



# ALGORITHMS OF BIOINFORMATICS

## 5

## String Matching

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# Outline

## 5 String Matching

- 5.1 Read Mapping
- 5.2 String Matching with Finite Automata
- 5.3 Constructing String Matching Automata
- 5.4 The Knuth-Morris-Pratt algorithm
- 5.5 The Aho-Corasick Algorithm

## 5.1 Read Mapping

# Shotgun Sequencing

Recall:

- ▶ *Shotgun sequencing* approach to determine a (human) genome:



Compeau & Pevzner, *Bioinformatics Algorithms*, Fig 3.1  
<https://cognterra.org/lesson/29884/step/2?unit=21962>

- ▶ For a single human genome need 300M reads of 200bp (30x coverage)
  - ~> 60 GB of raw data
  - ~> genome assembly from those is expensive and error prone

We now have carefully assembled *reference genomes* to compare with!

# Shotgun Sequencing in Medicine

Predominant medical use of whole genome sequencing:  
detecting known markers (mutations / gene combinations) for diseases

**Example:** (more details in Compeau & Pevzner 2015)

- ▶ *Ohdo syndrome* (form of mental retardation, “mask-like” face)
- ▶ known to be indicated by single protein-truncating mutation

Often even a **single base replacement** w.r.t. a human reference genome,  
a **SNP** (*single nucleotide polymorphism*)

~> *To find SNPs, we don't need a new patient's genome fully assembled!*

# Read Mapping

- ▶ We thus work towards solving the *read mapping problem*
  - ▶ **Given:** genome/text  $T[0..n)$ , reads/patterns  $P[0..p)$ ,  $P[r] = P_r[0..m_r)$
  - ▶ **Goal:** locations  $i_r$  of “best match” for  $P_r$  in  $T$  for  $r \in [0..p)$ .
- ▶ “best match” can be interpreted in several ways, leading to different problems:
  - (a) best **semilocal alignment** of  $P_r$  to  $T$  (gold standard, usually too expensive)
  - (b) match with **fewest mismatches**
  - (c) match with  $\leq d$  **mismatches** or **NO\_MATCH** if no such exists  
for SNPs can even set  $d = 1$
  - (d) **exact match** or **NO\_MATCH** if no such exists

*We will first focus on exact matches.*

- ▶ simplifies the problem (to get started)
- ▶ the SNPs variants can be reduced to it (using postprocessing)

# Part I

*Exact matches*

# Notation

- ▶ *alphabet*  $\Sigma$ : finite set of allowed **characters**;  $\sigma = |\Sigma|$  “a string over alphabet  $\Sigma$ ”
  - ▶ focus on nucleotides  $\{A, C, G, T\}$  and amino acids
  - ▶ but try to keep methods generic
  - ▶ letters (Latin, Greek, Arabic, Cyrillic, Asian scripts, ...) **Unicode characters**
    - comprehensive standard character set including emoji and all known symbols
- ▶  $\Sigma^n = \Sigma \times \cdots \times \Sigma$ : strings of **length**  $n \in \mathbb{N}_0$  ( $n$ -tuples)
  - ▶  $\Sigma^* = \bigcup_{n \geq 0} \Sigma^n$ : set of **all** (finite) strings over  $\Sigma$ ,  $\Sigma^+ = \bigcup_{n \geq 1} \Sigma^n$
  - ▶  $\varepsilon \in \Sigma^0$ : the *empty* string (same for all alphabets)
- ▶ for  $S \in \Sigma^n$ , write  $S = S[0..n]$ , so  $S[i]$  (other sources:  $S_i$ ) for ***i**th* character ( $0 \leq i < n$ )
  - zero-based (like arrays)!
- ▶ for  $S, T \in \Sigma^*$ , write  $ST = S \cdot T$  for **concatenation** of  $S$  and  $T$
- ▶ for  $S \in \Sigma^n$ , write  $S[i..j]$  for the **substring**  $S[i] \cdot S[i+1] \cdots S[j-1]$  ( $0 \leq i \leq j \leq n$ )
  - ▶  $S[i..i] = \varepsilon$
  - ▶  $S[0..j]$  is a **prefix** of  $S$ ;  $S[i..n]$  is a **suffix** of  $S$



# String matching – Definition

Search for a string (pattern) in a large body of text

## ► Input:

- $T \in \Sigma^n$ : The text being searched within
- $P \in \Sigma^m$ : The pattern being searched for; typically  $n \gg m$

## ► Output:

- the *first occurrence (match)* of  $P$  in  $T$ :  $\min\{i \in [0..n-m) : T[i..i+m) = P\}$
- or NO\_MATCH if there is no such  $i$  (“ $P$  does not occur in  $T$ ”)
- sometimes also: find **all** occurrences of  $P$  in  $T$ .

