

# Periodic string comparison

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1 Introduction

2 Semi-local string comparison

3 The seaweed algorithm

4 Conclusions and future work

## 1 Introduction

## 2 Semi-local string comparison

## 3 The seaweed algorithm

## 4 Conclusions and future work

# Introduction

String matching: finding an **exact** pattern in a string

String comparison: finding **similar** patterns in two strings

(Also known as “approximate string matching”, no relation to approximation algorithms!)

Applications: computational biology, image recognition, ...

# Introduction

String matching: finding an **exact** pattern in a string

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(Also known as “approximate string matching”, no relation to approximation algorithms!)

Applications: computational biology, image recognition, ...

Standard types of string comparison:

- **global**: whole string vs whole string
- **local**: substrings vs substrings

Main focus of this work:

- **semi-local**: whole string vs substrings; prefixes vs suffixes

Main tool: implicit **unit-Monge matrices**

# Introduction

## Terminology and notation

Integers:  $\dots - 2, -1, 0, 1, 2, \dots$

Odd half-integers:  $\dots - \frac{5}{2}, -\frac{3}{2}, -\frac{1}{2}, \frac{1}{2}, \frac{3}{2}, \frac{5}{2}, \dots$

We consider finite and infinite integer matrices over integer and odd half-integer indices. For simplicity, index range will usually be ignored.

A **permutation matrix** is a 0/1 matrix with exactly one nonzero per row and per column

# Introduction

## Terminology and notation

Given matrix  $D$ , its **distribution matrix** is  $D^\Sigma(i,j) = \sum_{i' > i, j' < j} D(i',j')$

In other words,  $D^\Sigma(i,j)$  is the sum of all  $D(i',j')$ , where  $(i',j')$  is **dominated** by  $(i,j)$

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Given matrix  $E$ , its **density matrix** is

$$E^\square(i,j) = E(i^-,j^+) - E(i^-,j^-) - E(i^+,j^+) + E(i^+,j^-)$$

where  $i^\pm = i \pm \frac{1}{2}$ ;  $D^\Sigma, E$  over integers;  $D, E^\square$  over odd half-integers

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$(D^\Sigma)^\square = D$  for all  $D$

Matrix  $E$  is **simple**, if  $(E^\square)^\Sigma = E$

# Introduction

## Terminology and notation

Matrix  $E$  is **Monge**, if  $E^\square$  is nonnegative

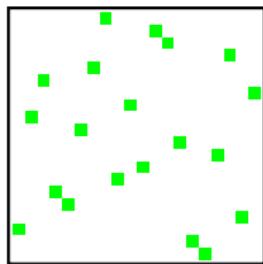
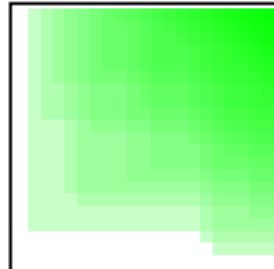
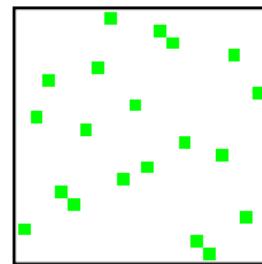
Intuition: border-to-border distances in a (weighted) planar graph

Matrix  $E$  is **unit-Monge**, if  $E^\square$  is a permutation matrix

Intuition: border-to-border distances in a grid-like graph

# Introduction

## Terminology and notation

 $P$  $P^\Sigma$  $(P^\Sigma)^\square = P$

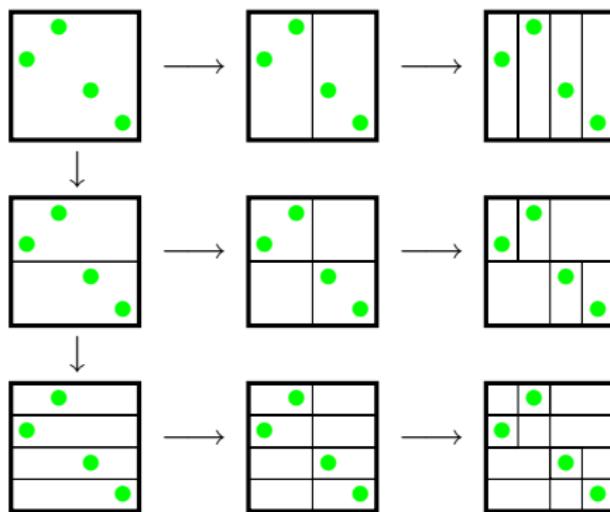
# Introduction

## Implicit unit-Monge matrices

Implicit  $P^\Sigma$ : range tree on nonzeros of  $P$

[Bentley: 1980]

- binary search tree by  $i$ -coordinate
- under every node, binary search tree by  $j$ -coordinate



# Introduction

## Implicit unit-Monge matrices

### Implicit $P^\Sigma$ (contd.)

Every node of the range tree represents a **canonical range** (rectangular region), and stores its nonzero count

Overall,  $\leq n \log n$  canonical ranges are non-empty

Range tree supports **dominance counting** queries: how many nonzeros are dominated by a given point? Answered by decomposing query range into  $\leq \log^2 n$  disjoint canonical ranges.

Total size  $O(n \log n)$ , query time  $O(\log^2 n)$

There are asymptotically more efficient (but less practical) data structures

# Introduction

## Matrix $\odot$ -multiplication

Matrix  $\odot$ -multiplication (a.k.a. **distance**,  $(\min, +)$  or **tropical multiplication**)

$$A \odot B = C \quad C(i, k) = \min_j (A(i, j) + B(j, k))$$

# Introduction

## Matrix $\odot$ -multiplication

Matrix  $\odot$ -multiplication (a.k.a. distance,  $(\min, +)$  or tropical multiplication)

$$A \odot B = C \quad C(i, k) = \min_j (A(i, j) + B(j, k))$$

Matrix classes closed under  $\odot$ -multiplication:

- general numerical (integer, real) matrices
- Monge matrices
- simple unit-Monge matrices

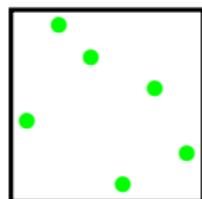
Simple unit-Monge matrices of size  $n$  form an aperiodic monoid (i.e. a monoid as far as possible from a group) under  $\odot$ -multiplication

We call it the seaweed monoid  $\mathcal{T}_n$

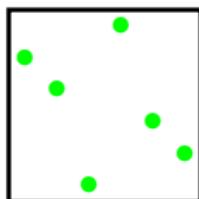
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## Matrix $\odot$ -multiplication

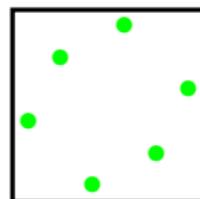
Simple unit-Monge matrices:  $\odot$ -multiplication = seaweed composition



$P_A$



$P_B$



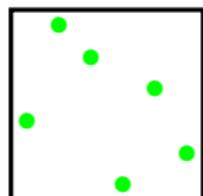
$P_C$

$$P_A^\Sigma \odot P_B^\Sigma = P_C^\Sigma$$

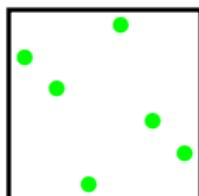
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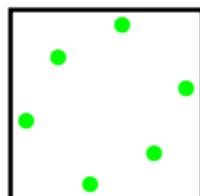
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$P_A$

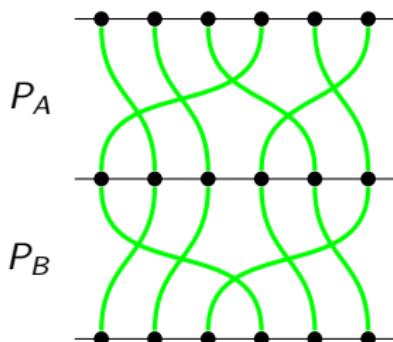


$P_B$



$P_C$

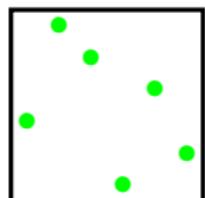
$$P_A^\Sigma \odot P_B^\Sigma = P_C^\Sigma$$



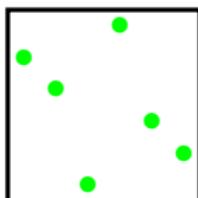
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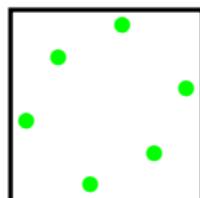
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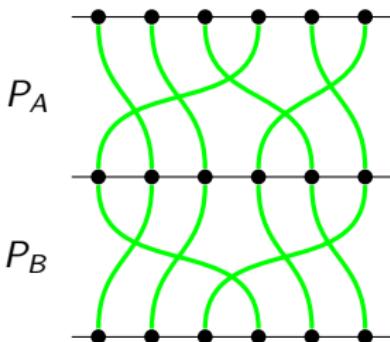


$P_B$

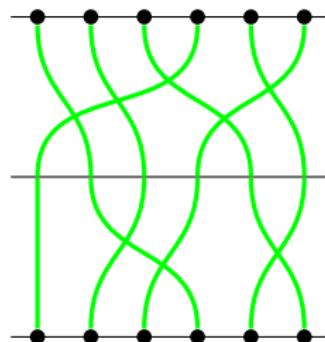


$P_C$

$$P_A^\Sigma \odot P_B^\Sigma = P_C^\Sigma$$



$P_A$

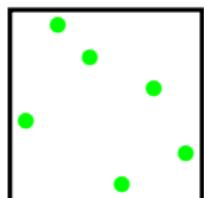


$P_B$

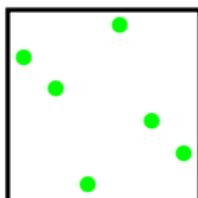
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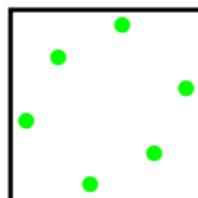
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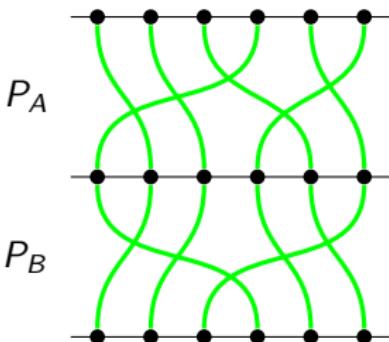


$P_B$

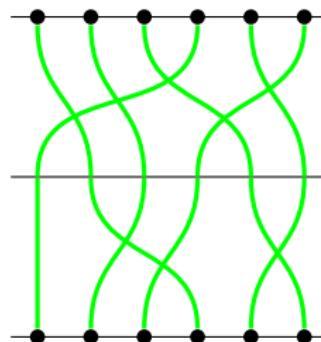


$P_C$

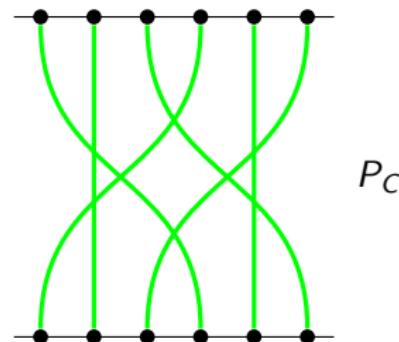
$$P_A^\Sigma \odot P_B^\Sigma = P_C^\Sigma$$



$P_A$



$P_B$



$P_C$

# Introduction

## Matrix $\odot$ -multiplication

Seaweeds: similar to braids, generated by strand crossings

Unlike in braids, all seaweed crossings are

- level (not underpass/overpass)
- idempotent, i.e. two seaweeds can cross at most once

Seaweed composition: associative, no inverse (a crossing cannot be cancelled)

Identity:  $1 \odot x = x$ , no seaweeds crossing

Zero:  $0 \odot x = 0$ , all seaweeds crossing

$$1 = \left( \begin{array}{c:c:c:c} \bullet & \cdot & \cdot & \cdot \\ \cdot & \bullet & \cdot & \cdot \\ \cdot & \cdot & \bullet & \cdot \\ \cdot & \cdot & \cdot & \bullet \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \bullet \end{array} \right)^\Sigma \quad 0 = \left( \begin{array}{c:c:c:c} \cdot & \cdot & \cdot & \bullet \\ \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \bullet & \cdot \\ \cdot & \bullet & \cdot & \cdot \\ \bullet & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \end{array} \right)^\Sigma$$

# Introduction

## Matrix $\odot$ -multiplication

The seaweed monoid  $\mathcal{T}_n$ :

- $n!$  elements (permutations of size  $n$ )
- $n - 1$  generators  $g_1, g_2, \dots, g_{n-1}$  (elementary crossings)

$$g_i^2 = g_i \quad \text{for all } i \quad (\text{idempotence})$$

$$g_i g_j = g_j g_i \quad j - i > 1 \quad (\text{far commutativity})$$

$$g_i g_j g_i = g_j g_i g_j \quad j - i = 1 \quad (\text{braid relations})$$

Computation: a confluent rewriting system can be obtained by software (SEMIGROUPE, GAP)

Generalisation: Coxeter monoids (subgroup monoids in groups)

[Tsaranov: 90]

# Introduction

## Matrix $\odot$ -multiplication

The seaweed monoid  $\mathcal{T}_3$

Generators: 1,  $a = g_1$ ,  $b = g_2$

Other elements:  $ab$ ,  $ba$ ,  $aba = 0$

Rewriting system:

$$aa \rightarrow a$$

$$bb \rightarrow b$$

$$bab \rightarrow 0$$

$$aba \rightarrow 0$$

# Introduction

## Matrix $\odot$ -multiplication

The seaweed monoid  $\mathcal{T}_4$

Generators:  $1, a = g_1, b = g_2, c = g_3$

Other elements:  $ab, ac, ba, bc, cb, aba, abc, acb, bac, bcb, cba, abac, abcb, acba, bacb, bcba, abacb, abcba, bacba, abacba = 0$

Rewriting system:

$$aa \rightarrow a$$

$$bb \rightarrow b$$

$$ca \rightarrow ac$$

$$cc \rightarrow c$$

$$bab \rightarrow aba$$

$$cbc \rightarrow bcb$$

$$cbac \rightarrow bcba$$

$$abacba \rightarrow 0$$

# Introduction

## Matrix $\odot$ -multiplication

### The implicit matrix $\odot$ -multiplication problem

Given permutation matrices  $P_A$ ,  $P_B$ , compute  $P_C$ , such that  
 $P_A^\Sigma \odot P_B^\Sigma = P_C^\Sigma$

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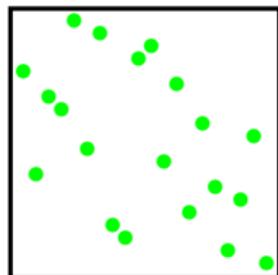
### Matrix $\odot$ -multiplication: running time

matrix type	time	
general	$O(n^3)$	standard
Monge	$O(n^2)$	by [Aggarwal+: 1987]
implicit simple unit-Monge ( $P^\Sigma$ )		
	$O(n^{1.5})$	[T: 2006]
	$O(n \log n)$	[T: NEW]

