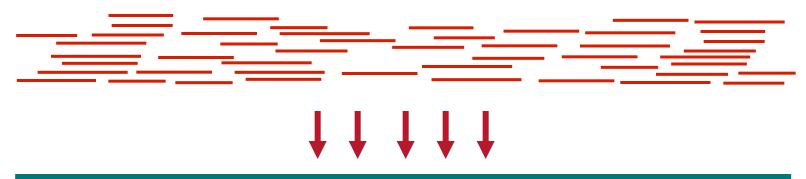
CATCGACCGAGCGCGATGCTAGCTAGGTGATCGT....

TGCCGCATCGACCGAGCGCGATGCTAGCTAGGTGATCGT...
GCATGCCGCATCGACCGAGCGCGATGCTAGCTAGGTGATCGT
GTGCATGCCGCATCGACCGAGCGCGATGCTAGCTAGGTGATC

- Want ultra fast, highly similar alignment
- Detection of genomic variation

### Read Mapping – Burrows-Wheeler Transform

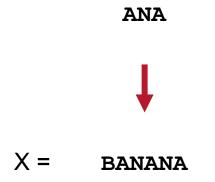




CATCGACCGAGCGCGATGCTAGCTAGCTGATCGT....

- Modern fast read aligners: BWT, Bowtie, SOAP
  - Based on Burrows-Wheeler transform



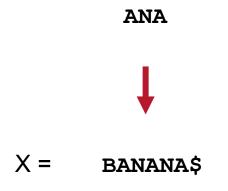


BANANA
ANAA
ANA
NA
ANA
AA
AA

BANANA
ANA
ANA
NA
A
A
A
A
A
A

suffixes of BANANA

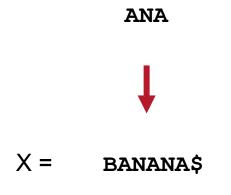




```
BANANA$
ANANA$
NANA$
NAS
ANA$
NA$
S
```

```
BANANA$
ANANA$
NANA$
NAS
NA$
NA$
```



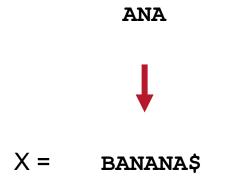


BANANA\$
ANANA\$B
NANA\$BA
ANA\$BAN
NA\$BANA
<b>A\$BANAN</b>
\$BANANA

BANANA\$	
ANANA\$B	
NANA\$BA	
ANA\$BAN	
NA\$BANA	
A\$BANAN	
\$BANANA	

BANANA\$
ANANA\$B
NANA\$BA
ANA\$BAN
NA\$BANA
<b>A\$BANAN</b>
\$BANANA

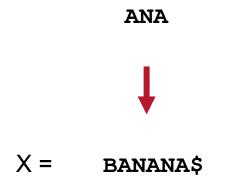




BANANA\$
ANANA\$B
NANA\$BA
ANA\$BAN
NA\$BANA
<b>A\$BANAN</b>
\$BANANA

BANANA\$	\$BANAN <mark>A</mark>
ANANA\$B	A\$BANA <mark>N</mark>
NANA\$BA	ANA\$BAN
ANA\$BAN	ANANA\$ <mark>B</mark>
NA\$BANA	BANANA\$
A\$BANAN	NA\$BAN <mark>A</mark>
\$BANANA	NANA\$B <mark>A</mark>



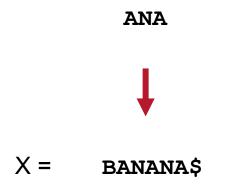


BANANA\$
ANANA\$B
NANA\$BA
ANA\$BAN
NA\$BANA
A\$BANAN
\$BANANA

BANANA\$
ANANA\$B
NANA\$BA
ANA\$BAN
NA\$BANA
A\$BANAN
\$BANANA

\$BANANA
<b>A\$BANAN</b>
ANA\$BAN
ANANA\$B
BANANA\$
NA\$BANA
NANA\$BA





BANANA\$BANA\\$BANA\\$BANA\\$BANA\\$BANA\\$BANA\\$BANA\\$BANA\\$BANA\\$BANAN

BANANA\$B
ANA\\$BAN
ANA\\$BAN
ANA\\$BANA
A\\$BANA
A\\$BANA

\$BANANA
A\$BANAN
ANA\$BAN
ANANA\$B
BANANA\$
NA\$BANA

BWT matrix of string 'BANANA'

