CSCI x490 Algorithms for Computational Biology

Lecture Note 1 (by Liming Cai)

January 19, 2016

▶ Part I. Introduction to Algorithms (Chapter 2)

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- ▶ Part II. Fundamental Techniques (Chapters 4 6)

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Chapter 2. Algorithms and Complexity

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Example: Algorithm MAX; 
 \textit{Input}: List x = \{a_1, \cdots, a_n\}; 
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An algorithm: a *finite process* to compute a function or a relation.



Notation conventions for algorithm writing (pseudo-code)

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Memory: variables, arrays, arguments, parameters

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For Loop: **for** $i \leftarrow low$ **to** high

bodu

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body 1

else

body 2

For Loop: **for** $i \leftarrow low$ **to** high body

While Loop: **while** condition is true body

Example: an iterative algorithm computing the nth number in the Fibonacci series 1, 1, 2, 3, 5, 8, 13, 21,

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Fibonacci (n)

- 1. $F_1 \leftarrow 1$
- 2. $F_2 \leftarrow 1$
- 3. for $i \leftarrow 3$ to n
- 4. $F_i \leftarrow F_{i-1} + F_{i-2}$
- 5. return (F_n)

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How is the algorithm executed?

Recursive algorithms

Recursive algorithms

5. **return** $(T_1 + T_2)$;

```
REC-FIBONACCI(n)

1. if n = 1 OR n = 2, return (1)

2. else

3. T_1 = \text{REC-FIBONACCI}(n-1);

4. T_2 = \text{REC-FIBONACCI}(n-2);
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Recursive algorithms

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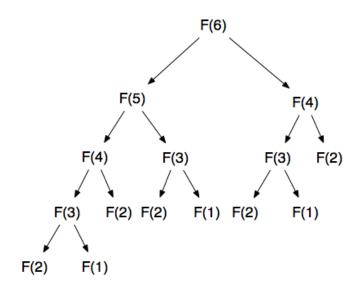
4. T_2 = \text{REC-FIBONACCI}(n-2);

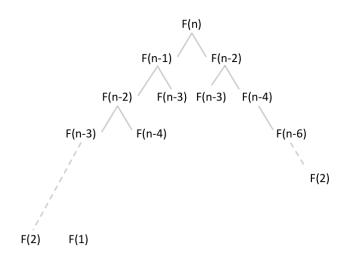
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Rec-Fibonacci(n)
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Advantages with recursive algorithms

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Key ingredients for admitting recursive algorithms

More examples

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More examples Sum(n), linear search,

Advantages with recursive algorithms

Example: recursive StringCopy

Key ingredients for admitting recursive algorithms

More examples Sum(n), linear search, summation over numbers in a 'triangle', etc.

A more complex example: Towers of Hanoi

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 $TowersOfHanoi(First,\,Second,\,Third,\,n)$

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- (1) overhead: use of stacks: push/pop
- (2) possible re-computation:
 - e.g., RecFib(5) may be computed several times

Algorithm Efficiency: how is it defined?

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Counting the number of basic operations used

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Counting the number of basic operations used

Example

```
 \begin{array}{l} \textbf{SelectionSort}(a,n) \\ 1 \textbf{ for } i \leftarrow 1 \textbf{ to } n-1 \\ 2. \quad j \leftarrow i \qquad \{ \text{starting of inner loop, assume } a_i \textbf{ to be} \\ \qquad \qquad \qquad the \textbf{ smallest elements in } a_i, \ldots, a_n \\ \qquad \qquad \qquad j \textbf{ memorizes the index of the smallest element} \ \} \\ 3. \quad \textbf{for } k \leftarrow i+1 \textbf{ to } n \quad \{ \text{search for the smallest element} \} \\ 4. \qquad \textbf{if } a_k < a_j \\ 5. \qquad j \leftarrow k \\ 6. \quad \text{Swap } a_i \textbf{ and } a_j \\ 7 \textbf{ return array } a \\ \end{array}
```

Algorithm Efficiency (cont')

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Count the total number of basic operations needed:

$$=c_1\times n + c_2\times (n-1) + c_3\times \sum_{i=1}^{n-1}(n-i) + c_{4,5}\times \sum_{i=1}^{n-1}(n-i-1) + c_6\times (n-1) + c_7$$

$$=an^2 + b^n + c \quad \text{for some constant } a>0,b,c$$

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\mathsf{RecFib}(n)
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$$\mathbf{return} \; \big(\mathsf{RecFib}(n-1) \, + \, \mathsf{RecFib}(n-2) \big)$$

Deriving and solving recurrences!

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- solve it exactly,

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- solve it exactly, or
- estimate lower and upper bounds.



$$t(n) = c + t(n-1) + t(n-2)$$

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 where $t(n) = 1, \ \ \text{when} \ n = 1, 2$

• Estimate the lower and upper bounds of t(n), based on the recursive tree structure:

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 where $t(n) = 1, \ \ \text{when} \ n = 1, 2$

• Estimate the lower and upper bounds of t(n), based on the recursive tree structure:

lower bound:
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ullet Solve it exactly: assume $t(n)=lpha^n$, we have

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$$\alpha^n = c + \alpha^{n-1} + \alpha^{n-2}$$

$$\alpha^2 = \alpha + 1$$

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$$\alpha^n = c + \alpha^{n-1} + \alpha^{n-2}$$

$$\alpha^2 = \alpha + 1 \text{ i.e., } \alpha^2 - \alpha - 1 = 0$$

$$t(n) = c + t(n-1) + t(n-2) \label{eq:tn}$$
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$$\begin{split} \alpha^n &= c + \alpha^{n-1} + \alpha^{n-2} \\ \alpha^2 &= \alpha + 1 \quad \text{i.e., } \alpha^2 - \alpha - 1 = 0 \\ \alpha &= (1 + \sqrt{5})/2 \approx 1.618 \end{split}$$

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$$\alpha^2 = \alpha + 1 \text{ i.e., } \alpha^2 - \alpha - 1 = 0$$

$$\alpha = (1 + \sqrt{5})/2 \approx 1.618$$
So $t(n) \approx 1.618^n$

Analysis of recursive algorithms (cont')

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```
Another example: Search a sorted list (of indexes i, \ldots, j) for a key
BINARYSEARCH (L, i, j, key)
1. if i > j return (0) {base case, list is empty, not found}
else
     let m \leftarrow \lceil \frac{i+j}{2} \rceil {get mid point index }
3.
     if key = L_m return(m) { found }
4.
5.
     else
        if key < L_m BINARYSEARCH (L, i, m-1, key) { search the left half list}
6.
7.
       else { key > L_m }
          BINARYSEARCH (L, m + 1, j, key) { search the right half list}
8.
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Analysis of recursive algorithms (cont')

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BINARYSEARCH (L,m+1,j,key) { search the right half list}
```

