# 7.1-7.4, 7.6 First Applications of Suffix Trees

2015/6/2 (Tue) ISA Donghyuk Kim

#### Contents

- APL1: Exact string matching
- APL2: Suffix trees and the exact set matching problem
- APL3: The substring problem for a database of patterns
- APL4: Longest common substring of two strings
- APL6: Common substrings of more than two strings

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- Case 1) Pattern and text are both known.
- Case 2) Only text is known first.
- Case 3) Only pattern is known first.

- Case 1) Considering the case that the pattern *P* and the text *T* are both known.
  - The use of suffix tree achieves the same worst-case bound, O(n+m+k), as the KMP or Boyer-Moore algorithms.
    - n: length of text T.
    - m: length of pattern P.

#### time complexity

suffix tree

Preprocessing : O(n)Search time : O(m+k) **KMP**, Boyer-Moore

Preprocessing : O(m)Search time : O(n+k)

- Case 2) When the text T is known first and kept fixed.
  - Using a suffix tree for T, all occurrences can be found in O(m+k) time.
    - m: length of pattern P.
    - k: the number of occurrences of P in T.
  - Totally independent of the size of *T*

KMP and Boyer-Moore can't.

- Case 3) When a pattern is first fixed and can be preprocessed before the text is known,
  - is the classic situation handled by KMP or Boyer-Moore algorithm.
  - Those algorithms spend O(m) preprocessing time,
    - so that the search can be done in O(n) time whenever a text T is specified.
  - Suffix trees can be used in this scenario to achieve the same time bound with reverse suffix trees.

- Case 1) Pattern and text are both known.
  - Suffix tree can run same performance as KMP and Boyer-Moore.
- Case 2) Only text is known first.
  - Suffix tree can run, but KMP and Boyer-Moore can't.
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This situation will be discussed along with a more general problem in Section 7.8.

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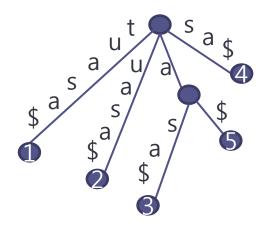
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Pattern 3: a s d m=3

**Exact set matching by suffix tree** 

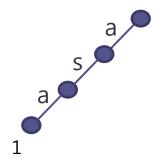
- preprocessing : O(n)

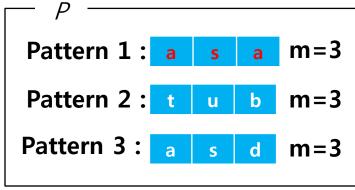
- searching : O(m)

#### Exact set matching problem

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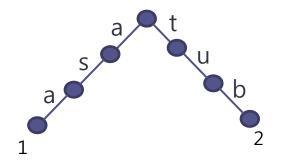


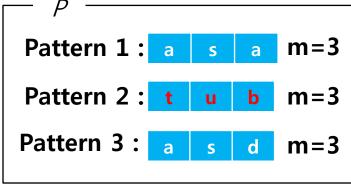
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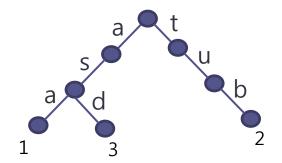


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**Exact set matching by keyword tree** 

- preprocessing : O(m)

- searching : O(n)

• The relative advantages of keyword trees versus suffix trees for the exact set matching problem.

n: length of text T

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- The relative advantages of keyword trees versus suffix trees for the exact set matching problem.
  - Aho-Corasick method (a keyword tree)
    - Build time : O(m)
    - Search time : O(n)
    - Find all occurrences in T of any pattern from P: O(m+n+k)

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  - Aho-Corasick method (a keyword tree)
    - Build time : O(m)
    - Search time : O(n)
    - Find all occurrences in T of any pattern from P : O(m+n+k)
  - Suffix tree T for T
    - Build time : O(n)
    - Search time : O(m)
    - Total time to search for all occurrences of each pattern in P: O(n+m+k)

n: length of text T

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- Case 1) set of patterns is larger than the text (n < m)
  - Space : suffix tree < Aho-Corasick method</li>
  - Search time: suffix tree > Aho-Corasick method
- Case 2) total size of the patterns is smaller than the text (n > m)
  - Space : suffix tree > Aho-Corasick method
  - Search time: suffix tree < Aho-Corasick method

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• There is a time/space trade-off and neither method is uniformly superior to the other in time and space.