- trivially solvable with  $(n-m+1) \cdot \overset{\text{try all starting positions}}{m} \sim nm$  character comparisons

⇒ too slow for read mapping!

- string matching available, e. g., Java in `String.indexOf`, Python in `str.find`
  - not always robust enough for bioinformatics data (small alphabet, long repetitions)

## 5.2 String Matching with Finite Automata

# Theoretical Computer Science to the rescue!

- ▶ string matching = deciding whether  $T \in \Sigma^* \cdot P \cdot \Sigma^*$
- ▶  $\Sigma^* \cdot P \cdot \Sigma^*$  is *regular* formal language
- $\rightsquigarrow \exists$  *deterministic finite automaton* (DFA) to recognize  $\Sigma^* \cdot P \cdot \Sigma^*$
- $\rightsquigarrow$  can check for occurrence of  $P$  in  $|T| = n$  steps!



Job done!



WTF!?

We are not quite done yet.

- ▶ (Problem 0: programmer might not know automata and formal languages ...)
- ▶ Problem 1: existence alone does not give an algorithm!
- ▶ Problem 2: automaton could be very big!

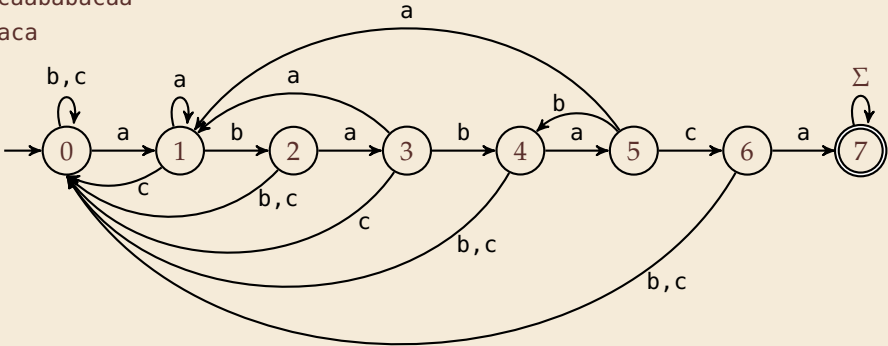
# String matching with DFA

- ▶ Assume first, we already have a deterministic automaton
- ▶ How does string matching work?

**Example:**

$T = \text{aabacaababacaa}$

$P = \text{ababaca}$



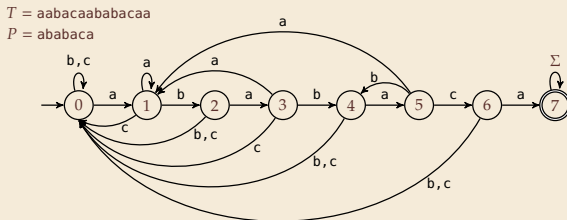
text:		a	a	b	a	c	a	a	b	a	b	a	c	a	a
state:	0	1	1	2	3	0	1	1	2	3	4	5	6	7	7

# String matching DFA – Intuition

Why does this work?

► Main insight:

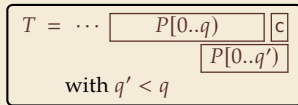
State  $q$  means:  
*“we have seen  $P[0..q)$  until here  
 (but not any longer prefix of  $P$ )”*



text:		a	a	b	a	c	a	a	b	a	b	a	c	a	a
state:	0	1	1	2	3	0	1	1	2	3	4	5	6	7	7

► If the next text character  $c$  does not match, we know:

- (i) text seen so far ends with  $P[0...q) \cdot c$
- (ii)  $P[0...q) \cdot c$  is not a prefix of  $P$
- (iii) without reading  $c$ ,  $P[0..q)$  was the *longest* prefix of  $P$  that ends here.