Can you write an iterative algorithm for binary search?

Assume t(n) to be total time to for BINARYSEARCH (L, i, j, key) where n = j - i + 1, the length of the list to be searched.

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$$\dots$$

$$t(n) = c + c + c + \dots + c + t(\lfloor \frac{n}{2^k} \rfloor)$$

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Big-O notation for complexity

O(n) includes n, 3n + 15, 1000n, 0.001n, etc.

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- O(n) also includes \sqrt{n} , $\log_2 n$, etc.

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polynomial time vs exponential time.

i.e, tractable problems vs intractable problems

Algorithm design techniques (included in this class)

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exhaustive search (including branch-and-bound)

Algorithm design techniques (included in this class)

exhaustive search (including branch-and-bound) greed algorithms

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Chapter 2. Algorithms and Complexity

Algorithm design techniques (included in this class)

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Part II. Fundamental Techniques

Chapter 4. Exhaustive Search

motif finding, median string problems

Chapter 5. Greedy Algorithms

genome rearrangement

Chapter 6. Dynamic Programming

sequence alignment, multiple alignment, gene finding

4.4 Regulatory motifs in DNA sequences

Sequence motifs regulate (turn on/off) gene expression

Example:

transcriptional binding sites TCGGGGATTCC transcriptional factor: protein that binds to the site allows RNA polymerase to transcribe downstream genes called l-mers

Upstream sequences of genes

CGGGGCTATGCAACTGGGTCGTCACATTCCCCTTTCGATA
TTTGAGGGTGCCCAATAAATGCAACTCCAAAGCGGACAAA
GGATGCAACTGATGCCGTTTGACGACCTAAATCAACGGCC
AAGGATGCAACTCCAGGAGCGCCTTTGCTGGTTCTACCTG
AATTTTCTAAAAAGATTATAATGTCGGTCCATGCAACTTC
CTGCTGTACAACTGAGATCATGCTGCATGAACTTTCAAC
TACATGATCTTTTGATGCAACTTGGATGATGATGAGGGAATGC

motifs are underscored.

Upstream sequences of genes

motifs are underscored.

CGGGGCTATGCAACTGGGTCGTCACATTCCCCTTTCGATA
TTTGAGGGTGCCCAATAAATGCAACTCCAAAGCGGACAAA
GGATGCAACTGATGCCGTTTGACGACCTAAATCAACGGCC
AAGGATGCAACTCCAGGAGCGCCTTTGCTGGTTCTACCTG
AATTTCTAAAAAGATTATAATGTCGGTCCATGCAACTTC
CTGCTGTACAACTGAGATCATGCTGCATGCAACTTTCAAC
TACATGATCTTTTGATGCAACTTGGATGATGATGAGGGAATGC

underlines are removed.

Upstream sequences of genes

CGGGGCTATGCAACTGGGTCGTCACATTCCCCTTTCGATA
TTTGAGGGTGCCCAATAAATGCAACTCCAAAAGCGGACAAA
GGATGCAACTGATGCCGTTTGACGACCTAAATCAACGGCC
AAGGATGCAACTCCAGGAGCGCCTTTGCTGGTTCTACCTG
AATTTTCTAAAAAAGATTATAATGTCGGTCCATGCAACTTC
CTGCTGTACAACTGAGATCATGCTGCATGCAACTTTCAAC
TACATGATCTTTTGATGCAACTTGGATGATGATGAGGGAATGC

motifs are underscored.

CGGGGCTATGCAACTGGGTCGTCACATTCCCCTTTCGATA
TTTGAGGGTGCCCAATAAATGCAACTCCAAAGCGGACAAA
GGATGCAACTGATGCCGTTTGACGACCTAAATCAACGGCC
AAGGATGCAACTCCAGGAGCGCCTTTGCTGGTTCTACCTG
AATTTTCTAAAAAGATTATAATGTCGGTCCATGCAACTTC
CTGCTGTACAACTGAGATCATGCTGCATGCAACTTTCAAC
TACATGATCTTTTGATGCAACTTGGATGATGATGAGGGAATGC

underlines are removed.