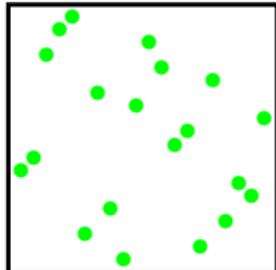
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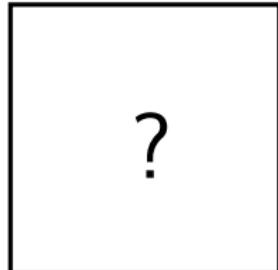
$P_B$



$P_A$

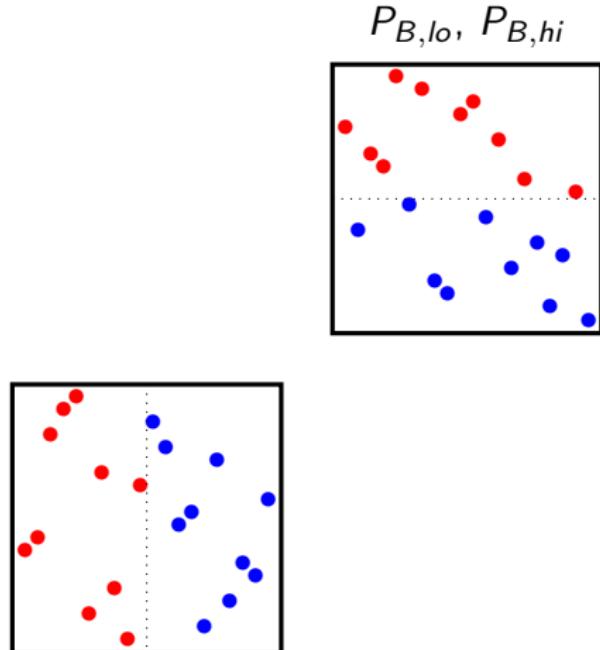


$P_C$



# Introduction

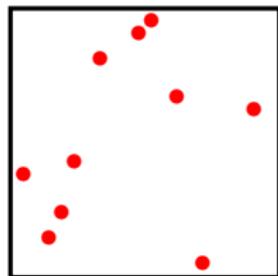
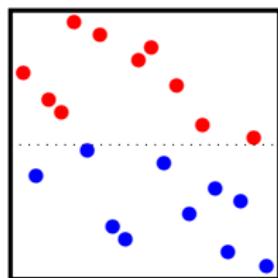
## Matrix $\odot$ -multiplication



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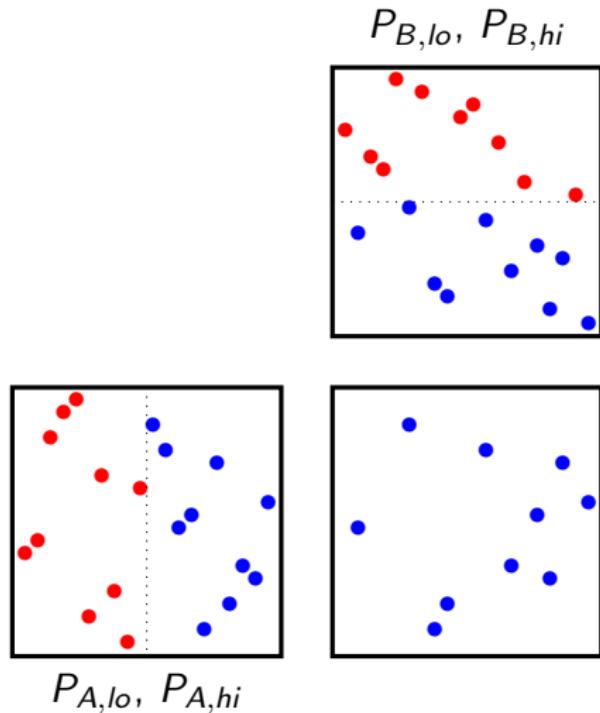
$P_{B,lo}, P_{B,hi}$



$P_{A,lo}, P_{A,hi}$

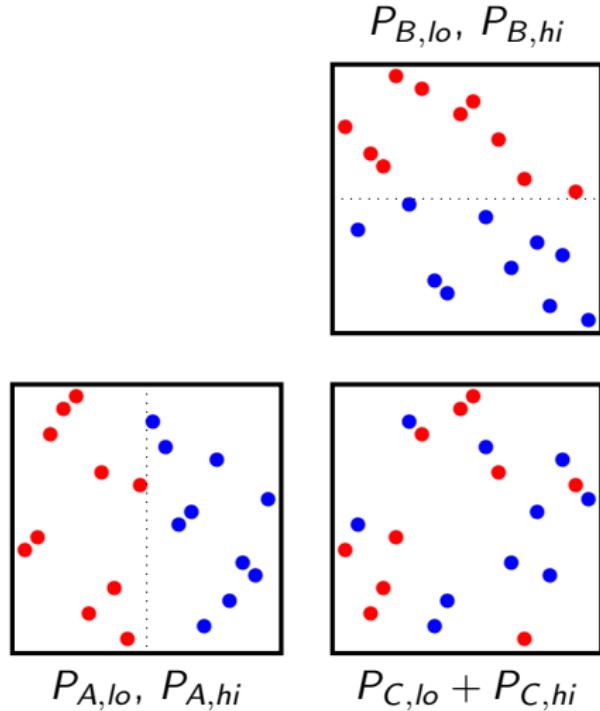
# Introduction

## Matrix $\odot$ -multiplication



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## Matrix $\odot$ -multiplication



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## Matrix $\odot$ -multiplication

### Implicit matrix $\odot$ -multiplication: the algorithm

$$P_C^\Sigma(i, k) = \min_j (P_A^\Sigma(i, j) + P_B^\Sigma(j, k))$$

Divide-and-conquer on the range of  $j$

Divide  $P_A$  horizontally,  $P_B$  vertically; two subproblems of effective size  $n/2$ :

$$P_{A,lo}^\Sigma \odot P_{B,lo}^\Sigma = P_{C,lo}^\Sigma \quad P_{A,hi}^\Sigma \odot P_{B,hi}^\Sigma = P_{C,hi}^\Sigma$$

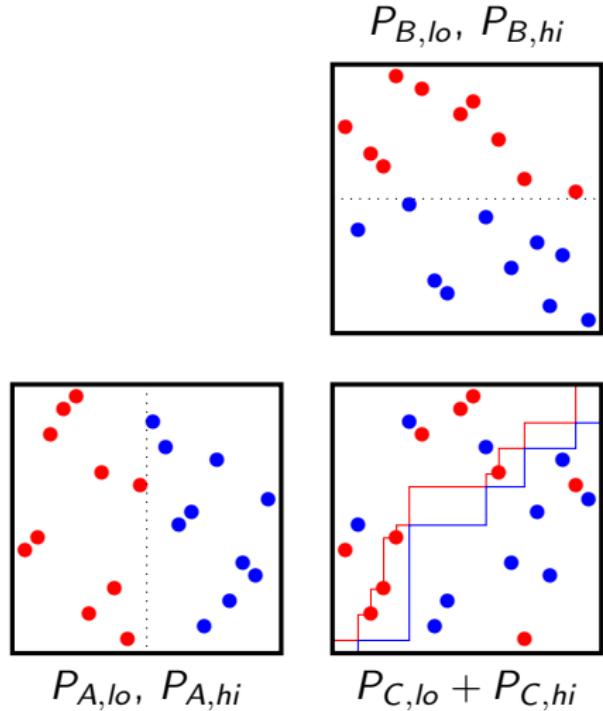
Conquer: most (but not all!) nonzeros of  $P_{C,lo}$ ,  $P_{C,hi}$  appear in  $P_C$

Missing nonzeros can be obtained in time  $O(n)$  using the Monge property

Overall time  $O(n \log n)$

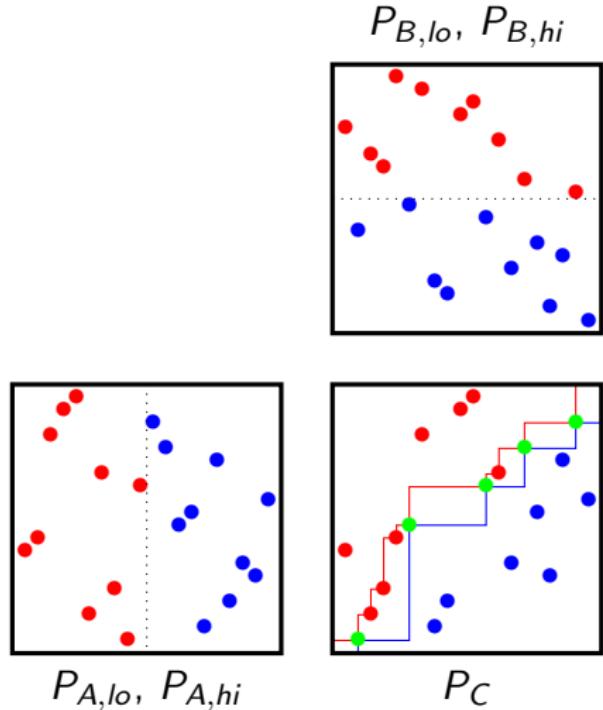
# Introduction

## Matrix $\odot$ -multiplication



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# Semi-local string comparison

Semi-local LCS and edit distance

Consider **strings** (= **sequences**) over an alphabet of size  $\sigma$

Distinguish contiguous **substrings** and not necessarily contiguous  
**subsequences**

Special cases of substring: **prefix**, **suffix**

Notation: strings  $a, b$  of length  $m, n$  respectively

Assume where necessary:  $m \leq n$ ;  $m, n$  reasonably close

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The **longest common subsequence (LCS) score**:

- length of longest string that is a subsequence of both  $a$  and  $b$
- equivalently, **alignment score**, where  $\text{score}(\text{match}) = 1$  and  $\text{score}(\text{mismatch}) = 0$

# Semi-local string comparison

Semi-local LCS and edit distance

## The LCS problem

Give the LCS score for  $a$  vs  $b$

# Semi-local string comparison

## Semi-local LCS and edit distance

### The LCS problem

Give the LCS score for  $a$  vs  $b$

### LCS: running time

$$O(mn)$$

$$O\left(\frac{mn}{\log n}\right)$$

$$\sigma = O(1)$$

[Wagner, Fischer: 1974]

[Masek, Paterson: 1980]

[Crochemore+: 2003]

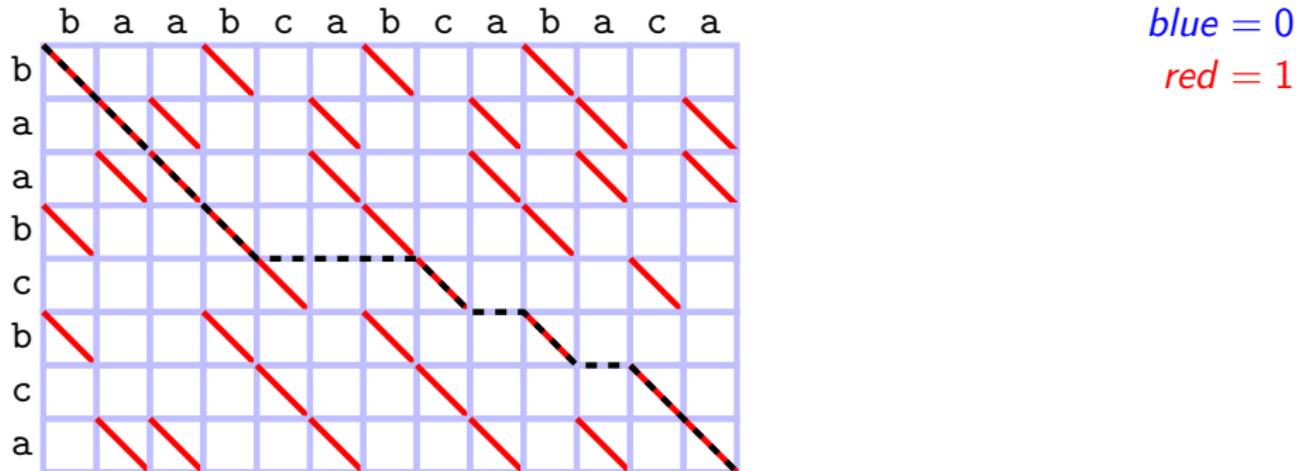
[Paterson, Dancik: 1994]

$$O\left(\frac{mn(\log \log n)^2}{\log n}\right)$$

# Semi-local string comparison

Semi-local LCS and edit distance

LCS on the **alignment graph** (directed, acyclic)



$$\text{LCS}(\text{"baabcbca"}, \text{"baabcabcabaca"}) = \text{"baabcbca"}$$

LCS = highest-score corner-to-corner path

# Semi-local string comparison

Semi-local LCS and edit distance

LCS: dynamic programming (DP) algorithm [Wagner, Fischer: 1974]

Sweep alignment graph, respecting node dependencies

Running time  $O(mn)$

# Semi-local string comparison

Semi-local LCS and edit distance

LCS: dynamic programming (DP) algorithm [Wagner, Fischer: 1974]

Sweep alignment graph, respecting node dependencies

Running time  $O(mn)$

LCS: micro-block DP algorithm

[Masek, Paterson: 1980]

Sweep alignment graph in square blocks, respecting block dependencies

Block size:  $t = O(\log n)$

Block interface:  $O(t)$  inputs/outputs, each of size  $O(\log \sigma)$

Use precomputed mapping of all possible input/output combinations

Running time  $O\left(\frac{mn}{\log n}\right)$  when  $\sigma = O(1)$ , even on log-cost RAM

# Semi-local string comparison

## Semi-local LCS and edit distance

### The semi-local LCS problem

Give the (implicit) matrix of  $O(m^2 + n^2)$  LCS scores:

- **string-substring LCS:** string  $a$  vs every substring of  $b$
- **prefix-suffix LCS:** every prefix of  $a$  vs every suffix of  $b$
- symmetrically, **substring-string** and **suffix-prefix LCS**

# Semi-local string comparison

## Semi-local LCS and edit distance

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### The three-way semi-local LCS problem

Give the (implicit) matrix of  $O(n^2)$  LCS scores:

- **string-substring, prefix-suffix, suffix-prefix LCS**
- no substring-string LCS

Suitable for  $m \gg n$

# Semi-local string comparison

## Semi-local LCS and edit distance

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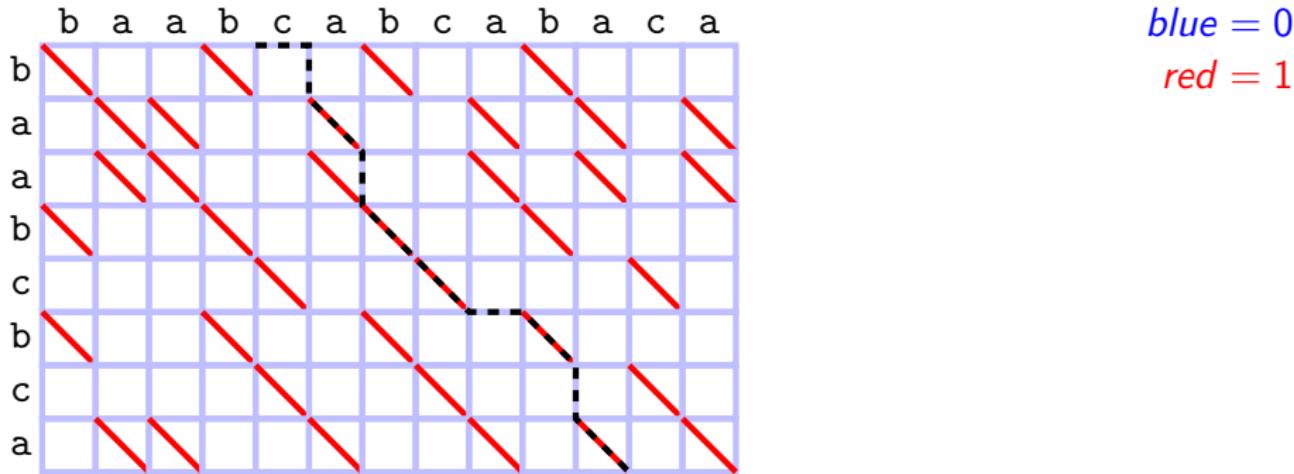
Suitable for  $m \gg n$

Cf.: dynamic programming gives **prefix-prefix LCS**

# Semi-local string comparison

Semi-local LCS and edit distance

Semi-local LCS on the alignment graph



$$\text{LCS}(\text{"baabcbca"}, \text{"...cabcbaba..."}) = \text{"abcba"}$$

Semi-local LCS = all highest-score border-to-border paths  
(string-substring = top-to-bottom, etc.)