BWT(BANANA) = ANNB\$AA

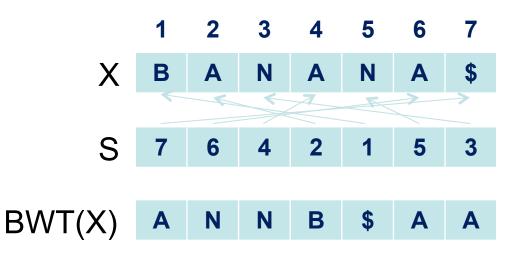
# **Suffix Arrays**



\$BANANA	1	\$BANANA
A\$BANA <mark>N</mark>	2	<b>A\$BANAN</b>
ANA\$BAN	3	ANA\$BAN
ANANA\$ <mark>B</mark>	4	ANANA\$B
BANANA\$	5	BANANA\$
NA\$BAN <mark>A</mark>	6	NA\$BANA
NANA\$B <mark>A</mark>	7	NANASBA

Suffixes are sorted in the BWT matrix

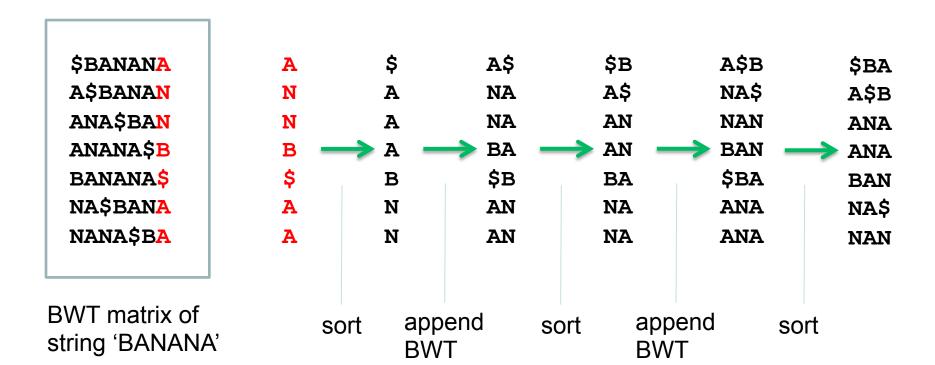
S(i) = j, where  $X_j ... X_n$  is the i-th suffix lexicographically



BWT(X) constructed from S: At each position, take the letter to the left of the one pointed by S

# **Reconstructing BANANA**







\$BANANA

**A\$BANAN** 

ANA\$BAN

ANANA\$B

BANANA\$

NA\$BANA

NANA\$BA

BWT matrix of string 'BANANA'

Lemma. The i-th occurrence of character c in last column is the same text character as the i-th occurrence of c in the first column

\$BANANA

**A\$BANAN** 

ANA\$BAN

ANANA\$B

BANANA\$

NA\$BANA

NANA\$BA



\$BANANA

**A\$BANAN** 

ANA\$BAN

ANANA\$B

BANANA\$

NA\$BANA

NANA\$BA

BWT matrix of string 'BANANA'

Lemma. The i-th occurrence of character c in last column is the same text character as the i-th occurrence of c in the first column

A \$BANAN

NA\$BANA

NANA\$BA

**BANANA**\$

\$BANANA

ANA\$BAN

ANANA\$B



\$BANANA

**A\$BANAN** 

ANA\$BAN

ANANA\$B

BANANA\$

NA\$BANA

NANA\$BA

BWT matrix of string 'BANANA'

Lemma. The i-th occurrence of character c in last column is the same text character as the i-th occurrence of c in the first column

A \$BANAN

NA\$BANA

NANA\$BA

BANANA\$

\$BANANA

ANA\$BAN

ANANA\$B

A\$BANAN ANA\$BAN ANANA\$B

Same words, same sorted order



\$BANANA

**A\$BANAN** 

ANA\$BAN

ANANA\$B

BANANA\$

NA\$BANA

NANA\$BA

BWT matrix of string 'BANANA'

Lemma. The i-th occurrence of character 'a' in last column is the same text character as the i-th occurrence of 'a' in the first column