All motifs are the same ATGCAACT.



two mutations in every motif.

CGGGGCTAT-CAgCTGGGTCGTCACATTCCCCTTTCGATA
TTTGAGGGTGCCCAATAAggGCAACTCCAAAGCGGACAAA
GGATGgA+CTGATGCCGTTTGACGACCTAAATCAACGGCC
AAGGAAGCAACCCCAGGAGCGCCTTTGCTGGTTCTACCTG
AATTTTCTAAAAAGATTATAATGTCGGTCC+TGgAACTTC
CTGCTGTACAACTGAGATCATGCTGCATGCAA+TTTCAAC
TACATGATCTTTTGATGgCACTTGGATGATGAGGGAATGC

two mutations in every motif.

CGGGGCTAT-CAgCTGGGTCGTCACATTCCCCTTTCGATA
TTTGAGGGTGCCCAATAAggGCAACTCCAAAGCGGACAAA
GGATGgA+CTGATGCCGTTTGACGACCTAAATCAACGGCC
AAGGAaGCAACCCCAGGAGCGCCTTTGCTGGTTCTACCTG
AATTTCTAAAAAGATTATAATGTCGGTCC+TGGAACTTC
CTGCTGTACAACTGAGATCATGCTGCATGCAA+TTTCAAC
TACATGATCTTTTGATGgCACTTGGATGATGAGGGAATGC

CGGGGCTATCCAGCTGGGTCGTCACATTCCCCTTTCGATA
TTTGAGGGTGCCCAATAAGGGCAACTCCAAAGCGGACAAA
GGATGGATCTGATGCCGTTTGACGACCTAAATCAACGGCC
AAGGAAGCAACCCCAGGAGCGCCTTTGCTGGTTCTACCTG
AATTTCTAAAAAGATTATAATGTCGGTCCTTGGAACTTC
CTGCTGTACAACTGAGATCATGCTGCATGCAATTTTCAAC
TACATGATCTTTTGATGGCACTTGGATGATGATGAGGGAATGC

underscores are removed.

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CGGGGCTAT-CAgCTGGGTCGTCACATTCCCCTTTCGATA
TTTGAGGGTGCCCAATAAggGCAACTCCAAAGCGGACAAA
GGATGgAtCTGATGCCGTTTGACGACCTAAATCAACGGCC
AAGGAaGCAACCCCAGGAGCGCCTTTGCTGGTTCTACCTG
AATTTCTAAAAAGATTATAATGTCGGTCCtTGgAACTTC
CTGCTGTACAACTGAGATCATGCTGCATGCAatTTTCAAC
TACATGATCTTTTGATGgCACTTGGATGATGAGGGAATGC

CGGGGCTATCCAGCTGGGTCGTCACATTCCCCTTTCGATA
TTTGAGGGTGCCCAATAAGGGCAACTCCAAAGCGGACAAA
GGATGGATCTGATGCCGTTTGACGACCTAAATCAACGGCC
AAGGAAGCAACCCCAGGAGCGCCTTTGCTGGTTCTACCTG
AATTTCTAAAAAGATTATAATGTCGGTCCTTGGAACTTC
CTGCTGTACAACTGAGATCATGCTGCATGCAATTTTCAAC
TACATGATCTTTTGATGGCACTTGGATGATGATGAGGGAATGC

underscores are removed.

How do identify these motifs?



4.5 Profiles for motifs

CGGGGCTatccagctGGGTCGTCACATTCCCCTTTCGATA

 ${\tt TTTGAGGGTGCCCAATAAgggcaactCCAAAGCGGACAAA}$

GGatggatctGATGCCGTTTGACGACCTAAATCAACGGCC

AAGGaagcaaccCCAGGAGCGCCTTTGCTGGTTCTACCTG

CTAAAAGATTATAATGTCGGTCCttggaactTC

 ${\tt CTGTACATCATGCTGCatgccatt}{\tt TTCAAC}$

TACATGATCTTTTGatggcactTGGATGATGAGGGAATGC

motifs are in lower case; they are aligned to build a profile.

4.5 Profiles for motifs

CGGGGCTatccagctGGGTCGTCACATTCCCCTTTCGATA

 ${\tt TTTGAGGGTGCCCAATAAgggcaactCCAAAGCGGACAAA}$

GGatggatctGATGCCGTTTGACGACCTAAATCAACGGCC

AAGGaagcaaccCCAGGAGCGCCTTTGCTGGTTCTACCTG

CTAAAAGATTATAATGTCGGTCCttggaactTC

 ${\tt CTGTACATCATGCTGCatgccattTTCAAC}$

TACATGATCTTTTGatggcactTGGATGATGAGGGAATGC

motifs are in lower case; they are aligned to build a profile.

Let $s = \{8, 19, 3, 5, 24, 17, 15\}$ be set of starting positions in sample sequences.