# Semi-local string comparison

## Semi-local LCS and edit distance

The LCS problem is a special case of the **alignment score** problem with weighted matches, mismatches and gaps

- **LCS score**:  $w_{match} = 1$ ,  $w_{mismatch} = w_{gap} = 0$
- **Levenshtein score**:  $w_{match} = 2$ ,  $w_{mismatch} = 1$ ,  $w_{gap} = 0$

An alignment score is **rational**, if  $w_{match}$ ,  $w_{mismatch}$ ,  $w_{gap}$  are rational;  
reduces to LCS score by constant-factor blow-up of alignment graph

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The LCS problem is a special case of the **alignment score** problem with weighted matches, mismatches and gaps

- **LCS score**:  $w_{match} = 1$ ,  $w_{mismatch} = w_{gap} = 0$
- **Levenshtein score**:  $w_{match} = 2$ ,  $w_{mismatch} = 1$ ,  $w_{gap} = 0$

An alignment score is **rational**, if  $w_{match}$ ,  $w_{mismatch}$ ,  $w_{gap}$  are rational;  
reduces to LCS score by constant-factor blow-up of alignment graph

The **semi-local alignment score** problem: string-substring, prefix-suffix,  
substring-string, suffix-prefix alignment scores

**Edit distance**: minimum cost to transform  $a$  into  $b$  by weighted character edits  
(insertion, deletion, substitution)

The **semi-local edit distance** problem: semi-local alignment score problem  
with  $w_{match} = 0$ ,  $w_{mismatch} = -w_{sub}$ ,  $w_{gap} = -w_{indel}$

# Semi-local string comparison

## Highest-score matrices

### The semi-local LCS score matrix

0	1	2	3	4	5	6	6	7	8	8	8	8	8
-1	0	1	2	3	4	5	5	6	7	7	7	7	7
-2	-1	0	1	2	3	4	4	5	6	6	6	6	7
-3	-2	-1	0	1	2	3	3	4	5	5	6	6	7
-4	-3	-2	-1	0	1	2	2	3	4	4	5	5	6
-5	-4	-3	-2	-1	0	1	2	3	4	4	5	5	6
-6	-5	-4	-3	-2	-1	0	1	2	3	3	4	4	5
-7	-6	-5	-4	-3	-2	-1	0	1	2	2	3	3	4
-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	3	4
-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4
-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3
-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2
-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1
-13	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0

$a = \text{"baabcbca"}$

$b = \text{"baabcabcabaca"}$

$A(0, 13) = \text{LCS}(a, b) = 8$

$b' = \dots \text{cabcaba} \dots$

$A(4, 11) = \text{LCS}(a, b') = 5$

$A(i, j) = j - i$  if  $i > j$

# Semi-local string comparison

## Highest-score matrices

### Semi-local LCS: output representation and running time

size	query time	
$O(n^2)$	$O(1)$	trivial
$O(m^{1/2}n)$	$O(\log n)$	string-substring [Alves+: 2003]
$O(n)$	$O(n)$	string-substring [Alves+: 2005]
$O(n \log n)$	$O(\log^2 n)$	[T: 2006]
running time		
$O(mn^2)$		naive
$O(mn)$	string-substring	[Schmidt: 1998]
	string-substring	[Alves+: 2005]
$O(mn)$		[T: 2006]
$O\left(\frac{mn}{\log^{0.5} n}\right)$		[T: 2006]
$O\left(\frac{mn(\log \log n)^2}{\log n}\right)$		[T: 2007]

# Semi-local string comparison

## Highest-score matrices

$A$ : the semi-local LCS score matrix for  $a$  vs  $b$

$A(i, j)$ : the number of matched characters for  $a$  vs substring of  $b$

$Q(i, j) = j - i - A(i, j)$ : the number of unmatched characters

Properties of matrix  $Q$ :

- $Q$  is simple unit-Monge
- therefore,  $Q = P\Sigma$  for some permutation matrix  $P$

$P = Q^\square = -A^\square$  is an **implicit representation** of  $A$

Range tree for  $P$ : memory  $O(n \log n)$ , query time  $O(\log^2 n)$

# Semi-local string comparison

## Highest-score matrices

### The semi-local LCS score matrix

0	1	2	3	4	5	6	6	7	8	8	8	8	8
-1	0	1	2	3	4	5	5	6	7	7	7	7	7
-2	-1	0	1	2	3	4	4	5	6	6	6	6	7
-3	-2	-1	0	1	2	3	3	4	5	5	6	6	7
-4	-3	-2	-1	0	1	2	2	3	4	4	4	5	6
-5	-4	-3	-2	-1	0	1	2	3	4	4	5	5	6
-6	-5	-4	-3	-2	-1	0	1	2	3	3	4	4	5
-7	-6	-5	-4	-3	-2	-1	0	1	2	2	3	3	4
-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	3	4
-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4
-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3
-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2
-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1
-13	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0

$a = \text{"baabcbca"}$

$b = \text{"baabcabcabaca"}$

$b' = \dots \text{cabcaba} \dots$

$A(4, 11) = \text{LCS}(a, b') = 5$

$A(i, j) = j - i$  if  $i > j$

# Semi-local string comparison

## Highest-score matrices

### The semi-local LCS score matrix

0	1	2	3	4	5	6	6	7	8	8	8	8	8
-1	0	1	2	3	4	5	5	6	7	7	7	7	7
-2	-1	0	1	2	3	4	4	5	6	6	6	6	7
-3	-2	-1	0	1	2	3	3	4	5	5	6	6	7
-4	-3	-2	-1	0	1	2	2	3	4	4	4	5	6
-5	-4	-3	-2	-1	0	1	2	3	4	4	5	5	6
-6	-5	-4	-3	-2	-1	0	1	2	3	3	4	4	5
-7	-6	-5	-4	-3	-2	-1	0	1	2	2	3	3	4
-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	3	4
-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4
-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3
-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2
-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1
-13	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0

$a = \text{"baabcbca"}$

$b = \text{"baabcabcabaca"}$

$b' = \dots \text{cabcaba} \dots$

$$A(4, 11) = \text{LCS}(a, b') = 5$$

$$A(i, j) = j - i \text{ if } i > j$$

blue: difference 0

red: difference 1

# Semi-local string comparison

## Highest-score matrices

### The semi-local LCS score matrix

0	1	2	3	4	5	6	6	7	8	8	8	8	8
-1	0	1	2	3	4	5	5	6	7	7	7	7	7
-2	-1	0	1	2	3	4	4	5	6	6	6	6	7
-3	-2	-1	0	1	2	3	3	4	5	5	6	6	7
-4	-3	-2	-1	0	1	2	2	3	4	4	4	5	6
-5	-4	-3	-2	-1	0	1	2	3	4	4	5	5	6
-6	-5	-4	-3	-2	-1	0	1	2	3	3	4	4	5
-7	-6	-5	-4	-3	-2	-1	0	1	2	2	3	3	4
-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	3	4
-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4
-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3
-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2
-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1
-13	-12	-11	-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	0

$a = \text{"baabcbca"}$

$b = \text{"baabcabcabaca"}$

$b' = \dots \text{cabcaba} \dots$

$A(4, 11) = \text{LCS}(a, b') = 5$

$A(i, j) = j - i$  if  $i > j$

blue: difference 0

red: difference 1

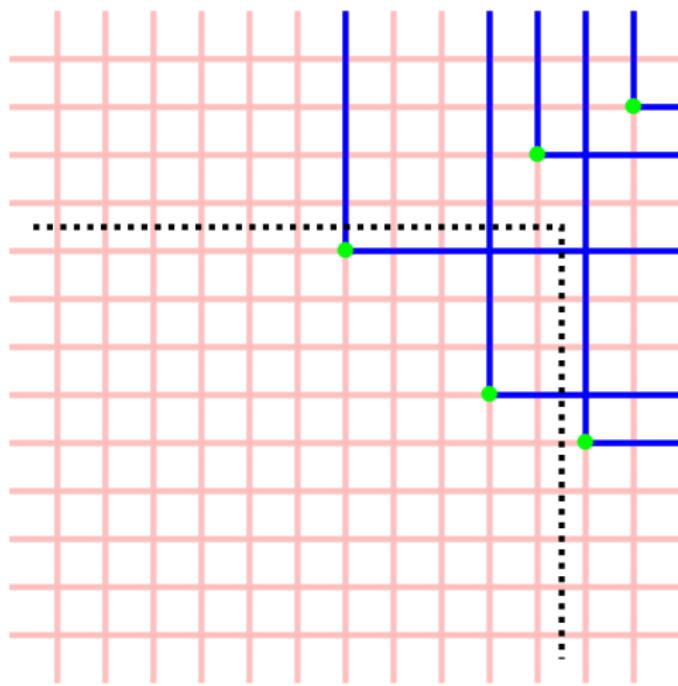
green:  $P(i, j) = 1$

$A(i, j) = j - i - P^\Sigma(i, j)$

# Semi-local string comparison

## Highest-score matrices

### The semi-local LCS score matrix



$a = \text{"baabcbca"}$

$b = \text{"baabcabcabaca"}$

$b' = \dots \text{cabcaba} \dots$

$A(4, 11) = \text{LCS}(a, b') =$

$11 - 4 - P^\Sigma(i, j) =$

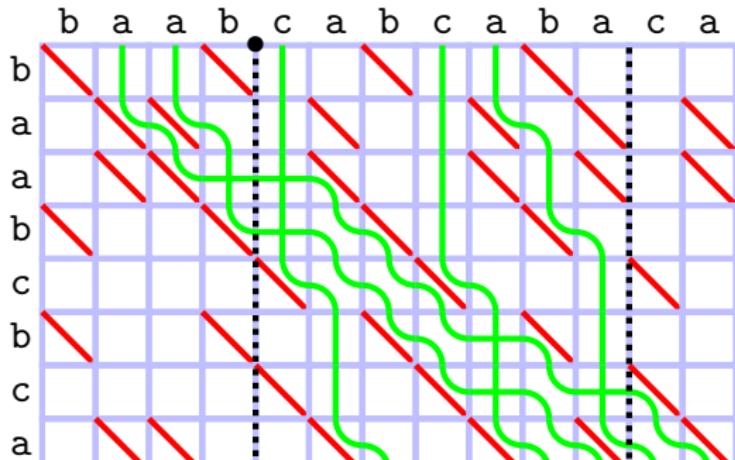
$11 - 4 - 2 = 5$

$P$  gives an **implicit representation** of  $A$

# Semi-local string comparison

## Highest-score matrices

The **seaweeds** in the alignment graph



$P(i, j) = 1$  corresponds to seaweed  $(\text{top}, i) \rightsquigarrow (\text{bottom}, j)$

$$a = \text{"baabcbca"}$$

$$b = \text{"baabcabcabaca"}$$

$$b' = \text{"...cabcaba..."}$$

$$A(4, 11) = \text{LCS}(a, b') =$$

$$11 - 4 - P^\Sigma(i, j) =$$

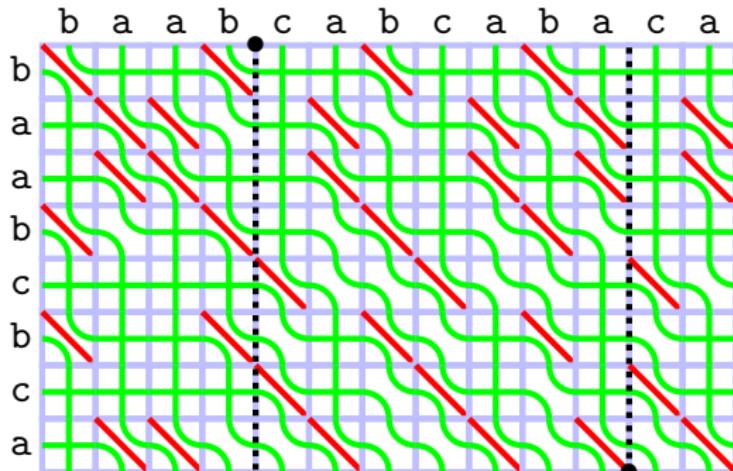
$$11 - 4 - 2 = 5$$

$P$  gives an **implicit representation** of  $A$

# Semi-local string comparison

## Highest-score matrices

The **seaweeds** in the alignment graph



$P(i, j) = 1$  corresponds to seaweed  $(\text{top}, i) \rightsquigarrow (\text{bottom}, j)$

Also define  $\text{top} \rightsquigarrow \text{right}$ ,  $\text{left} \rightsquigarrow \text{right}$ ,  $\text{left} \rightsquigarrow \text{bottom}$  seaweeds