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- The substring problem, a set of strings, or a database
  - Is first known and fixed.
  - Later, a sequence of strings will be presented and for each presented string *S*, the algorithm must find all the strings in the database containing *S* as a substring.

- In the context of databases for genomic DNA data,
  - The problem of finding substrings is cannot be solved by exact set matching.
- The DNA database contains a collection of previously sequenced DNA strings.

- When a new DNA string is sequenced,
  - It could be contained in an already sequenced string.
  - An efficient method to check that is of value.

#### **Example**)

#### A set of strings, or a database

$$S_1 = a p p l e$$
  
 $S_3 = m e l o n$ 

$$S_3 = \text{melon}$$

$$S_2 = t o m a t o$$

$$S_4 = b a n a n a$$

 $P_1$ : tom

 $P_2$ : melon

 $P_3$ : pineapple

 $P_4$ : watermelon

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- The opposite case is also possible
  - The new string contains one of the database strings.
    - But that is the case of exact set matching.

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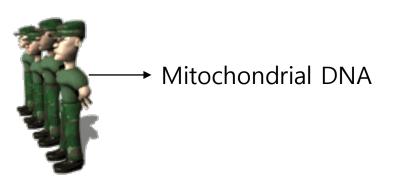
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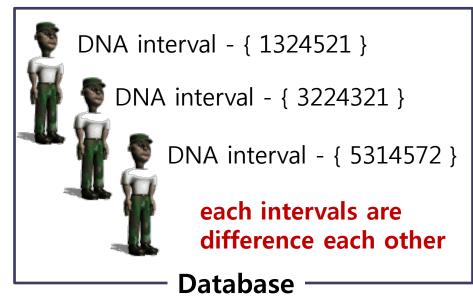
$$P_1$$
: tom  $P_2$ : melon

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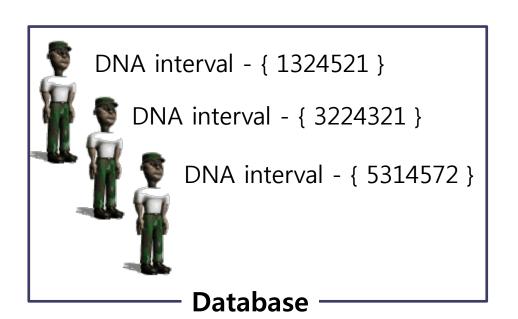
• Identifying the remains of U.S. military personnel.

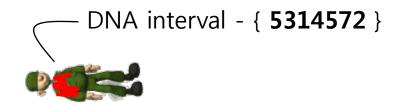
- Identifying the remains of U.S. military personnel.
  - Mitochondrial DNA from live military personnel is collected and a small **interval** of each person's DNA is sequenced.
  - The interval is used as a "nearly unique" identifier.



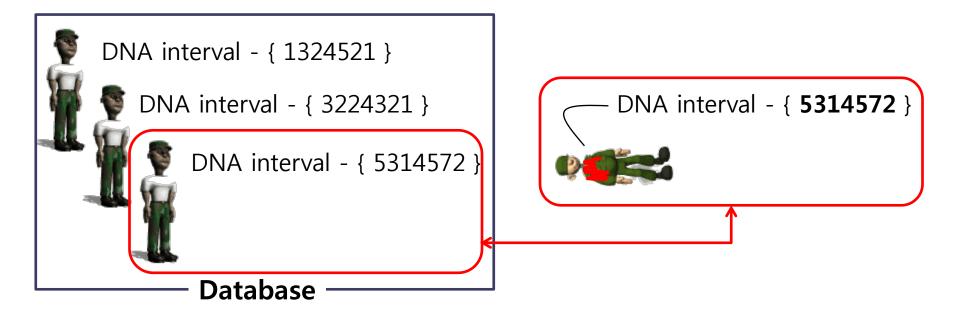


- Later, a person who have been killed can be identified
  - That matching the database of the strings with the person's DNA interval.