Then profile P(s)

CGGGGCTatccagctGGGTCGTCACATTCCCCTTTCGATA

 ${\tt TTTGAGGGTGCCCAATAAgggcaactCCAAAGCGGACAAA}$

GGatggatctGATGCCGTTTGACGACCTAAATCAACGGCC

AAGGaagcaaccCCAGGAGCGCCTTTGCTGGTTCTACCTG

CTAAAAGATTATAATGTCGGTCCttggaactTC

 ${\tt CTGTACATCATGCTGCatgccattTTCAAC}$

 ${\tt TACATGATCTTTTGatggcactTGGATGATGAGGGAATGC}$

Then profile P(s)

CGGGGCTatccagctGGGTCGTCACATTCCCCTTTCGATA

TTTGAGGGTGCCCAATAAgggcaactCCAAAGCGGACAAA

GGatggatctGATGCCGTTTGACGACCTAAATCAACGGCC

AAGGaagcaaccCCAGGAGCGCCTTTGCTGGTTCTACCTG

CTAAAAGATTATAATGTCGGTCCttggaactTC

CTGTACATCATGCTGCatgccattTTCAAC

TACATGATCTTTTGatggcactTGGATGATGAGGGAATGC

Consensus of 7 motifs (of length 8)

nucleotide/position	1	2	3	4	5	6	7	8
А	5	1	0	0	5	5	0	0
C	0	0	1	4	2	0	6	1
G	1	1	6	3	0	1	0	0
T	1	5	0	0	0	1	1	6
Consensus	Α	T	G	С	Α	Α	С	T

4.6 The motif finding problem

Given profile P(s)

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A	5	1	0	0	5	5	0	0
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Consensus	Α	Т	G	С	Α	A	С	T

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Consensus	A	T	G	С	A	Α	С	T

Let $M_{P(s)}(j)$ be the largest count in column j, e.g., $M_{P(s)}(1)=5\,$

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Consensus	A	T	G	С	A	Α	С	T

Let $M_{P(s)}(j)$ be the largest count in column j, e.g., $M_{P(s)}(1)=5$

Then consensus score
$$Score(s, DNA) = \sum_{j=1}^{l} M_{P(s)}(j)$$
.

e.g.
$$Score(s, DNA) = 5 + 5 + 6 + 4 + 5 + 5 + 6 + 6 = 42$$

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Let $M_{P(s)}(j)$ be the largest count in column j, e.g., $M_{P(s)}(1)=5$

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e.g.
$$Score(s, DNA) = 5 + 5 + 6 + 4 + 5 + 5 + 6 + 6 = 42$$

If the motif has length \boldsymbol{l} and there are \boldsymbol{t} sequences, then

The best possible alignment has score: $l \times t$

The worst possible alignment score is $\frac{lt}{4}$

MOTIF FINDING PROBLEM: Given a set of DNA sequences, find a set of l-mers, one from each sequence, that maximizes the consensus score.

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A related problem is finding a *median string*.

Given two l-mers v and w, we can compute the $Hamming\ distance$ between v and w:

 $d_H(v,w)$ as the number of positions that differ in v and w.

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By abusing the notation a little, let $d_H(v,s_i)$ be the Hamming distance between v and the l-mer starting at position s_i in the ith sequence.

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By abusing the notation a little, let $d_H(v,s_i)$ be the Hamming distance between v and the l-mer starting at position s_i in the ith sequence.

And define

$$d_H(v,s) = \sum_{i=1}^t d_H(v,s_i)$$

where $s = \{s_1, s_2, \dots, s_t\}.$

Define

$$TotalDistance(v,DNA) = \min_{all\,s}(d_H(v,s))$$

where the minimization is taken over all s's.

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MEDIAN STRING PROBLEM: Given a set of DNA sequences, find a median string

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MEDIAN STRING PROBLEM: Given a set of DNA sequences, find a median string

Input: A $t \times n$ matrix DNA sequences and length l Output: A string v of length l that minimizes TotalDistance(v,DNA) over all strings of length l.

MEDIAN STRING PROBLEM and MOTIF FINDING PROBLEM are computationally equivalent!

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e.g., w = ATGCAACT, $s = \{8, 19, 3, 5, 24, 17, 15\}$, l = 8, t = 7, Score(s, DNA) = 42. Indeed,

$$d_H(w,s) = 2 \times 7 = 14 = 7 \times 8 - 42$$

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But why?

The consensus string w minimizes $d_H(v,s)$ over all choices of v and it maximizes score Score(s,DNA):

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$$d_H(w,s) = \min_{all\ v} d_H(v,s) = lt - Score(s,DNA)$$

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$$d_H(w,s) = \min_{all\; v} d_H(v,s) = lt - Score(s,DNA)$$

$$\min_{all \, s} \min_{all \, v} d_H(v, s) = lt - \max_{all \, s} Score(s, DNA)$$

The consensus string w minimizes $d_H(v,s)$ over all choices of v and it maximizes score Score(s,DNA):

$$d_H(w, s) = \min_{all \ v} d_H(v, s) = lt - Score(s, DNA)$$

$$\min_{all \ s} \min_{all \ v} d_H(v, s) = lt - \max_{all \ s} Score(s, DNA)$$

Left is the goal of MEDIAN FINDING PROBLEM; and right is the goal of MOTIF FINDING PROBLEM.

The two problems can also be solved using the same technique!

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The main general issue is to consider all k^L L-mers for k-letter alphabet.

The two problems can also be solved using the same technique!

Exhaustive search for MOTIF FINDING PROBLEM: By considering all $(n-l+1)^t$ positions s.

Exhaustive search for MEDIAN STRING PROBLEM: By considering all 4^l l-mers.