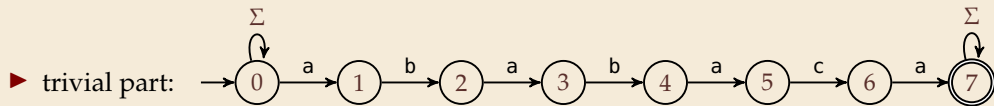
↪ New longest matched prefix will be (weakly) shorter than  $q$

↪ All information about the text needed to determine it is contained in  $P[0...q) \cdot c$ !

## 5.3 Constructing String Matching Automata

# NFA instead of DFA?

It remains to *construct* the DFA.



► that actually is a *nondeterministic finite automaton* (NFA) for  $\Sigma^*P\Sigma^*$

↪ We *could* use the NFA directly for string matching:

- at any point in time, we are in a **set of states**
- accept when one of them is final state

**Example:**

text:		a	a	b	a	c	a	a	b	a	b	a	c	a	a
state:	0	0,1	0,1	0,2	0,1,3	0	0,1	0,1	0,2	0,1,3	0,2,4	0,1,3,5	0,6	0,1,7	0,1,7

But maintaining a whole set makes this slow . . .

# Computing DFA directly



You have an NFA and want a DFA?  
Simply apply the power-set construction  
(and maybe DFA minimization)!

The powerset method has exponential state blow up!  
I guess I might as well use brute force string matching ...




**Ingenious algorithm** by Knuth, Morris, and Pratt: construct DFA *inductively*:

Suppose we add character  $P[j]$  to automaton  $A_j$  for  $P[0..j)$  to construct  $A_{j+1}$

- ▶ add new state and matching transition  $\rightsquigarrow$  easy  $\xrightarrow{P[j+1]} \textcircled{j+1}$
- ▶ for each  $c \neq P[j]$ , we need  $\delta(j, c)$  (transition from  $\textcircled{j}$  when reading  $c$ )
- ▶  $\delta(j, c) =$  length of the longest prefix of  $P[0..j)c$  that is a suffix of  $P[1..j)c$   
= state of automaton after reading  $P[1..j)c$   
 $\leq j \rightsquigarrow$  can use known automaton  $A_j$  for that!

$\rightsquigarrow$  can directly compute  $A_{j+1}$  from  $A_j$ !

 seems to require simulating automata  $m \cdot \sigma$  times

State  $q$  means:  
“we have seen  $P[0..q)$  until here  
(but not any longer prefix of  $P$ )”



# Computing DFA efficiently

- ▶ **KMP's second insight:** simulations in one step differ only in last symbol

↪ simply maintain state  $x$ , the state after reading  $P[1..j]$ .

- ▶ copy its transitions
- ▶ update  $x$  by following transitions for  $P[j]$

---

```
1 procedure constructDFA( $P[0..m]$ ):  
2   //  $\delta[q][c]$  = target state when reading  $c$  in state  $q$   
3   for  $c \in \Sigma$  do  
4      $\delta[0][c] := 0$   
5    $\delta[0][P[0]] := 1$   
6    $x := 0$   
7   for  $j = 1, \dots, m - 1$  do  
8     for  $c \in \Sigma$  do // copy transitions  
9        $\delta[j][c] := \delta[x][c]$   
10     $\delta[j][P[j]] := j + 1$  // match edge  
11     $x := \delta[x][P[j]]$  // update  $x$ 
```

---

**Example:**  $P[0..7] = \text{ababaca}$

$\delta(c, q)$	0	1	2	3	4	5	6
a	1	1	3	1	5	1	7
b	0	2	0	4	0	4	0
c	0	0	0	0	0	6	0

# String matching with DFA – Discussion

## ► Time:


- Matching:  $n$  table lookups for DFA transitions
- building DFA:  $\Theta(m\sigma)$  time (constant time per transition edge).


$\rightsquigarrow \Theta(m\sigma + n)$  time for string matching.

## ► Space:

- $\Theta(m\sigma)$  space for transition matrix.