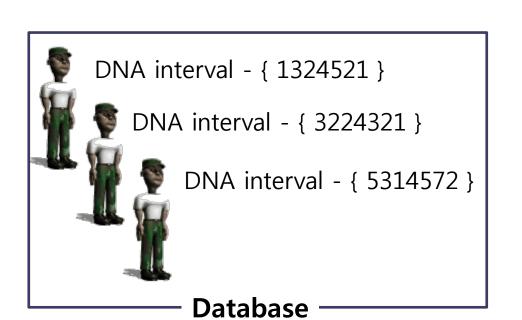


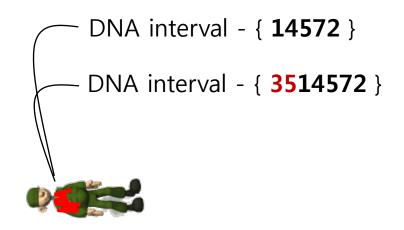


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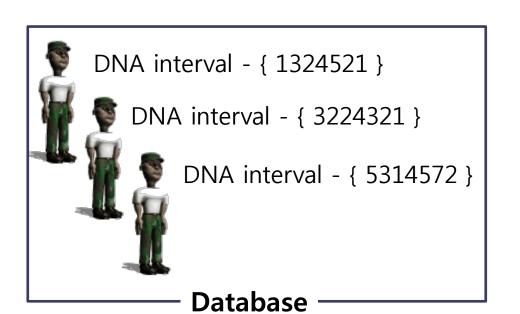


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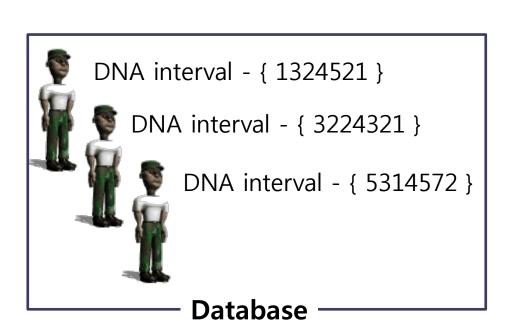


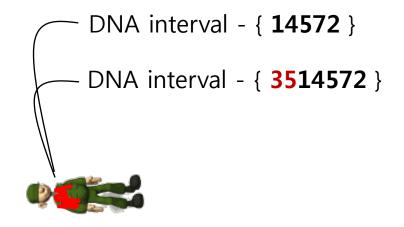
DNA interval - { **14572** }

DNA interval - { **3514572** }

#### In this case,

• One looks to see if the extracted and sequenced string is a substring of one of the strings in the database.





- Good data structure and lookup algorithm for the substring problem.
  - Database should be stored in a small amount of space.
  - Each lookup should be fast.
  - The preprocessing of the database should be relatively fast.

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**Suffix Tree** 

- Suffix trees yield a very attractive solution to this database problem.
  - A generalized suffix tree T for the strings in the database is **built in**,
    - O(m) time.
    - O(m) space.
  - Any single string S of length n is **found** in the database, or declared not to be there,
    - O(n) time.
  - The algorithm can **find all strings** in the database containing *S* as a substring.
    - O(n+k) time.
      - *k* is the number of occurrences of the substring.

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- The longest common substring problem.
  - A classic problem in string analysis is to find the longest substring common to two given strings  $S_1$  and  $S_2$ .

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- $S_2 = s e a l i v e r$

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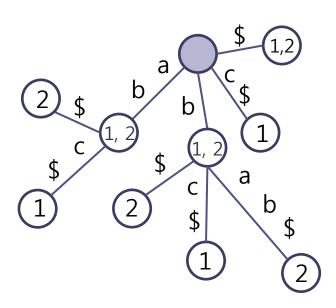
- $S_1 = superior californialives$
- $S_2 = s e a liver$ 
  - The longest common substring of  $S_1$  and  $S_2$  is alive.

- An efficient and conceptually simple way to find a longest common substring is
  - To build a 'generalized suffix tree'.
    - Each leaf of the tree represents either
      - A suffix from one of the two strings or a suffix that occurs in both strings.

#### • For example)

$$S_1 = a b c$$
\$

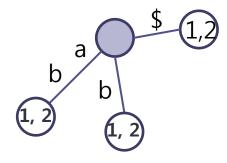
$$S_2 = b \ a \ b \$$



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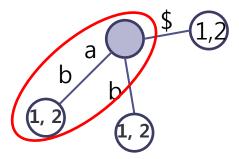
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#### • For example)

$$S_1 = a b c$$
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$$S_2 = b \ a \ b \$$



The longest common substring : *ab* 

- Construction of the suffix tree can be done in linear time.
  - Proportional to the total length of  $S_1$  and  $S_2$ .
- The node markings and calculations of string-depth can be done by standard linear-time tree traversal methods.