LF(): Map the i-th occurrence of character 'a' in last column to the first column

LF(r): Let row r contain the i-th occurrence of 'a' in last column

Then, LF(r) = r'; r': i-th row starting with 'a'



\$BANANA

**A\$BANAN** 

ANA\$BAN

ANANA\$B

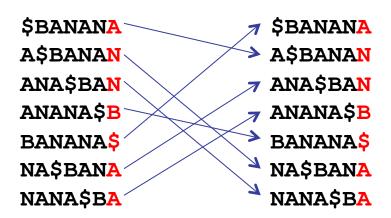
BANANA\$

NA\$BANA

NANA\$BA

BWT matrix of string 'BANANA'

LF(r): Let row r be the i-th occurrence of 'a' in last column Then, LF(r) = r'; r': i-th row starting with 'a'



$$LF[] = [2, 6, 7, 5, 1, 3, 4]$$

Row LF(r) is obtained by rotating row r one position to the right



\$BANANA

**A\$BANAN** 

ANA\$BAN

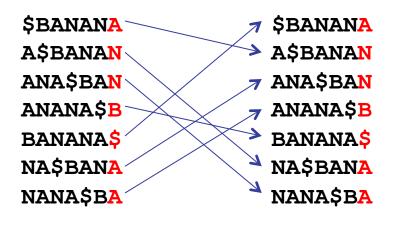
ANANA\$B

BANANA\$

NA\$BANA

NANA\$BA

BWT matrix of string 'BANANA'



$$LF[] = [2, 6, 7, 5, 1, 3, 4]$$

Computing LF() is easy:

Let C(a): # of characters smaller than 'a'

Example: C(\$) = 0; C(A) = 1; C(B) = 4; C(N) = 5

Let row r end with the i-th occurrence of 'a' in last column

Then, 
$$LF(r) = C(a) + i$$

(why?)



\$BANANA
A\$BANAN
ANA\$BAN
ANANA\$B
BANANA\$
NA\$BANA

BWT matrix of string 'BANANA'

```
S := ""; r := 1; c := BWT[r];

UNTIL c = '$' {

    S := cS;

    r := LF(r);

    c := BWT(r); }
```

Reconstruct BANANA:

Credit: Ben Langmead thesis

# **Searching for ANA**



\$BANANA

**A\$BANAN** 

ANA\$BAN

ANANA\$B

BANANA\$

NA\$BANA

NANA\$BA

BWT matrix of string 'BANANA'

L(W): lowest index in BWT matrix where W is prefix U(W): highest index in BWT matrix where W is prefix

### Example:

$$L("NA") = 6$$
  
 $U("NA") = 7$ 

#### Lemma (prove as exercise)

$$L(aW) = C(a) + i + 1,$$

$$where i = \# 'a's up to L(W) - 1 in BWT(X)$$

$$U(aW) = C(a) + j,$$

$$where j = \# 'a's up to U(W) in BWT(X)$$

### Example:

# **Searching for ANA**



```
$BANANA
A$BANAN
ANA$BAN
ANANA$B
BANANA$
NA$BANA
```

BWT matrix of string 'BANANA'

```
Let
LFC(r, a) = C(a) + i, where i = \#'a's up to r in BWT
ExactMatch(W[1...k]) {
   a := W[k];
   low := C(a) +1;
   high := C(a+1); // a+1: lexicographically next char
   i := k - 1;
   while (low \leq high && i \geq 1) {
         a = W[i];
         low = LFC(low - 1, a) + 1;
         high = LFC(high, a);
         i := i - 1; 
   return (low, high);
```

# **Summary of BWT algorithm**



### Suffix array of string X:

S(i) = j, where  $X_j ... X_n$  is the j-th suffix lexicographically

- BWT follows immediately from suffix array
  - Suffix array construction possible in O(n), many good O(n log n) algorithms
- Reconstruct X from BWT(X) in time O(n)
- Search for all exact occurrences of W in time O(|W|)
- BWT(X) is easier to compress than X