The two searches are similar if we consider the 4 nucleotides to be numbers.

The main general issue is to consider all k^L L-mers for k-letter alphabet.

How to enumerate them?

4.7 Search trees

4.7 Search trees

```
\begin{array}{ll} \text{NEXTLEAF}(a,L,k) \\ 1. & \text{for } i \leftarrow L \text{ to } 1 \\ 2. & \text{if } a_i < k \\ 3. & a_i \leftarrow a_i + 1 \\ 4. & \text{return } a \\ 5. & a_i \leftarrow 1 \\ 6. & \text{return } a \end{array}
```

4.7 Search trees

```
\begin{array}{lll} \operatorname{NEXTLEAF}(a,L,k) \\ 1. & \text{ for } i \leftarrow L \text{ to } 1 \\ 2. & \text{ if } a_i < k \\ 3. & a_i \leftarrow a_i + 1 \\ 4. & \text{ return } a \\ 5. & a_i \leftarrow 1 \\ 6. & \text{ return } a \\ \end{array} where  a \text{ is an } L\text{-mer, an array of length } L \text{ (indexed } 1 \text{ to } L); \\ \text{ for } i, 1 \leq i \leq L, \text{ element } a_i \text{ has value ranging from } 1 \text{ to } k; \\ \end{array}
```

What does the function NEXTLEAF do?

4.7 Search trees

```
NextLeaf(a, L, k)
1. for i \leftarrow L to 1
2. if a_i < k
3. a_i \leftarrow a_i + 1
4.
    return a
5.
  a_i \leftarrow 1
6.
     return a
where
    a is an L-mer, an array of length L (indexed 1 to L);
    for i, 1 \le i \le L, element a_i has value ranging from 1 to k;
```

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```
NEXTLEAF(a, L, k) { with comments }

1. for i \leftarrow L to 1 { from low to high digits }

2. if a_i < k

3. a_i \leftarrow a_i + 1 {increment the first digit not yet reaching k}

4. return a

5. a_i \leftarrow 1 {set the digit back to 1 if having reached k, carried to the next higher digit}

6. return a
```

```
NEXTLEAF(a, L, k) { with comments }

1. for i \leftarrow L to 1 { from low to high digits }

2. if a_i < k

3. a_i \leftarrow a_i + 1 {increment the first digit not yet reaching k}

4. return a

5. a_i \leftarrow 1 {set the digit back to 1 if having reached k, carried to the next higher digit}

6. return a
```

Search tree:

- each node can have k children;
- there are L levels of nodes;
- leaves are L-mers;
- NEXTLEAF is used to navigate from one leaf to the next one;

Enumerate all L-mers for a k-letter alphabet

Enumerate all L-mers for a k-letter alphabet

```
ALLLEAVES(L,k)
1. a \leftarrow (1,\ldots,1)
2. continue \leftarrow \mathsf{TRUE}
3. while continue
4. print a
5. NEXTLEAF(a,L,k)
6. if a=(1,\ldots,1)
7. continue \leftarrow \mathsf{FALSE}
8. return
```

Enumerate all L-mers for a k-letter alphabet

```
ALLLEAVES(L,k)
1. a \leftarrow (1,\ldots,1)
2. continue \leftarrow \mathsf{TRUE}
3. while continue
4. print a
5. NEXTLEAF(a,L,k)
6. if a=(1,\ldots,1)
7. continue \leftarrow \mathsf{FALSE}
8. return
```

Only go through all leaves, not internal nodes.

How big is such a search tree?

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- Number of leaves is k^L for a k-letter alphabet.

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- Number of leaves is k^L for a k-letter alphabet.
- Number of internal nodes is $(k^L 1)/(k 1)$.

How big is such a search tree?

- Number of leaves is k^L for a k-letter alphabet.
- Number of internal nodes is $(k^L 1)/(k 1)$.
- Total number of nodes is $(k^{L+1}-1)/(k-1)$.

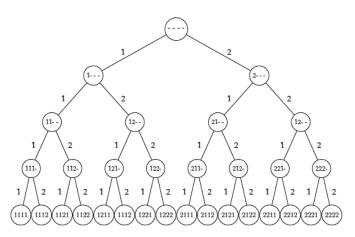


Figure 4.6 All 4-mers in the two-letter alphabet $\{1,2\}$ can be represented as leaves in a tree.

An alternative search program (going through internal nodes):

```
\begin{array}{lll} \operatorname{NEXTVERTEX}(a,i,L,k) \\ 1. & \text{ if } i < L & \{ \text{ not yet at the bottom level, go one level } \} \\ 2. & a_{i+1} \leftarrow 1 & \{ \text{ deeper, follow the leftmost branch } \} \\ 3. & \text{ return } (a,i+1) \\ 4. & \text{ else } & \{ \text{ do as NEXTLEAF } \} \\ 5. & \text{ for } j \leftarrow L \text{ to } 1 & \{ \text{ when this starts, } j = L, \text{ bottom level } \} \\ 6. & \text{ if } a_j < k & \{ \text{ when } j \neq L, \text{ it is not at bottom level} \} \\ 7. & a_j \leftarrow a_j + 1 & \{ \text{ but an internal node} \} \\ & \text{ return}(a,j) \\ 9. & \text{ return } (a,0) \\ \end{array}
```

An alternative search program (going through internal nodes):