 **fast matching** time    actually: hard to beat!

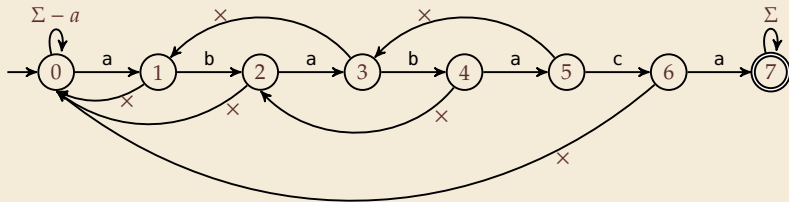
 total time asymptotically optimal for small alphabet    (for  $\sigma = O(n/m)$ )

 substantial **space overhead**, in particular for large alphabets

## 5.4 The Knuth-Morris-Pratt algorithm

# Failure Links

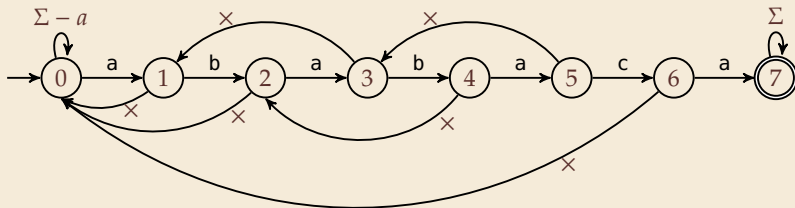
- ▶ Recall: String matching with DFA is fast, but needs table of  $m \times \sigma$  transitions.
- ▶ in fast DFA construction, we used that all simulations differ only by *last* symbol
- ↪ **KMP's third insight:** do this last step of simulation from state  $x$  during *matching*!  
... but how?
- ▶ **Answer:** Use a new type of transition:  $\times$ , the *failure links*
  - ▶ Use this transition (only) if no other one fits.
  - ▶  $\times$  does not consume a character. ↪ might follow several failure links



↪ Computations are deterministic (but automaton is not a classic DFA.)

# Failure link automaton – Example

**Example:**  $T = \text{abababaaaca}$ ,  $P = \text{ababaca}$



$T$ :    a   b     a     b     a     b   a       a     b   a   b

$P$ :

a	b	a	b	a	×						
		(a)	(b)	(a)	b	a	×				
							a	b	a	b	

to state 3

to state 1

$q$ :

1	2	3	4	5	3,4	5	3,1,0,1	2	3	4
---	---	---	---	---	-----	---	---------	---	---	---

(after reading this character)

# The Knuth-Morris-Pratt Algorithm

```
1 procedure KMP( $T[0..n]$ ,  $P[0..m]$ ):  
2    $fail[0..m] := failureLinks(P)$   
3    $i := 0$  // current position in  $T$   
4    $q := 0$  // current state of KMP automaton  
5   while  $i < n$  do  
6     if  $T[i] == P[q]$  then  
7        $i := i + 1$ ;  $q := q + 1$   
8       if  $q == m$  then  
9         return  $i - q$  // occurrence found  
10      else // i.e.  $T[i] \neq P[q]$   
11        if  $q \geq 1$  then  
12           $q := fail[q]$  // follow one  $\times$   
13        else  
14           $i := i + 1$   
15      end while  
16      return NO_MATCH
```

► only need single array *fail* for failure links

► (failureLinks on next slide)

**Analysis:** (matching part)

► always have  $fail[j] < j$  for  $j \geq 1$

↪ in each iteration

► either advance position in text ( $i := i + 1$ )

► or shift pattern forward (guess  $i - q$ )

► each can happen at most  $n$  times

↪  $\leq 2n$  symbol comparisons!

# Computing failure links

► failure links point to error state  $x$  (from DFA construction)

↪ run same algorithm, but store  $fail[j] := x$  instead of copying all transitions

---

```
1 procedure failureLinks( $P[0..m]$ ):  
2    $fail[0] := 0$   
3    $x := 0$   
4   for  $j := 1, \dots, m - 1$  do  
5      $fail[j] := x$   
6     // update failure state using failure links:  
7     while  $P[x] \neq P[j]$   
8       if  $x == 0$  then  
9          $x := -1$ ; break  
10      else  
11         $x := fail[x]$   
12      end while  
13       $x := x + 1$   
14 end for
```

---

## Analysis:

►  $m$  iterations of for loop

► while loop always decrements  $x$

►  $x$  is incremented only once per iteration of for loop

↪  $\leq m$  iterations of while loop *in total*

↪  $\leq 2m$  symbol comparisons

# Knuth-Morris-Pratt – Discussion

## ► Time:

- $\leq 2n + 2m = O(n + m)$  character comparisons
  - clearly must at least *read* both  $T$  and  $P$  in the worst case
- ~> KMP has optimal worst-case complexity