Gives complete border-to-border graph-theoretic matching

$$a = \text{"baabcbca"}$$

$$b = \text{"baabcabcabaca"}$$

$$b' = \text{"...cabcaba..."}$$

$$A(4, 11) = \text{LCS}(a, b') =$$

$$11 - 4 - P^\Sigma(i, j) =$$

$$11 - 4 - 2 = 5$$

$P$  gives an **implicit representation** of  $A$

1 Introduction

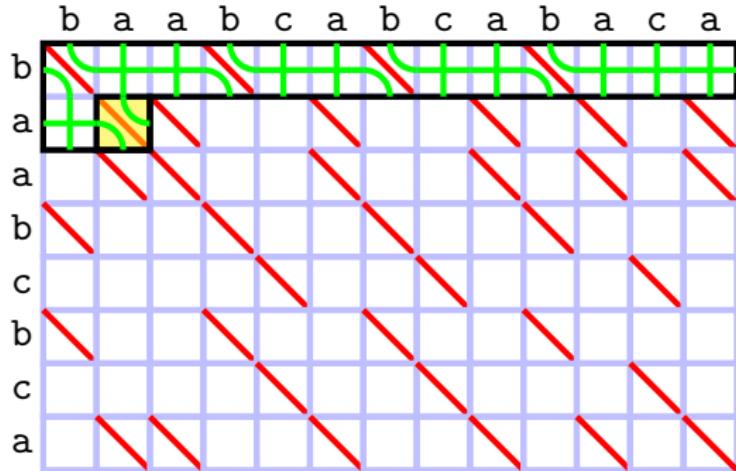
2 Semi-local string comparison

3 The seaweed algorithm

4 Conclusions and future work

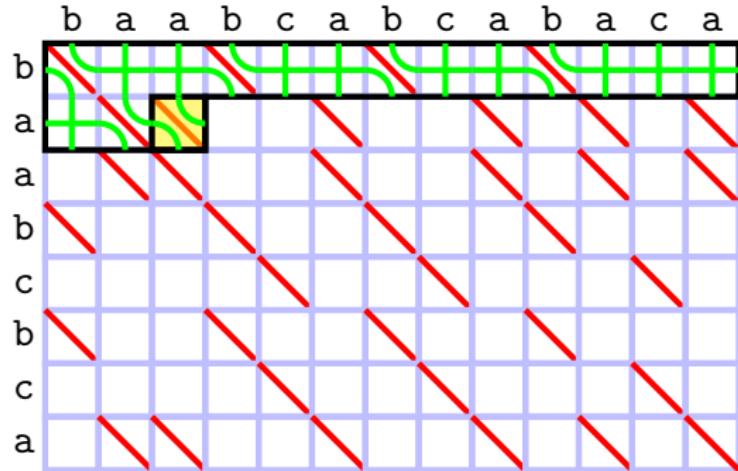
# The seaweed algorithm

## The seaweed algorithm



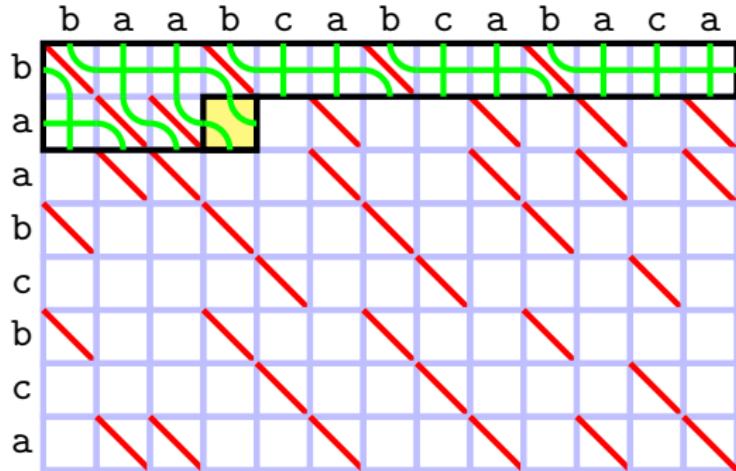
# The seaweed algorithm

## The seaweed algorithm



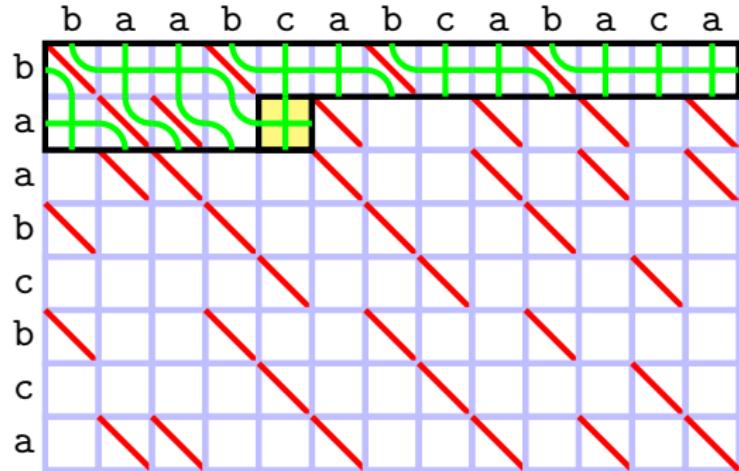
# The seaweed algorithm

## The seaweed algorithm



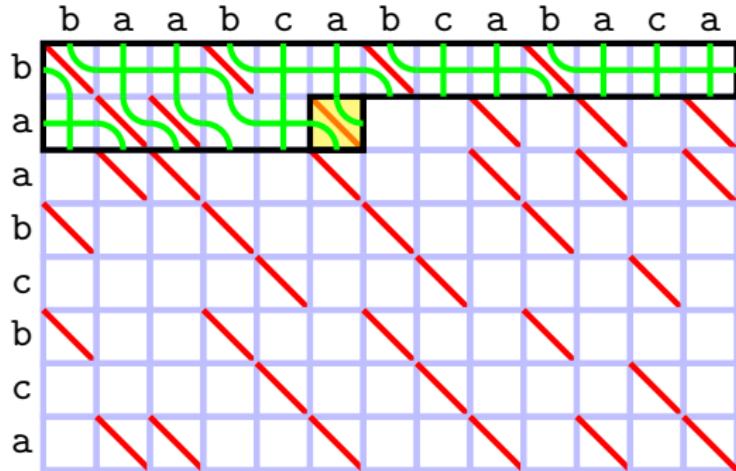
# The seaweed algorithm

## The seaweed algorithm



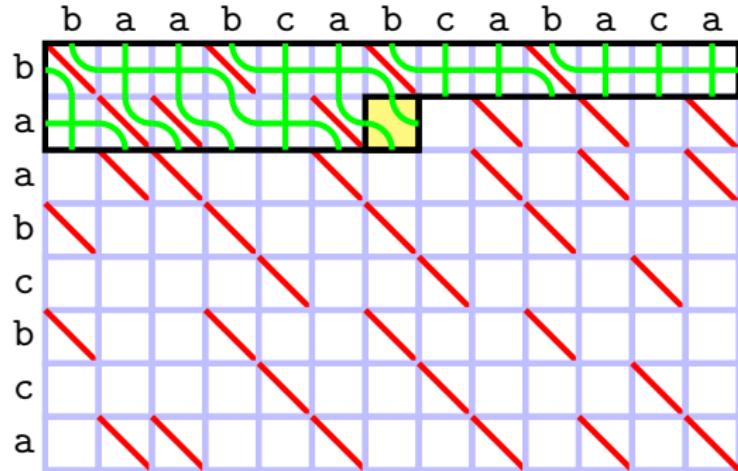
# The seaweed algorithm

## The seaweed algorithm



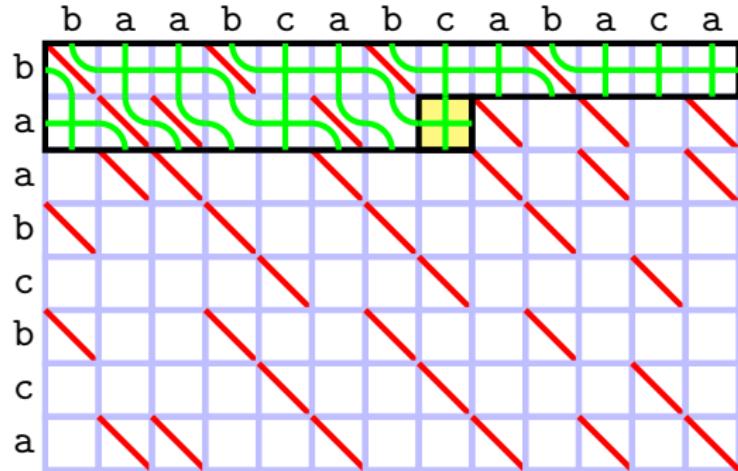
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## The seaweed algorithm