```
\begin{array}{lll} \operatorname{NEXTVERTEX}(a,i,L,k) \\ 1. & \text{ if } i < L & \{ \text{ not yet at the bottom level, go one level } \} \\ 2. & a_{i+1} \leftarrow 1 & \{ \text{ deeper, follow the leftmost branch } \} \\ 3. & \text{ return } (a,i+1) \\ 4. & \text{ else } & \{ \text{ do as NEXTLEAF } \} \\ 5. & \text{ for } j \leftarrow L \text{ to } 1 & \{ \text{ when this starts, } j = L, \text{ bottom level } \} \\ 6. & \text{ if } a_j < k & \{ \text{ when } j \neq L, \text{ it is not at bottom level} \} \\ 7. & a_j \leftarrow a_j + 1 & \{ \text{ but an internal node} \} \\ 8. & \text{ return}(a,j) \\ 9. & \text{ return } (a,0) \\ \end{array}
```

Why going through internal nodes?

An alternative search program (going through internal nodes):

```
NextVertex(a, i, L, k)
1. if i < L { not yet at the bottom level, go one level }
  a_{i+1} \leftarrow 1 { deeper, follow the leftmost branch }
3.
      return (a, i+1)
4.
  else { do as NextLeaf }
5.
      for j \leftarrow L to 1 { when this starts, j = L, bottom level }
        if a_i < k { when i \neq L, it is not at bottom level}
6.
          a_i \leftarrow a_i + 1 { but an internal node}
8.
          return(a, j)
    return (a,0)
9.
```

Why going through internal nodes?

For the purpose of pruning tree branches (avoiding unnecessary enumerations) to save time!

The method of **branch-and-bound**:

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While traversing a search tree, it is possible to skip a whole subtree rooted at certain vertex.

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While traversing a search tree, it is possible to skip a whole subtree rooted at certain vertex.

How?

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While traversing a search tree, it is possible to skip a whole subtree rooted at certain vertex.

How?

At each vertex, we calculate a bound – the most optimistic score of any leaves within its subtree (which will be discussed later).

And using the following function to skip:

The method of **branch-and-bound**:

While traversing a search tree, it is possible to skip a whole subtree rooted at certain vertex.

How?

At each vertex, we calculate a bound – the most optimistic score of any leaves within its subtree (which will be discussed later).

And using the following function to skip:

```
\begin{array}{lll} {\rm ByPASS}(a,i,L,k) \\ {\rm 1.} & \mbox{ for } j \leftarrow i \mbox{ to } 1 \\ {\rm 2.} & \mbox{ if } a_j < k \\ {\rm 3.} & a_j \leftarrow a_j + 1 \\ {\rm 4.} & \mbox{ return}(a,j) \\ {\rm 5.} & \mbox{ return } (a,0) \end{array}
```

4.8 Algorithms for Finding Motifs

First brute force algorithm for motif finding:

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First brute force algorithm for motif finding:

```
BRUTEFORCEMOTIFSEARCH(DNA, t, n, l)
```

- 1. $bestScore \leftarrow 0$
- 2. for each $s=(s_1,...,s_t)$ from (1,...,1) to (n-l+1,...,n-l+1)
- $\mathbf{3.} \qquad \mathbf{if} \ Score(s,DNA) > bestScore$
- 4. $bestScore \leftarrow Score(s, DNA)$
- 5. $bestMotif \leftarrow s$
- 6. return bestMotif

4.8 Algorithms for Finding Motifs

First brute force algorithm for motif finding:

```
BRUTEFORCEMOTIFSEARCH(DNA,t,n,l)

1. bestScore \leftarrow 0

2. for each s = (s_1,...,s_t) from (1,...,1) to (n-l+1,...,n-l+1)

3. if Score(s,DNA) > bestScore

4. bestScore \leftarrow Score(s,DNA)

5. bestMotif \leftarrow s

6. return bestMotif
```

Line 2 enumerates of all tuples (1, ..., 1) to (n - l + 1, ..., n - l + 1);

Using subroutine $\ensuremath{\mathrm{NEXTLEAF}}$ to enumerate tuples;

Using subroutine $\operatorname{NEXTLEAF}$ to enumerate tuples;

```
BruteForceMotifSearchAgain(DNA, t, n, l)
     s \leftarrow (1, ..., 1)
   bestScore \leftarrow Score(s, DNA)
3.
     while forever
    s \leftarrow \text{NextLeaf}(s, t, n - l + 1)
4.
5.
       if Score(s, DNA) > bestScore
6.
         bestScore \leftarrow Score(s, DNA)
7.
         bestMotif \leftarrow (s1,...,s_t)
8.
    if s = (1, ..., 1)
9.
         return bestMotif
```

Using subroutine $\operatorname{NEXTLEAF}$ to enumerate tuples;

```
\begin{array}{lll} \text{BruteForceMotifSearchAgain}(DNA,t,n,l) \\ 1. & s \leftarrow (1,...,1) \\ 2. & bestScore \leftarrow Score(s,DNA) \\ 3. & \textbf{while} \text{ forever} \\ 4. & s \leftarrow \text{NextLeaf}(s,t,n-l+1) \\ 5. & \textbf{if } Score(s,DNA) > bestScore \\ 6. & bestScore \leftarrow Score(s,DNA) \\ 7. & bestMotif \leftarrow (s1,...,s_t) \\ 8. & \textbf{if } s = (1,...,1) \\ 9. & \textbf{return } bestMotif \end{array}
```

There are $(n-l+1)^t$ such tuples;

Using subroutine $\operatorname{NEXTLEAF}$ to enumerate tuples;