# **BWT Index Construction**



Reference Sequence Construction



**BWT Construction** 



BWT-auxiliary
Structure Construction
(C & O arrays)
and Compression



.bwt

#### Reference

Forward

Reverse Complement

ACGTTA..TTCTGAATGTGACC...TCCAGACGA...CCATT....AGTTC...CGGATT AGAT...AAGTACCGTGTGAT...CCAGAT

Compressed BWT (4 bases/byte)
TTATTT...ATGTGCCTT.......sGTTGGTTAATAA

#### C-array

\$: 0 T: 55000 C: 1044814 G: 7814189

A: 1

#### **O**-array

#### SA

0: |G|-1 1: 64 2: 144814 3: 781414689 ... ... |G|-1: 1484

# Memory Consumption

### For a genome of length n:

- -- occurrence array O(.,.) needs 4nlogn bits
  - $\rightarrow$  sampling: store only O(.,k) for e.g. k = 128
  - → use BWT to compute missing counts
- -- suffix array SA(.) needs nlogn bits
  - $\rightarrow$  sampling: store SA(k) for e.g. k = 32
  - → use inverse compressed suffix array

# **BWA Inexact Matching**

#### Allow up to n mismatches/gaps.

Backwards-search extension: Given read W, keep track of multiple possible partial alignments of W

Partial alignment 4-tuple: (i, z, L, U)

```
\begin{split} I \leftarrow \emptyset \\ I \leftarrow I \cup \operatorname{InexRecur}(W, i-1, z-1, k, l) \\ \textbf{for } \operatorname{each} b \in \{A, C, G, T\} \ \textbf{do} \\ k \leftarrow C(b) + O(b, k-1) + 1 \\ l \leftarrow C(b) + O(b, l) \\ \textbf{if } k \leq l \ \textbf{then} \\ I \leftarrow I \cup \operatorname{InexRecur}(W, i, z-1, k, l) \\ \textbf{if } b = W[i] \ \textbf{then} \\ I \leftarrow I \cup \operatorname{InexRecur}(W, i-1, z, k, l) \\ \textbf{else} \\ I \leftarrow I \cup \operatorname{InexRecur}(W, i-1, z-1, k, l) \end{split}
```

# **BWA Inexact Matching**

 $I \leftarrow I \cup INEXRECUR(W, i-1, z-1, k, l)$ 

 $I \leftarrow I \cup INEXRECUR(W, i, z-1, k, l)$ 

 $I \leftarrow I \cup InexRecur(W, i-1, z, k, l)$ 

for each  $b \in \{A, C, G, T\}$  do  $k \leftarrow C(b) + O(b, k-1) + 1$  $l \leftarrow C(b) + O(b, l)$ 

if b = W[i] then

if  $k \le l$  then

else

W = ACTGTGT

Partial alignment 4-tuple: (i = 4, z = 3, L, U)

#### Recursive step:

Α	C	T	G	gap-ref	gap-read $I \leftarrow I \cup InexRecur(W, i-1, z-1, k, l)$
AGT	CGT	TGT	GGT	∓GT	*GT
z-1	z-1	Z	z-1	z-1	z-1
i-1	i-1	i-1	i-1	i-1	i
$L^AU^A$	$\Gamma_{c}\Omega_{c}$	$L^TU^T$	$\Gamma_{e}\Omega_{e}$	LU	LAUA LCUC LTUT LGUG
GAGT	GCGT	GTGT	G <mark>G</mark> GT	G-GT	GT[A/C/T/G]GT
GTGT	GTGT	GTGT	GTGT	GTGT	GT - GT

$$L^{A}=C(A) + O(A, L-1) + 1$$
  
 $U^{A}=C(A) + O(A, L)$ 

## **BWA Heuristics**

- Lower bound array D, where D(i) := LB on number of differences of exactly matching R[0,i] with the reference (can be computed in O(|R|) time  $\rightarrow$  check n < D(i) instead of n < 0)
- Process best partial alignments first: use a *min*-priority heap to store alignment entries (instead of recursion)
- Prune out alignments considered sub-optimal (although they might have fewer than *n* differences):
   dynamically adjust search parameters (e.g. *n*):
  - (1) stop if # top hits exceeds a threshold (=30),
  - (2) set n = nbest + 1, where nbest is the # of differences in top hit
- $^{\circ}$  Seeding: limit the number of differences in the **seed** sequence (first k bp)
- Disallow indels at the ends of the read