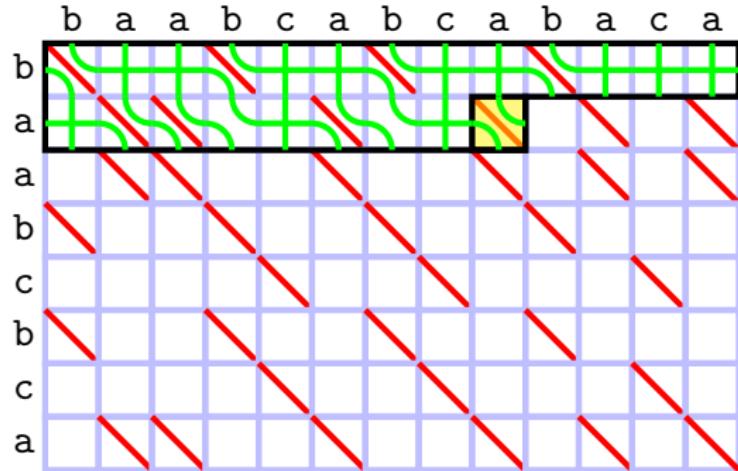
# The seaweed algorithm

## The seaweed algorithm



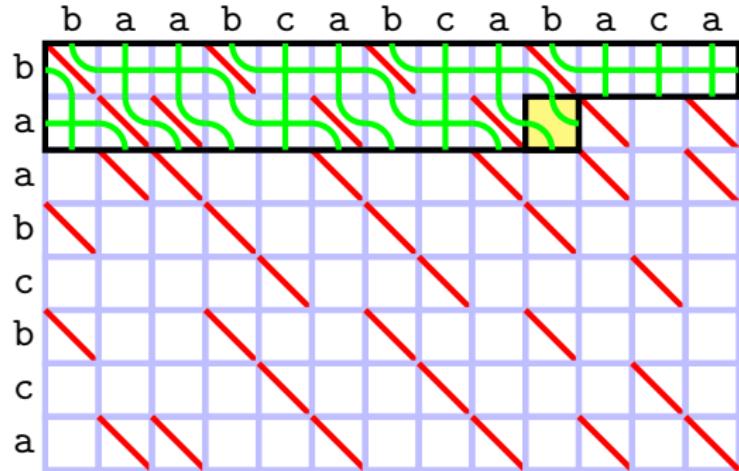
# The seaweed algorithm

## The seaweed algorithm



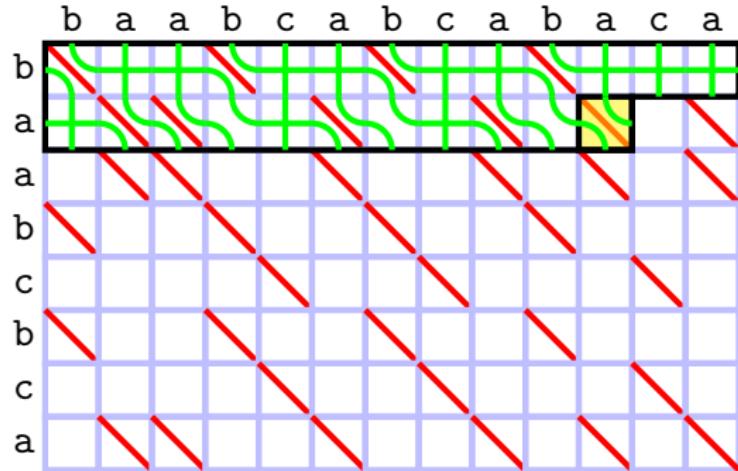
# The seaweed algorithm

## The seaweed algorithm



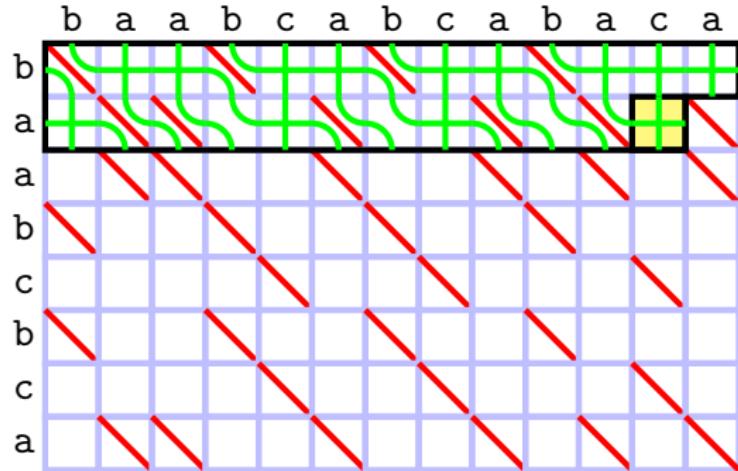
# The seaweed algorithm

## The seaweed algorithm



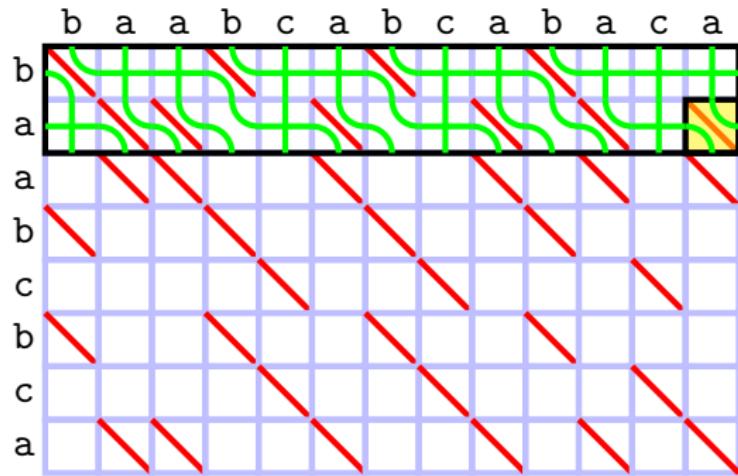
# The seaweed algorithm

## The seaweed algorithm



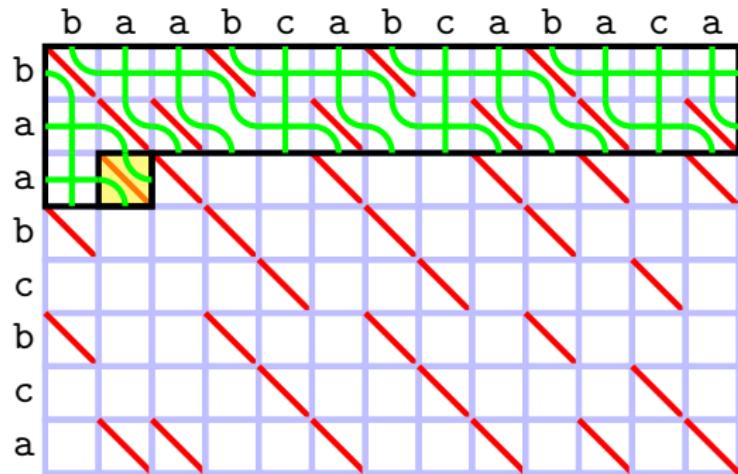
# The seaweed algorithm

## The seaweed algorithm



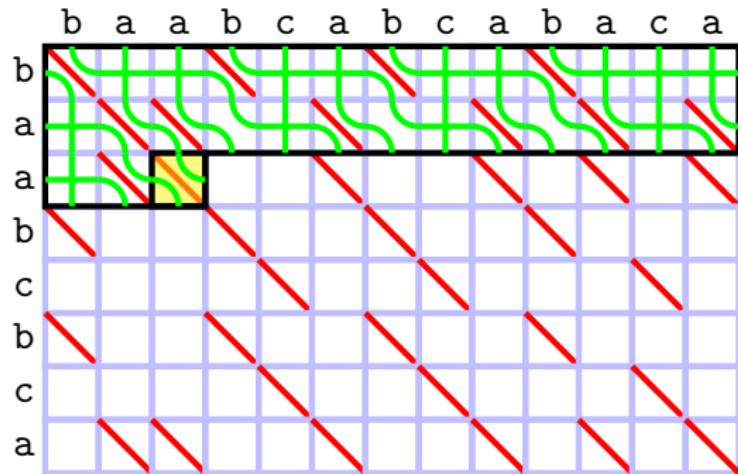
# The seaweed algorithm

## The seaweed algorithm



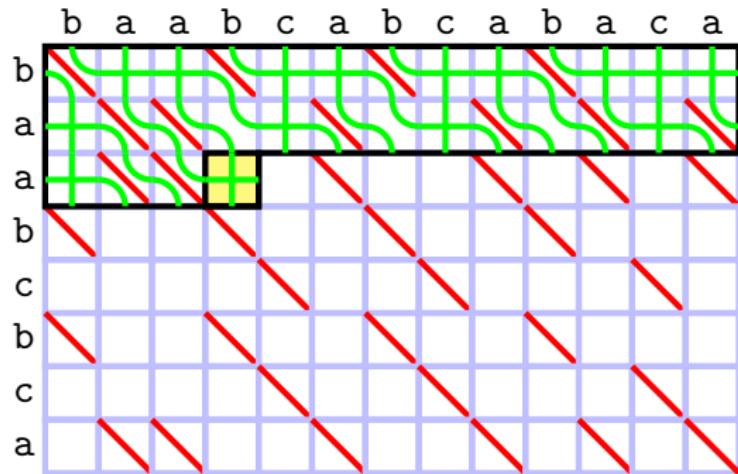
# The seaweed algorithm

## The seaweed algorithm



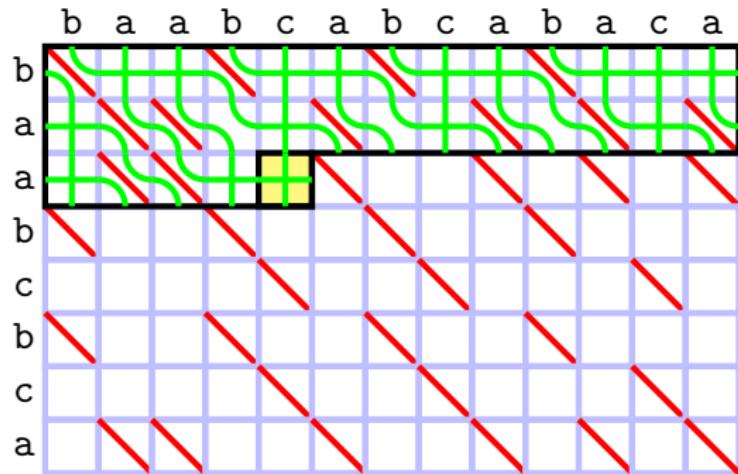
# The seaweed algorithm

## The seaweed algorithm



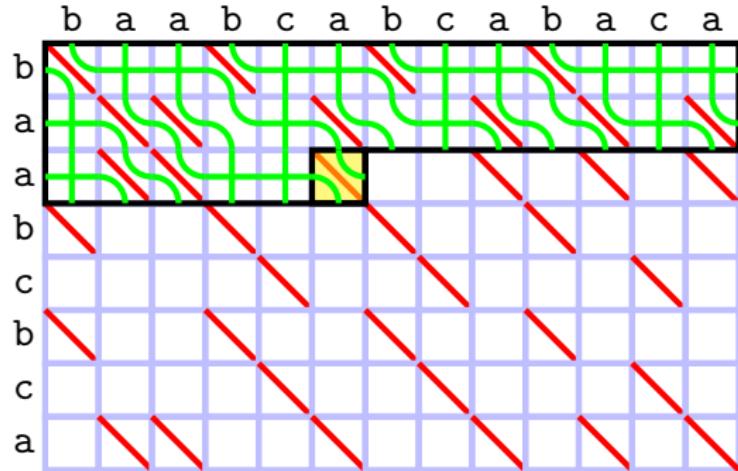
# The seaweed algorithm

## The seaweed algorithm



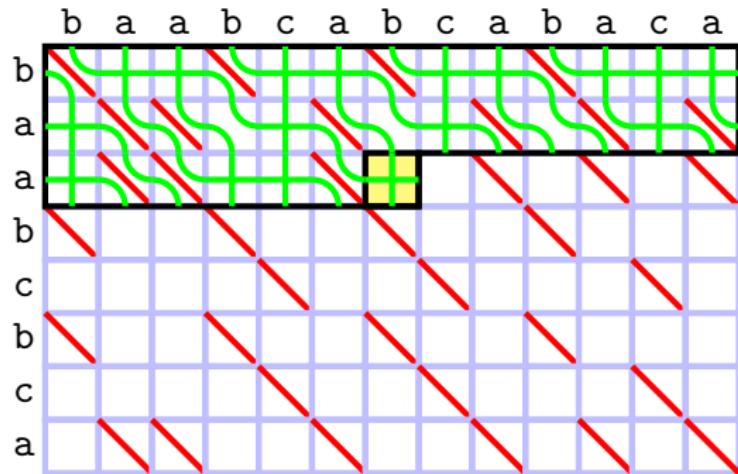
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## The seaweed algorithm