```
BruteForceMotifSearchAgain(DNA, t, n, l)
     s \leftarrow (1, ..., 1)
   bestScore \leftarrow Score(s, DNA)
3.
     while forever
4. s \leftarrow \text{NextLeaf}(s, t, n - l + 1)
5. if Score(s, DNA) > bestScore
6.
         bestScore \leftarrow Score(s, DNA)
7.
        bestMotif \leftarrow (s1, ..., s_t)
8. if s = (1, ..., 1)
9.
         return bestMotif
There are (n-l+1)^t such tuples;
```

Computing Score(s, DNA) takes $O(l \times t)$ steps;

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Using subroutine $\operatorname{NEXTLEAF}$ to enumerate tuples;

```
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     s \leftarrow (1, ..., 1)
   bestScore \leftarrow Score(s, DNA)
3.
     while forever
4. s \leftarrow \text{NextLeaf}(s, t, n - l + 1)
5. if Score(s, DNA) > bestScore
6.
         bestScore \leftarrow Score(s, DNA)
7.
         bestMotif \leftarrow (s1, ..., s_t)
8. if s = (1, ..., 1)
9.
         return bestMotif
There are (n-l+1)^t such tuples:
Computing Score(s, DNA) takes O(l \times t) steps;
So the complexity is O(lt(n-l+1)^t);
```

Using subroutine $\ensuremath{\mathrm{NEXTVERTEX}}\xspace$:

Using subroutine NEXTVERTEX:

```
SIMPLEMOTIFSEARCH(DNA, t, n, l)
     s \leftarrow (1, ..., 1)
2. bestScore \leftarrow 0
3. \quad i \leftarrow 1
     while i > 0
5. if i < t
6.
           (s, i) \leftarrow \text{NEXTVERTEX} (s, i, t, n - l + 1)
7.
       else
8.
          if Score(s, DNA) > bestScore
9.
             bestScore \leftarrow Score(s, DNA)
10.
              bestMotif \leftarrow s
11.
            (s, i) \leftarrow \text{NextVertex}(s, i, t, n - l + 1)
       return bestMotif
12.
```

Using subroutine NEXTVERTEX:

```
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7.
      else
8.
          if Score(s, DNA) > bestScore
9.
             bestScore \leftarrow Score(s, DNA)
10.
              bestMotif \leftarrow s
11.
            (s, i) \leftarrow \text{NextVertex}(s, i, t, n - l + 1)
       return bestMotif
12.
```

Still without branch-and-bound heuristics

With a branch-and-bound heuristics:

With a branch-and-bound heuristics:

```
BranchAndBoundMotifSearch(DNA, t, n, l)
     s \leftarrow (1, ..., 1)
   bestScore \leftarrow 0
2.
3. i \leftarrow 1
    while i > 0
5.
    if i < t
6.
          optimisticScore \leftarrow Score(s, i, DNA) + (t - i) \cdot l
7.
          if optimisticScore < bestScore
             (s,i) \leftarrow \text{ByPass}(s,i,t,n-l+1)
8.
9.
          else
10.
              (s, i) \leftarrow \text{NextVertex} (s, i, t, n - l + 1)
11.
         else
12.
            if Score(s, DNA) > bestScore
13.
              bestScore \leftarrow Score(s, DNA)
14.
              bestMotif \leftarrow s
15.
            (s, i) \leftarrow \text{NEXTVERTEX}(s, i, t, n - l + 1)
16.
       return bestMotif
```

4.9 Finding a median string

4.9 Finding a median string

BruteForceMedianSearch(DNA, t, n, l)

- 1. $bestWord \leftarrow \texttt{AAA}...\texttt{AAA}$
- 2. $bestDistance \leftarrow \infty$
- 3. **for** each l-mer $word \leftarrow \texttt{AAA}...\texttt{AAA}$ **to** TTT...TTT
- 4. **if** TotalDistance (word, DNA) < bestDistance
- 5. $bestDistance \leftarrow TotalDistance(word, DNA)$
- 6. $bestWord \leftarrow word$
- 7. $return \ bestWord$

Using subroutine NEXTVERTEX:

Using subroutine NEXTVERTEX:

```
SIMPLEMEDIANSEARCH(DNA, t, n, l)
1. s \leftarrow (1, ...1)
2. bestDistance \leftarrow \infty
3. i \leftarrow 1
4. while i > 0
5. if i < l
6.
          (s,i) \leftarrow \text{NEXTVERTEX}(s,i,l,4)
7.
      else
8.
          word \leftarrow \text{nucleotide string from } (s_1, ..., s_l)
          if TotalDistance (word, DNA) < best Distance
9.
10.
              bestDistance \leftarrow TotalDistance (word, DNA)
11.
              bestWord \leftarrow word
12.
           (s,i) \leftarrow \text{NEXTVERTEX}(s,i,l,4)
13.
       return bestWord.
```

With a branch-and-bound strategy:

With a branch-and-bound strategy:

```
BranchAndBoundMedianSearch(DNA, t, n, l)
     s \leftarrow (1, ...1)
1.
2. bestDistance \leftarrow \infty
3. i \leftarrow 1
    while i > 0
5.
        if i < l
6
          prefix \leftarrow \text{nucleotide string from } (s_1, ... s_i)
7.
          optimisticDistance \leftarrow TotalDistance(prefix, DNA)
           if optimisticDistance > bestDistance
8.
             (s, i) \leftarrow \text{ByPass}(s, i, l, 4)
9.
10.
            else
               (s,i) \leftarrow \text{NextVertex}(s,i,l,4)
11.
12.
         else
13.
            word \leftarrow \text{nucleotide string from } (s_1, ..., s_l)
14
            if TotalDistance (word, DNA) < best Distance
               bestDistance \leftarrow TotalDistance (word, DNA)
15.
16.
               bestWord \leftarrow word
            (s,i) \leftarrow \text{NextVertex}(s,i,l,4)
17.
18.
       return bestWord.
```

How much time does it need to compute

TOTAL DISTANCE (word, DNA)?

How much time does it need to compute

TOTAL DISTANCE (word, DNA)?

and

TotalDistance(prefix, DNA)?

4.9 $\frac{1}{2}$ Profile-based Motif Search

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Extending the motif finding question:

Once a motif profile is established, how to find a motif from a new DNA sequence which fits the profile "well" ?

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Once a motif profile is established, how to find a motif from a new DNA sequence which fits the profile "well" ?

I.e., consider the following problem:

INPUT: a DNA sequence D, and motif profile P; OUTPUT: some position s in D such that Score(s,P) achieves the optimal.

4.9 $\frac{1}{2}$ Profile-based Motif Search

Extending the motif finding question:

Once a motif profile is established, how to find a motif from a new DNA sequence which fits the profile "well" ?

I.e., consider the following problem:

INPUT: a DNA sequence D, and motif profile P; OUTPUT: some position s in D such that Score(s,P) achieves the optimal.

where Score(s,P) is computed with the motif starting at position s against the profile P.

Two components are needed for the profile-based motif search:

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(1) scanning algorithm

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enumerating all positions on the DNA sequence

Two components are needed for the profile-based motif search:

- (1) scanning algorithm enumerating all positions on the DNA sequence
- (2) scoring method

Two components are needed for the profile-based motif search:

- (1) scanning algorithm enumerating all positions on the DNA sequence
- (2) scoring method computing score Score(sP), how ?

nucleotide/position	1	2	3	4	5	6	7	8
A	5	1	0	0	5	5	0	0
C	0	0	1	4	5 2	0	6	1
G	1	1	6	3	0	1	0	0
Т	1	5	0	0	0	1	1	6
Consensus	A	Т	G	С	Α	A	С	T

nucleotide/position	1	2	3	4	5	6	7	8
A	5	1	0	0	5	5	0	0
C	0	0	1	4	2	0	6	1
G	1	1	6	3	5 2 0	1	0	0
T	1	5	0	0	0	1	1	6
Consensus	Α	Т	G	С	Α	Α	С	Т
motif at position s :	G	Т	G	G	A	A	С	Т

nucleotide/position	1	2	3	4	5	6	7	8
A	5	1	0	0	5	5	0	0
C	0	0	1	4	2	0	6	1
G	1	1	6	3	0	1	0	0
T	1	5	0	0	0	1	1	6
Consensus	Α	Т	G	С	Α	Α	С	T
motif at position s :	G *	T +	G +	G *	A +	A +	C +	T +

nucleotide/position	1	2	3	4	5	6	7	8
A	5	1	0	0	5	5	0	0
C	0	0	1	4	2	0	6	1
G	1	1	6	3	0	1	0	0
Т	1	5	0	0	0	1	1	6
Consensus	A	T	G	С	A	A	С	Т
motif at position s :	G	T	G	G	A	A	C	T
	*	+	+	*	+	+	+	+

One method is to use Hamming distance,

$$Score(s, P) = 2$$

nucleotide/position	1	2	3		5		7	8
A	5	1	0	0	5	5	0	0
C	0	0	1	4	5 2	0	6	1
G	1	1	6	3	0	1	0	0
Т	1	5	0	0		1	1	6
Consensus	Α	T	G	С	Α	Α	С	T
motif at position s :	G	Т	G	G	A	A	С	Т

One method is to use Hamming distance,

$$Score(s, P) = 2$$

disadvantage?

(2) Statistical method

The profile gives probability $p_i(x)$ in the ith column, for $x \in \{A, C, G, T\}$, and $i = 1, 2, \dots, 8$.

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The profile gives probability $p_i(x)$ in the ith column, for $x \in \{A, C, G, T\}$, and $i = 1, 2, \dots, 8$.

$$Score(s, P) = p_1(G) \times p_2(T) \times \cdots \times p_8(T)$$

(2) Statistical method

The profile gives probability $p_i(x)$ in the ith column, for $x \in \{A, C, G, T\}$, and $i = 1, 2, \dots, 8$.

$$Score(s, P) = p_1(G) \times p_2(T) \times \cdots \times p_8(T)$$

But one question remains:

(2) Statistical method

The profile gives probability $p_i(x)$ in the ith column, for $x \in \{A, C, G, T\}$, and $i = 1, 2, \dots, 8$.

$$Score(s, P) = p_1(G) \times p_2(T) \times \cdots \times p_8(T)$$

But one question remains:

how high a probability is for a motif to be considered acceptable?