## ► Space:

- $\Theta(m)$  space for failure links



total time asymptotically optimal (for any alphabet size)



reasonable extra space



# The KMP prefix function

- ▶ It turns out that the failure links are useful beyond KMP
- ▶ a slight variation is (more?) widely used: (for historic reasons)  
the (KMP) *prefix function*  $F : [1..m - 1] \rightarrow [0..m - 1]$ :

$F[j]$  *is the length of the longest prefix of  $P[0..j]$   
that is a suffix of  $P[1..j]$ .*

- ▶ Can show:  $fail[j] = F[j - 1]$  for  $j \geq 1$ , and hence

$fail[q] =$ *length of the  
longest prefix of  $P[0..q)$   
that is a suffix of  $P[1..q)$ .*

← memorize this!

- ▶ EAA Buch: String indices are 1-based, but definition of failure links matches!  $\Pi_P(q) = fail[q]$

$\Pi_P : [1..m] \rightarrow [0..m - 1]$  with  $\Pi_P(q) = \max\{k \in \mathbb{N}_0 : k < q \wedge P[0..k] \sqsupseteq P[0..q)\} = fail[q]$

## 5.5 The Aho-Corasick Algorithm

# Multiple-Pattern Matching

- ▶ So far: process a single pattern  $P$  in one pass over  $T$ .

↪ Cannot beat time  $\Omega(p \cdot n)$

- ▶ The essence of KMP can be generalized to deal with several patterns!

↪ The *Aho-Corasick Algorithm*

## The Multiple-Pattern Matching Problem

- ▶ **Given:** text  $T[0..n)$ , patterns  $P[0..p)$ ,  $P[r] = P_r[0..m_r)$

- ▶ all over  $\Sigma = [0..\sigma)$  for **constant**  $\sigma$

- ▶ total length of patterns:  $m := \sum_{0 \leq r < p} m_r$

- ▶ **Goal:** all matches, i. e., all pairs  $(i, r)$  such that  $P_r = T[i..i + m_r)$

single pass!

Aho-Corasick can do this with  $O(m)$  preprocessing and  $O(n + \text{output})$  matching time!

Here *output* is the number of match pairs  $(i, r)$ .

# Aho-Corasick Automaton – Overview

## Aho-Corasick Automaton

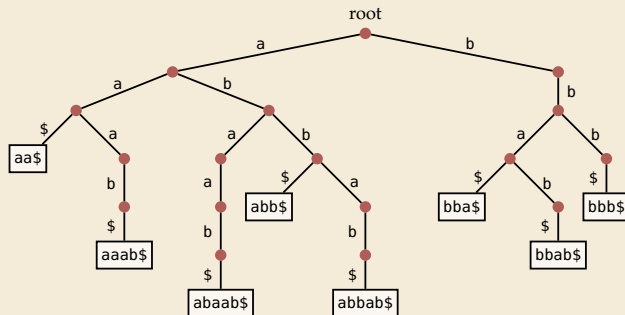
1. Build trie  $A$  from patterns  $P[0..p)$ .
2. Add *failure links* to  $A$ .
3. Add *output links* to  $A$ .

# Recap: Tries

- ▶ efficient dictionary data structure for strings
- ▶ name from **re**trieval, but pronounced “try”
- ▶ tree based on symbol comparisons

▶ **Example:**

{aa\$, aaab\$, abaab\$, abb\$,  
abbab\$, bba\$, bbab\$, bbb\$}



*When stored string is a strict prefix of another, internal nodes can correspond to strings.*

# Aho-Corasick Automaton – Adding Failure Links

*Trie for  $P_r$  corresponds to match-edges-only NFA.*

- ↪ Interpreting the trie as automaton, add  $\varepsilon$ -edges back to the root.
- ▶ as in KMP, instead of determinizing the automation classically, we again use failure links
- ↪ construction as for KMP using failure state  $x$ , repeated for each word.

# Aho-Corasick Automaton – Output Links

*An automaton state might contain other patterns as suffix  $\rightsquigarrow$  must output match(es)! But we are not in an accepting state, so direct use of automaton so far would miss occurrence!*

- ▶ **output links:** each state points to longest suffix pattern (if any).
  - ▶ During matching, traverse linked list of matches and output each  $\rightsquigarrow O(\text{output})$  cost overall
  - ▶ Computation of output links similar to failure links! (handle patterns by length)

# Part II

## *Inexact Matches*



## Hamming distance – Brute Force

# Kangaroo