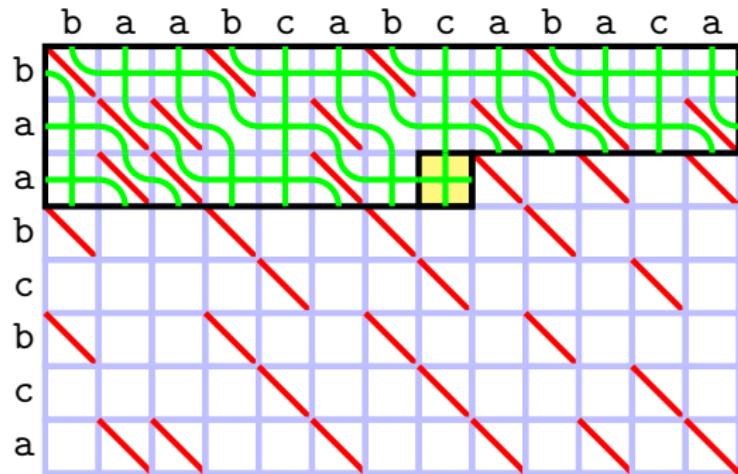
# The seaweed algorithm

## The seaweed algorithm



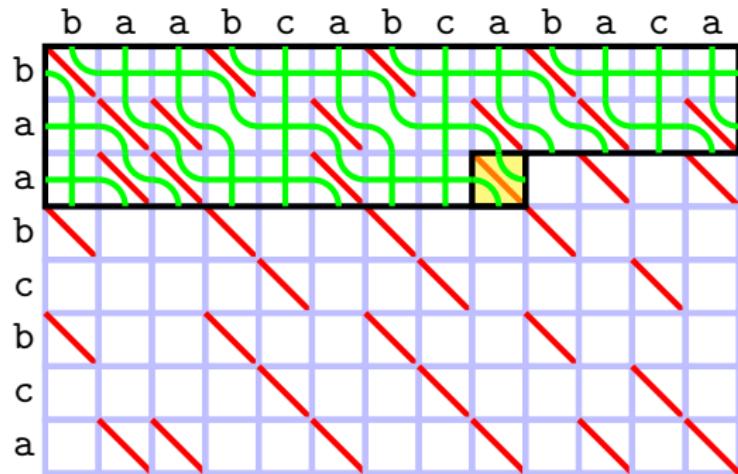
# The seaweed algorithm

## The seaweed algorithm



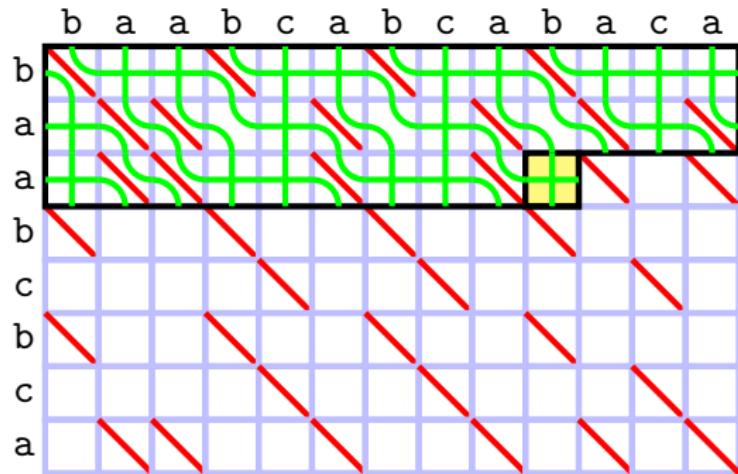
# The seaweed algorithm

## The seaweed algorithm



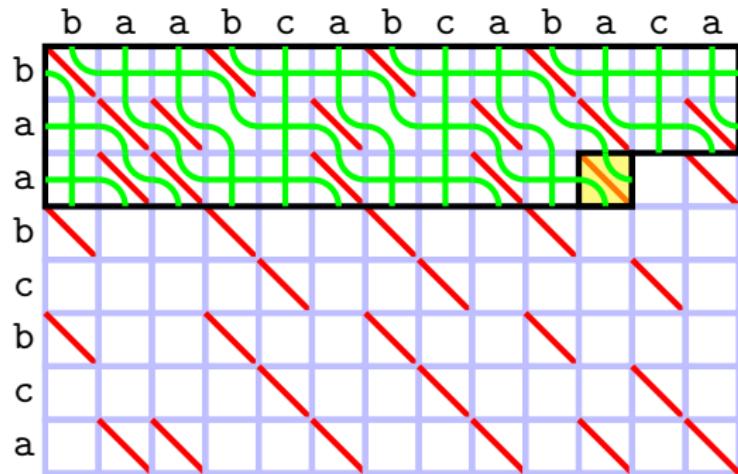
# The seaweed algorithm

## The seaweed algorithm



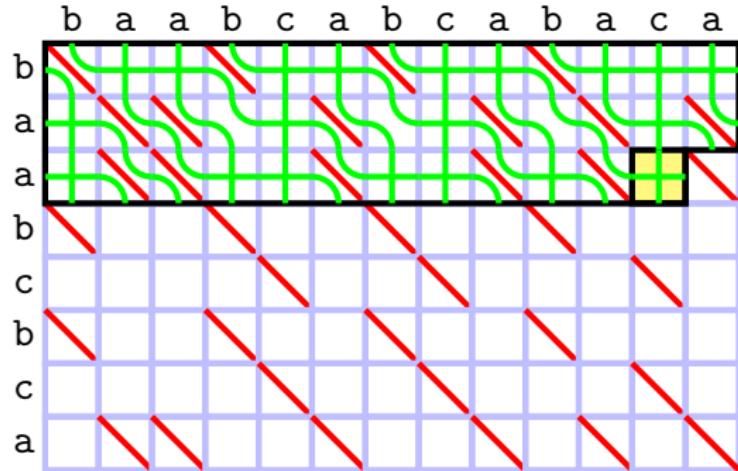
# The seaweed algorithm

## The seaweed algorithm



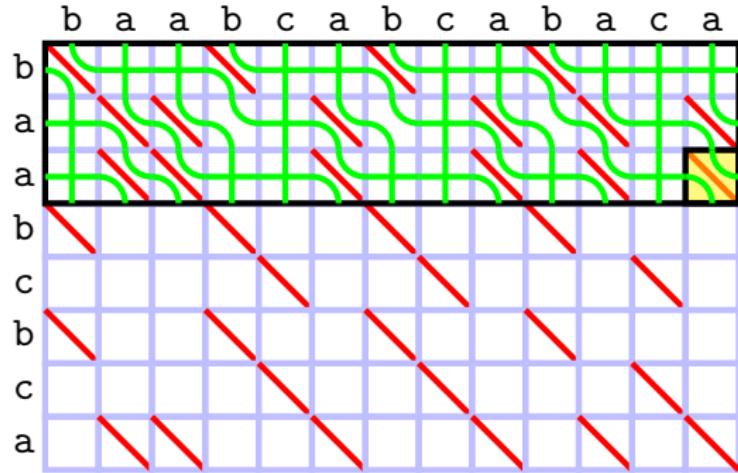
# The seaweed algorithm

## The seaweed algorithm



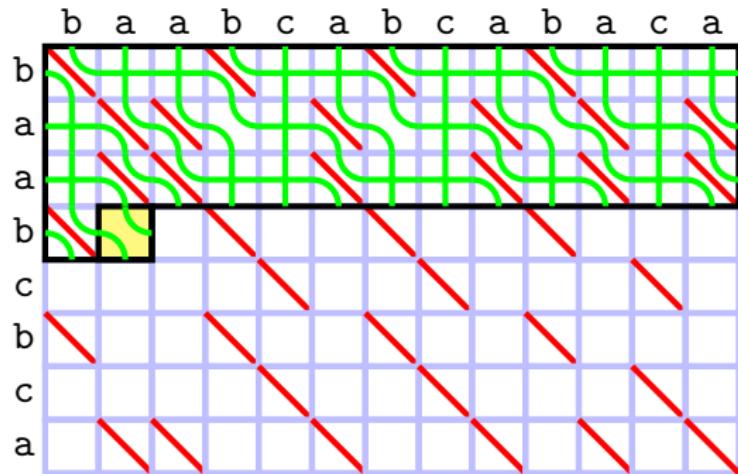
# The seaweed algorithm

## The seaweed algorithm



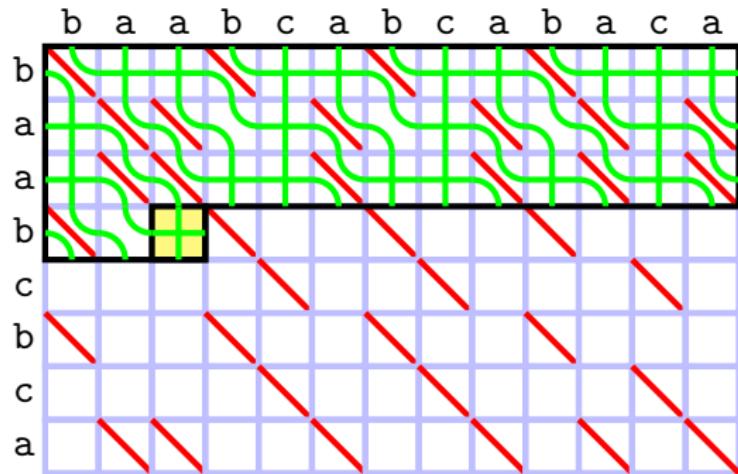
# The seaweed algorithm

## The seaweed algorithm



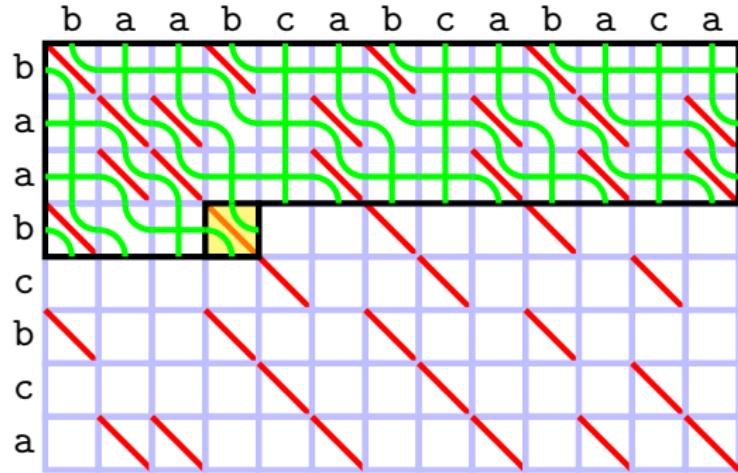
# The seaweed algorithm

## The seaweed algorithm



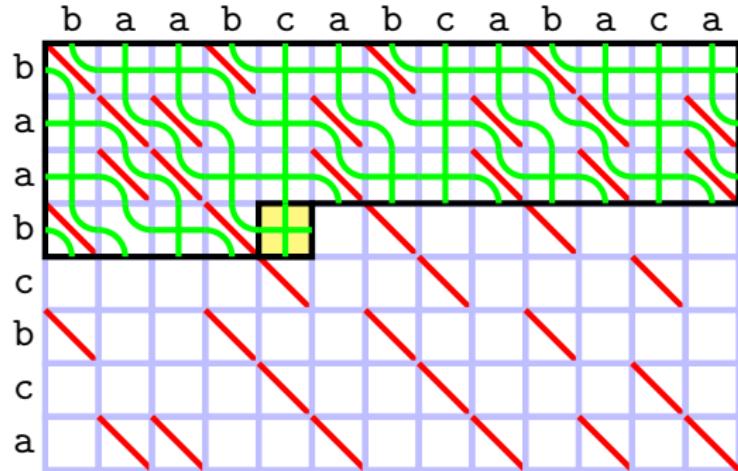
# The seaweed algorithm

## The seaweed algorithm



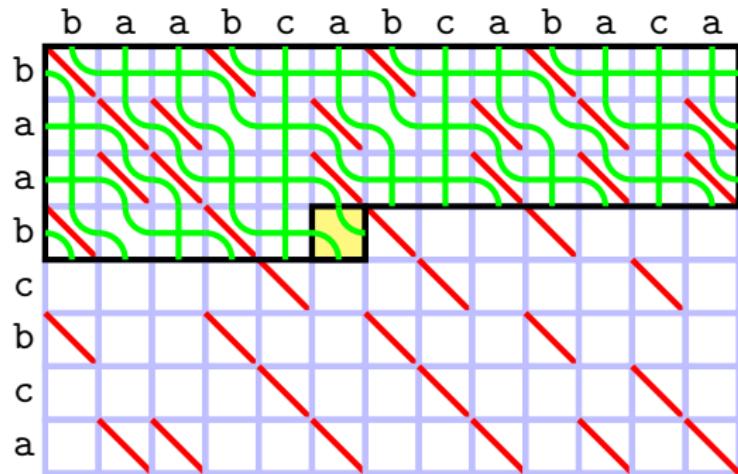
# The seaweed algorithm

## The seaweed algorithm



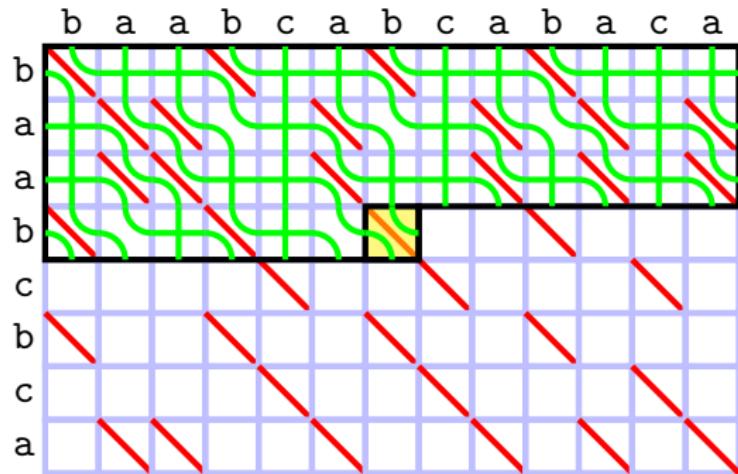
# The seaweed algorithm

## The seaweed algorithm



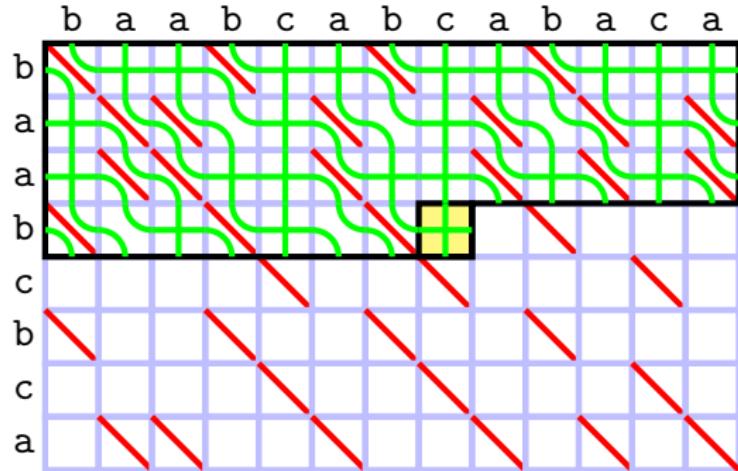
# The seaweed algorithm

## The seaweed algorithm



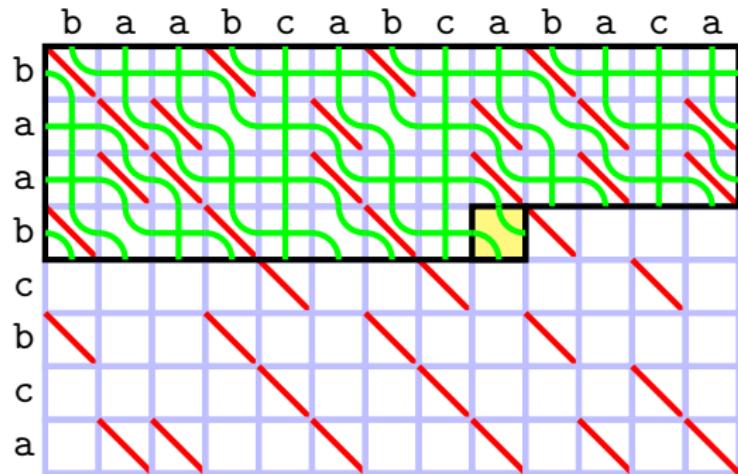
# The seaweed algorithm

## The seaweed algorithm



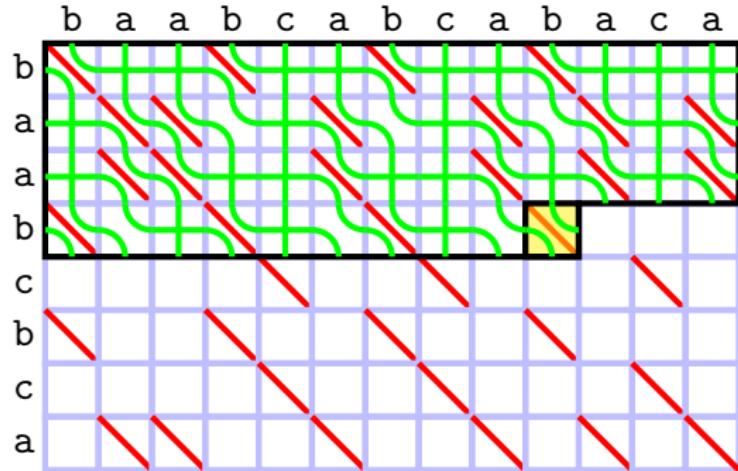
# The seaweed algorithm

## The seaweed algorithm



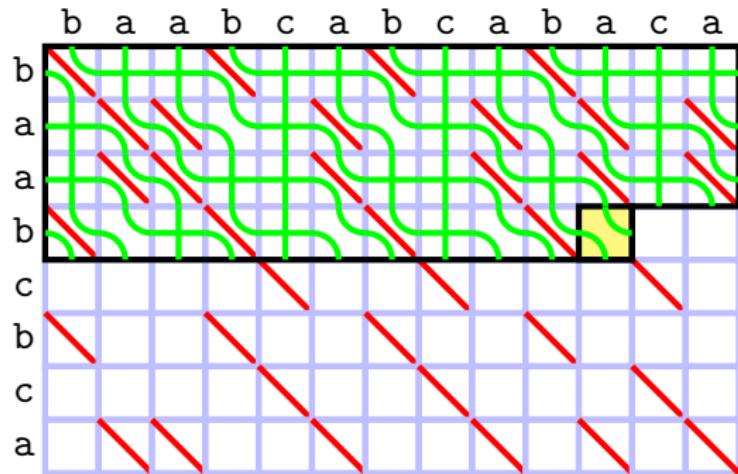
# The seaweed algorithm

## The seaweed algorithm



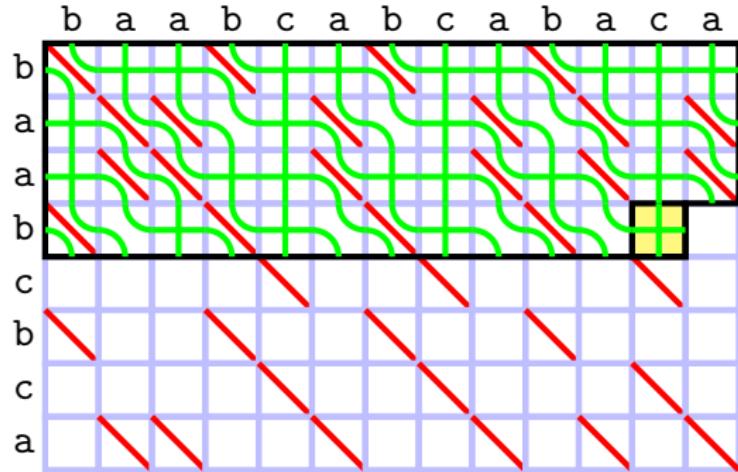
# The seaweed algorithm

## The seaweed algorithm



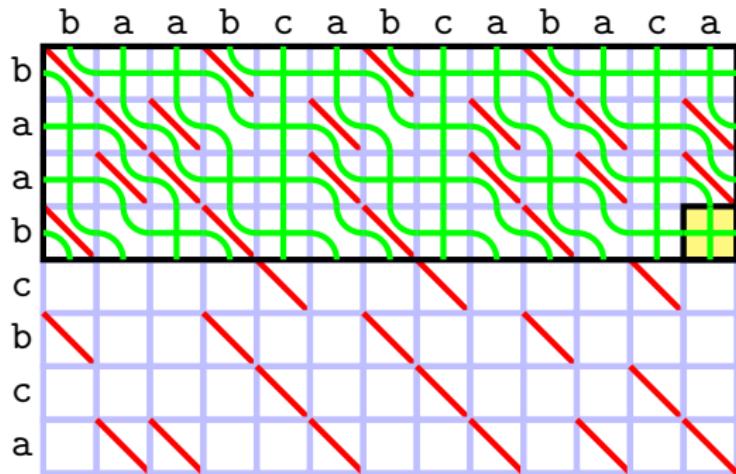
# The seaweed algorithm

## The seaweed algorithm



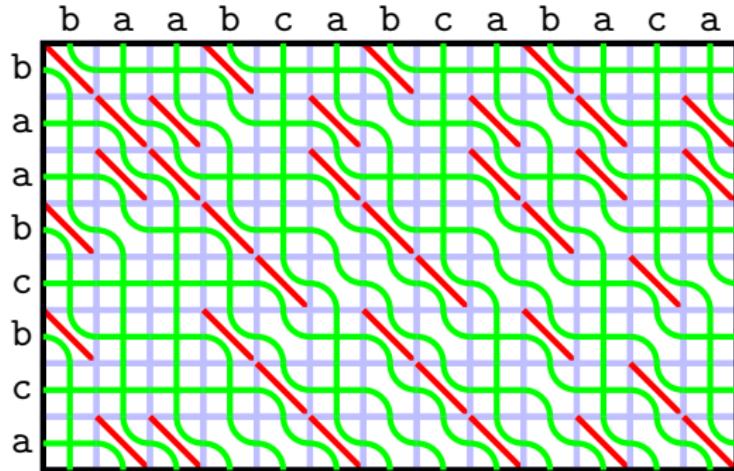
# The seaweed algorithm

## The seaweed algorithm



# The seaweed algorithm

## The seaweed algorithm



# The seaweed algorithm

## The seaweed algorithm

### Semi-local LCS: the seaweed algorithm

[T: 2006]

Iterate over alignment graph, tracing seaweeds

Pick cells in any order, respecting dependencies

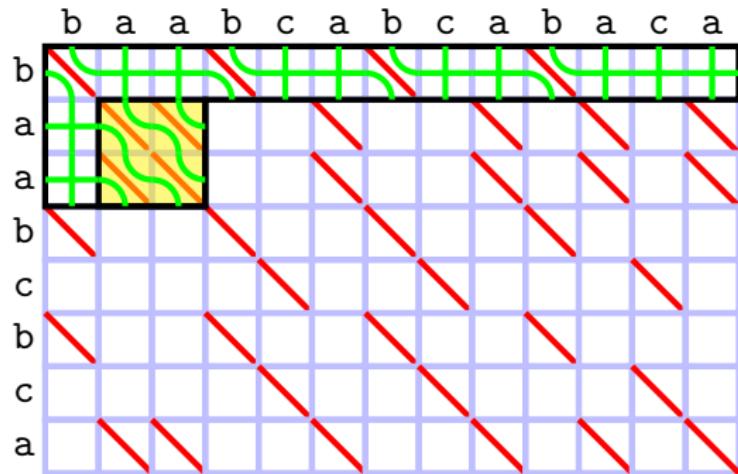
In every cell, the two entering seaweeds

- cross, if mismatch and they have not crossed before
- bend otherwise

Running time  $O(mn)$

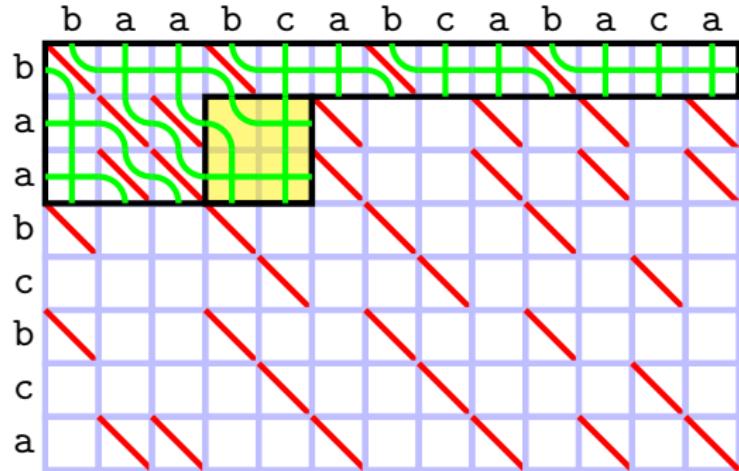
# The seaweed algorithm

## The micro-block seaweed algorithm



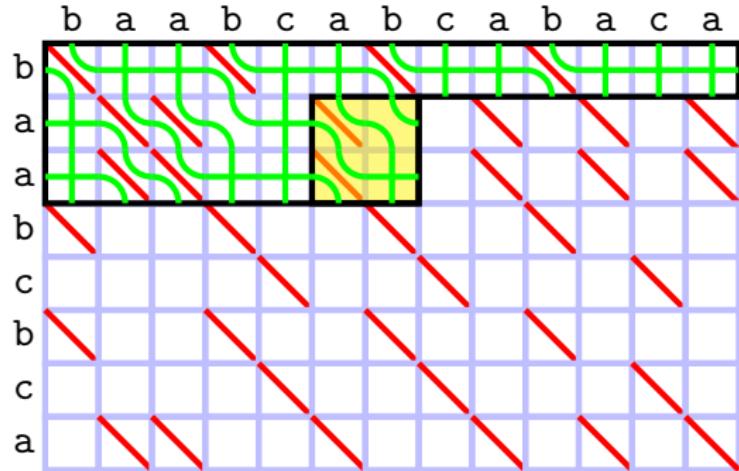
# The seaweed algorithm

## The micro-block seaweed algorithm



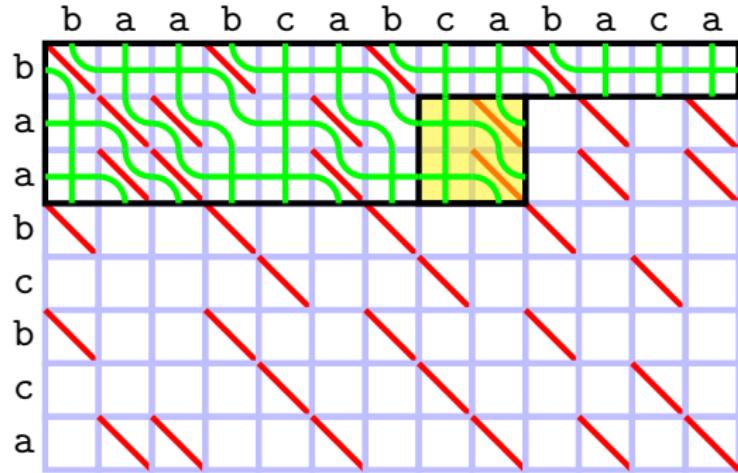
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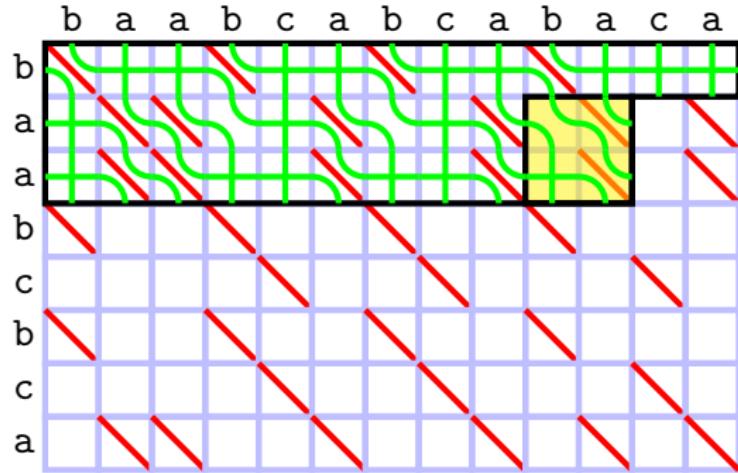
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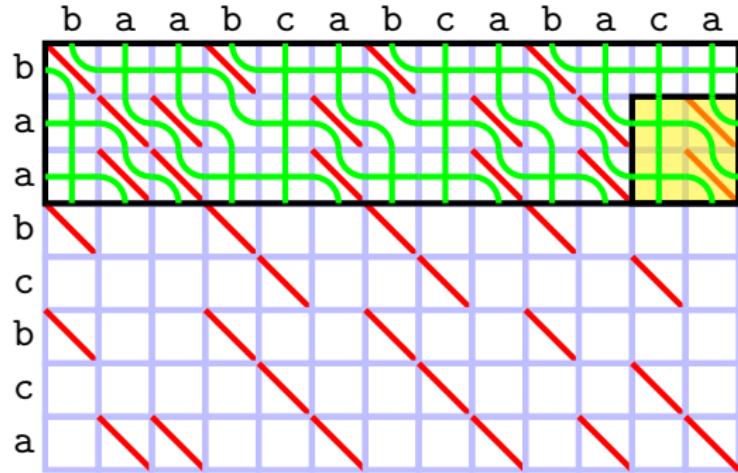
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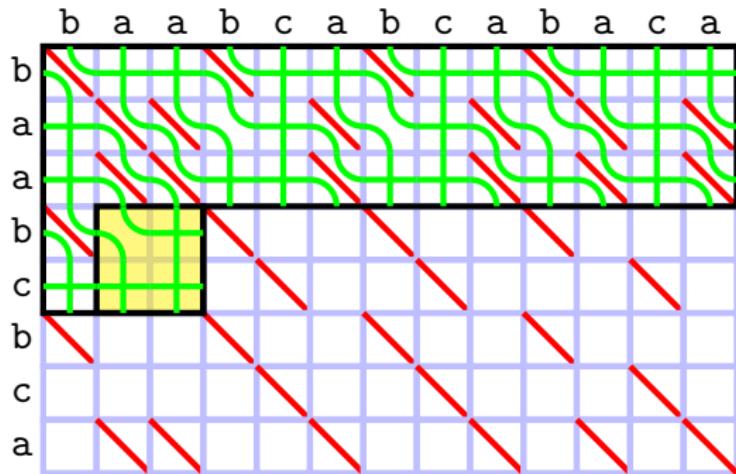
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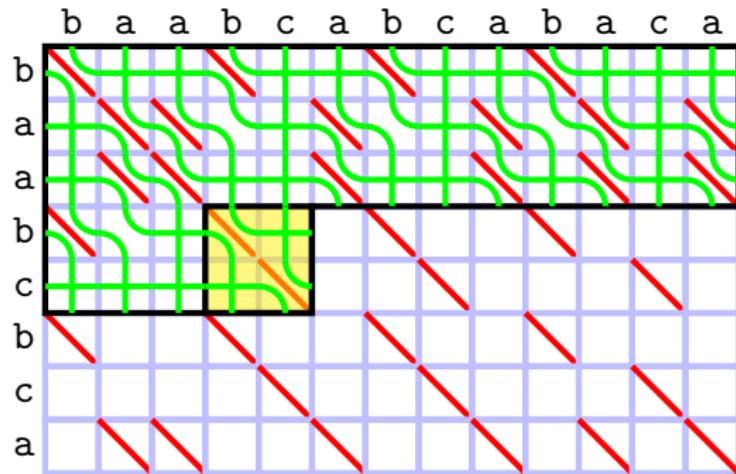
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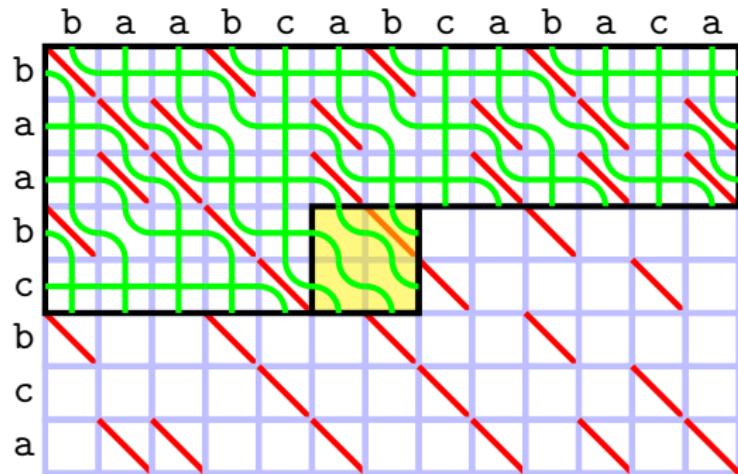
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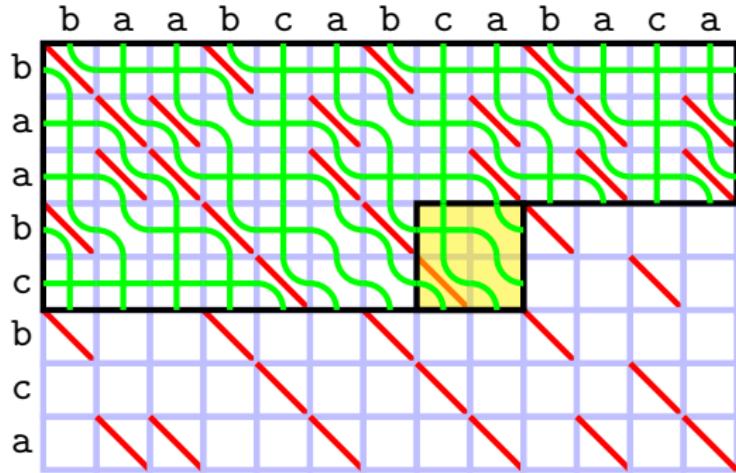
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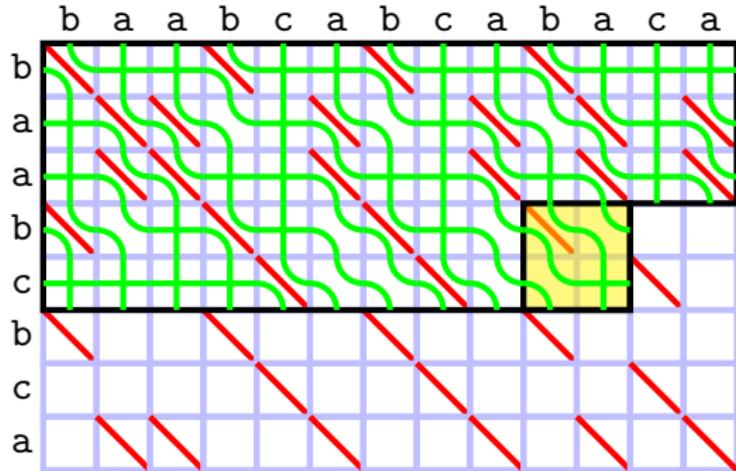
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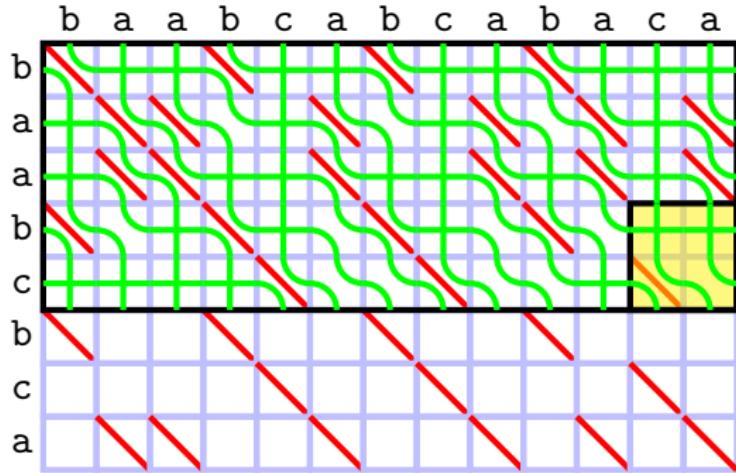
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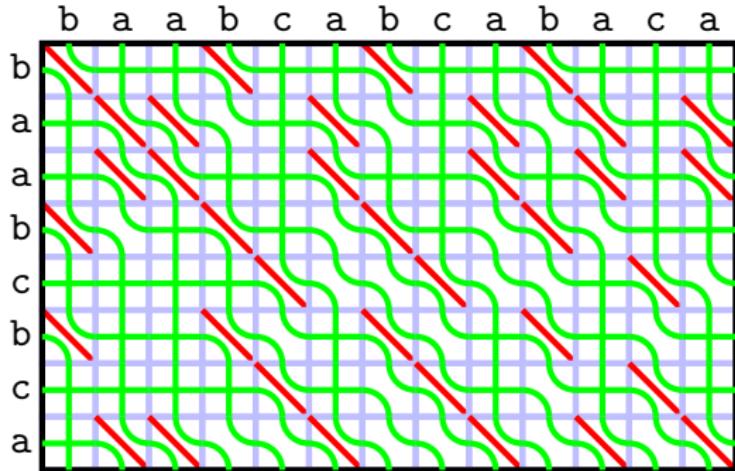
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# The seaweed algorithm

## The micro-block seaweed algorithm

Semi-local LCS: the micro-block seaweed algorithm

[T: 2007]

Iterate over alignment graph in blocks, tracing seaweeds

Use precomputed mapping of all possible block inputs to outputs

Block size:  $t = O\left(\frac{\log n}{\log \log n}\right)$

Block interface:  $O(t)$  values (input chars and seaweeds), each of size  $O(\log n)$  but can be compressed to  $O(\log \log n)$  by a recursive scheme

Running time  $O\left(\frac{m}{t} \cdot \frac{n}{t} \cdot t \log \log n\right) = O\left(\frac{mn(\log \log n)^2}{\log n}\right)$ , even on log-cost RAM

# The seaweed algorithm

## Cyclic LCS

### The cyclic LCS problem

Give the maximum LCS score for  $a$  vs all cyclic rotations of  $b$

# The seaweed algorithm

## Cyclic LCS

### The cyclic LCS problem

Give the maximum LCS score for  $a$  vs all cyclic rotations of  $b$

### Cyclic LCS: running time

$$O\left(\frac{mn^2}{\log n}\right)$$

naive

$$O(mn \log m)$$

[Maes: 1990]

$$O(mn)$$

[Bunke, Bühler: 1993; Landau+: 1998; Schmidt: 1998]

$$O\left(\frac{mn(\log \log n)^2}{\log n}\right)$$

[T: 2007]

### Cyclic LCS: the algorithm

Run the micro-block seaweed algorithm on  $a$  vs  $bb$ , time  $O\left(\frac{mn(\log \log n)^2}{\log n}\right)$

Make  $n$  string-substring LCS queries, time negligible

# The seaweed algorithm

Longest repeating subsequence

## The longest repeating subsequence problem

Find the longest subsequence of  $a$  that is a square (a repetition of two identical strings)

Motivated by “tandem repeats” in genome

# The seaweed algorithm

Longest repeating subsequence

## The longest repeating subsequence problem

Find the longest subsequence of  $a$  that is a square (a repetition of two identical strings)

Motivated by “tandem repeats” in genome

## Longest repeating subsequence: running time

$$O(n^3)$$

naive

$$O(n^2)$$

[Kosowski: 2004]

$$O\left(\frac{n^2(\log \log n)^2}{\log n}\right)$$

[T: 2007]

## Longest repeating subsequence: the algorithm

Run the micro-block seaweed algorithm on  $a$  vs  $bb$ , time  $O\left(\frac{mn(\log \log n)^2}{\log n}\right)$

Make  $n - 1$  suffix-prefix LCS queries, time negligible

# The seaweed algorithm

## Approximate matching

### The approximate pattern matching problem

Give the substring closest to  $a$  by alignment score, starting at each position in  $b$

Assume rational alignment score

### Approximate pattern matching: running time

$$O(mn)$$

$$O\left(\frac{mn}{\log n}\right)$$

$$\sigma = O(1)$$

[Sellers: 1980]

via [Masek, Paterson: 1980]

via [Paterson, Dancik: 1994]

# The seaweed algorithm

## Approximate matching

### Approximate pattern matching: the algorithm

Run the micro-block seaweed algorithm on  $a$  vs  $b$  under given alignment score in time  $O\left(\frac{mn(\log \log n)^2}{\log n}\right)$

The implicit semi-local edit score matrix:

- an anti-Monge matrix
- approximate pattern matching  $\sim$  row minima

Row minima in  $O(n)$  element queries

[Aggarwal+: 1987]

Each query in time  $O(\log^2 n)$  using the range tree representation,  
combined query time negligible

Overall running time dominated by block seaweed algorithm, same as  
[Paterson, Dancik: 1994]

# The seaweed algorithm

The periodic seaweed algorithm

## The periodic string-substring LCS problem

Give (implicit) LCS scores for  $a$  vs each substring of  $b = \dots uuu\dots = u^{\pm\infty}$

Let  $u$  be of length  $p$ ; may assume that every character of  $a$  occurs in  $u$

## The tandem LCS problem

Give LCS score for  $a$  vs  $b = u^k$

We have  $n = kp$ ; may assume  $k \leq m$  (otherwise LCS score is  $m$ )

## Tandem LCS: running time

$O(mkp)$

naive

$O(m(k + p))$

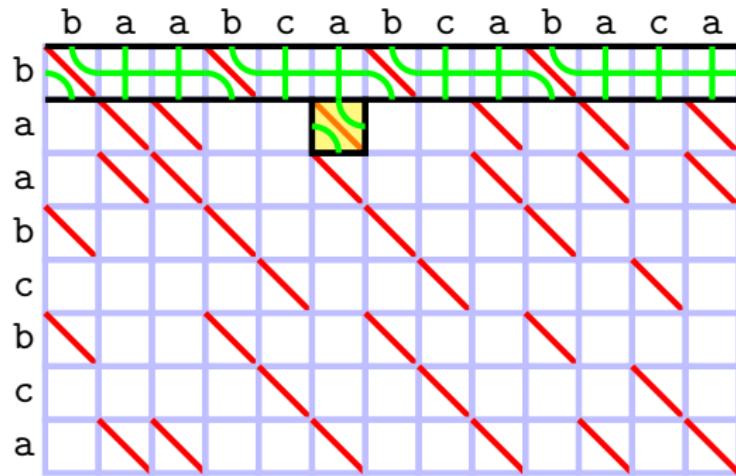
[Landau, Ziv-Ukelson: 2001]

$O(mp)$

[NEW]

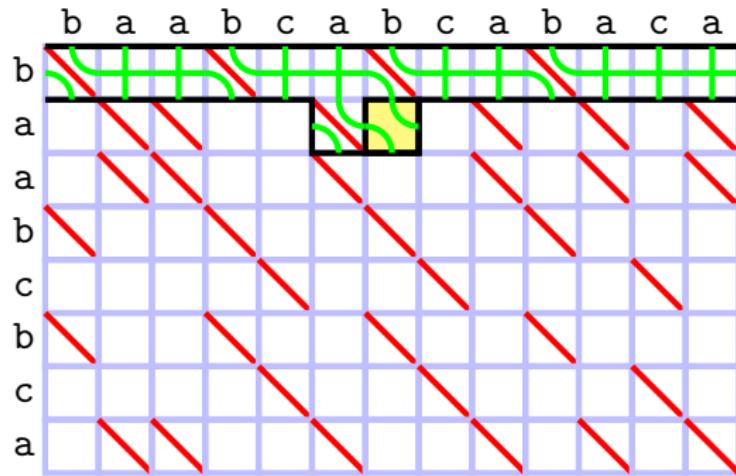
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## The periodic seaweed algorithm



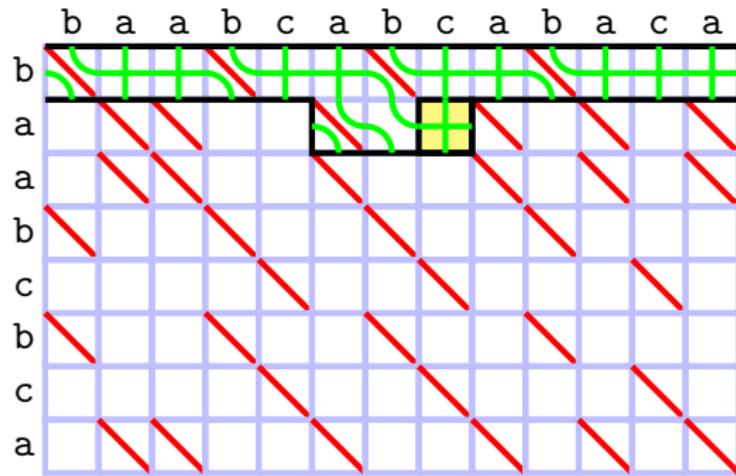
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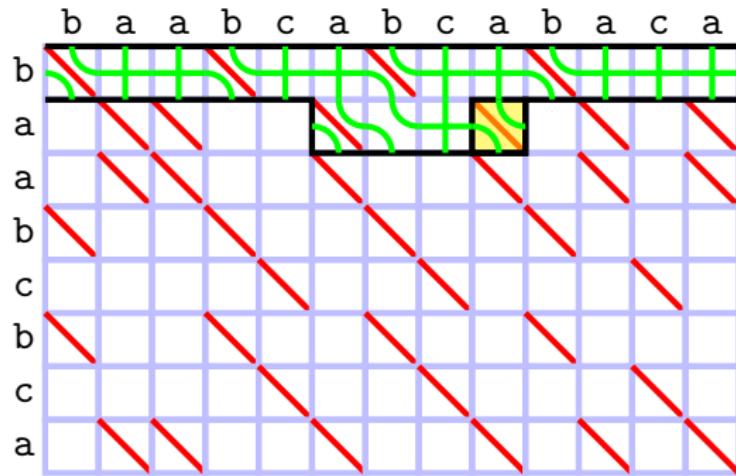
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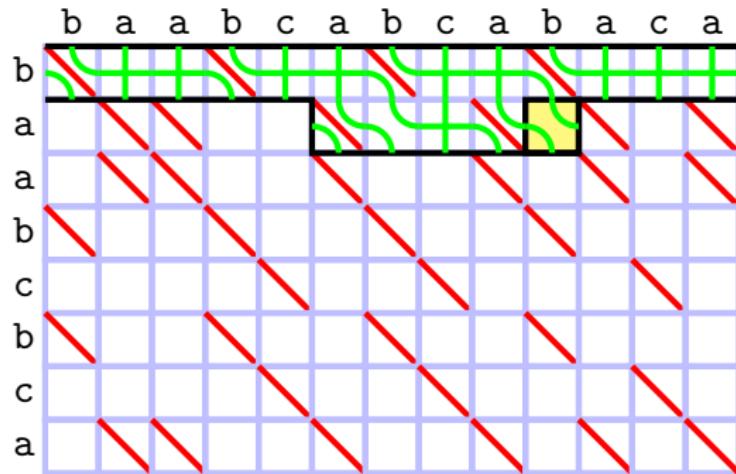
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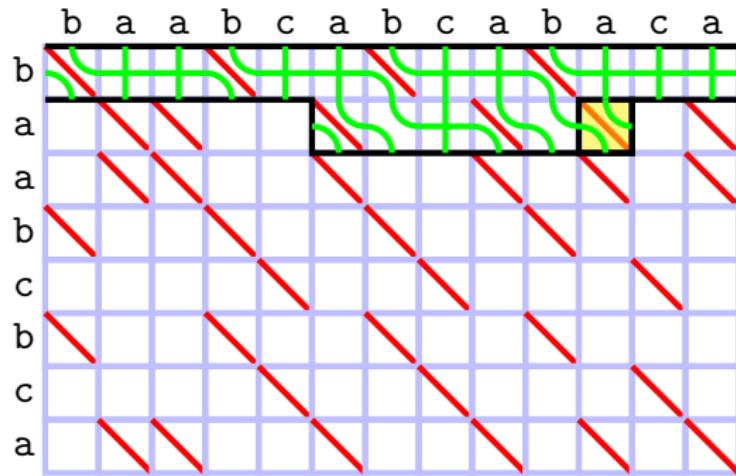
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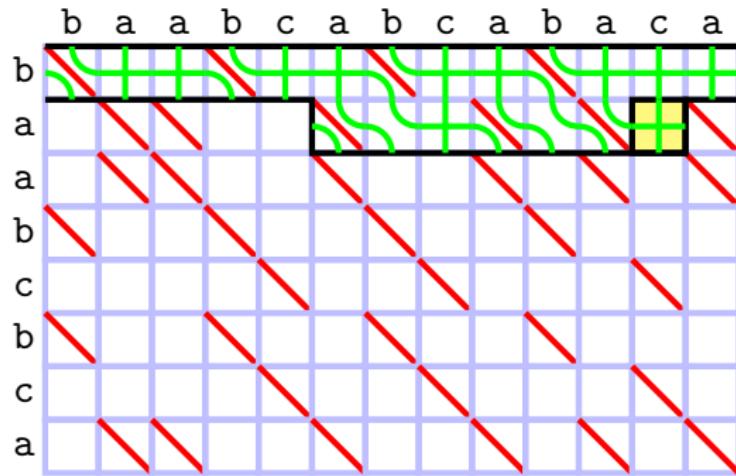
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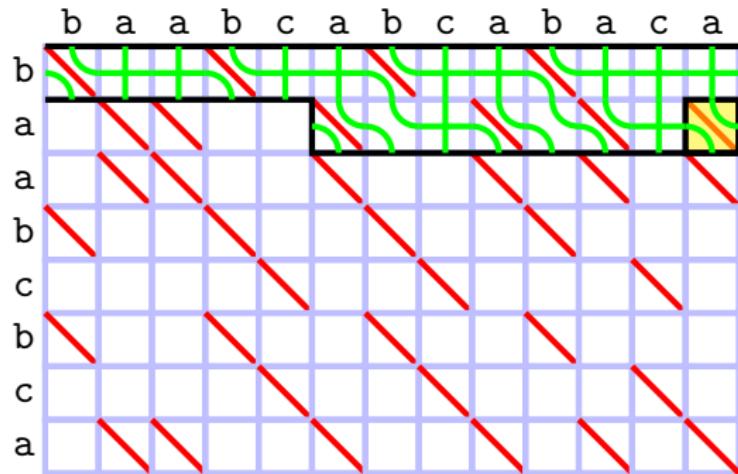
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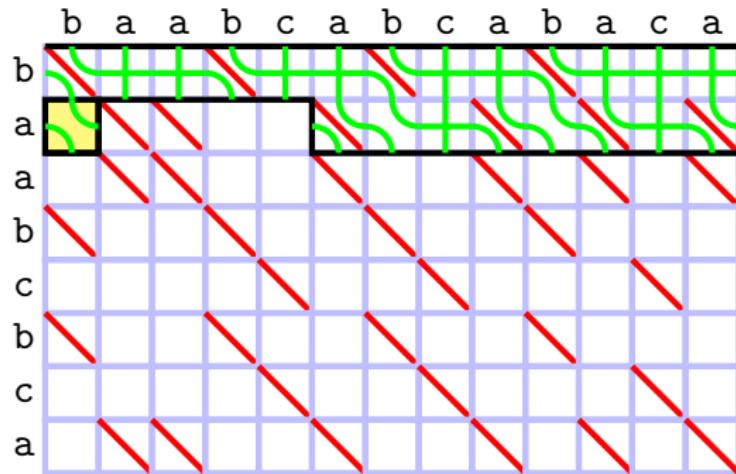
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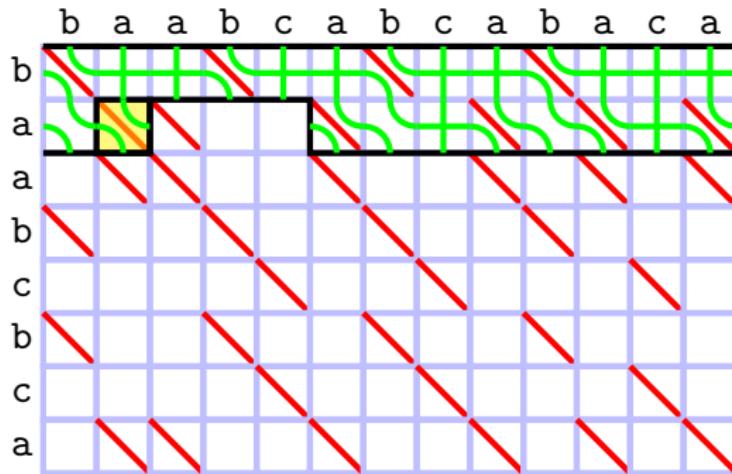
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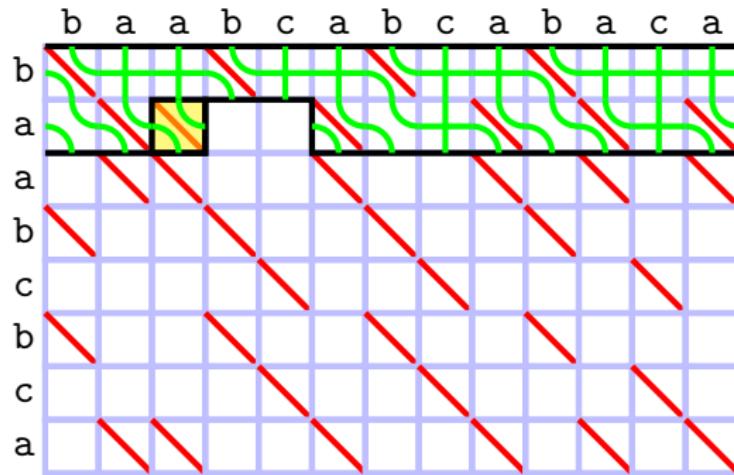
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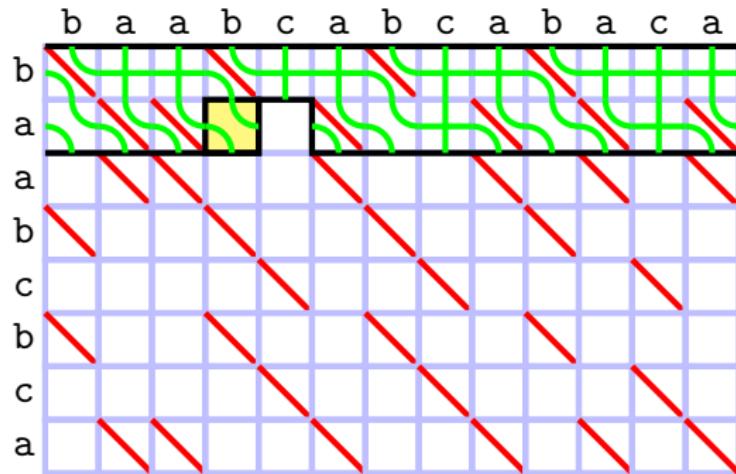
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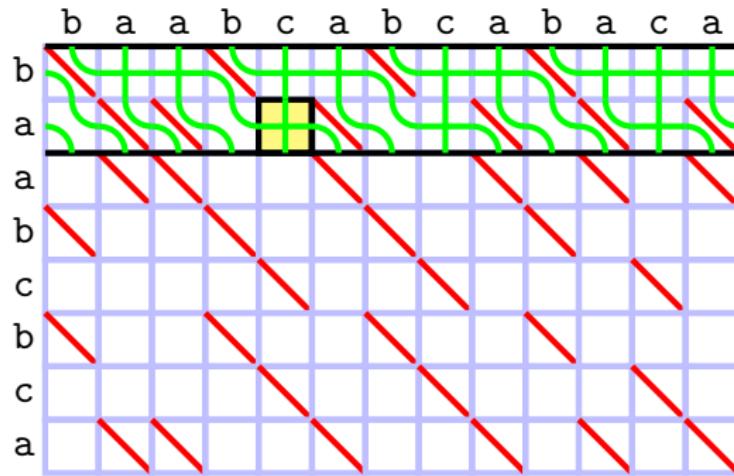
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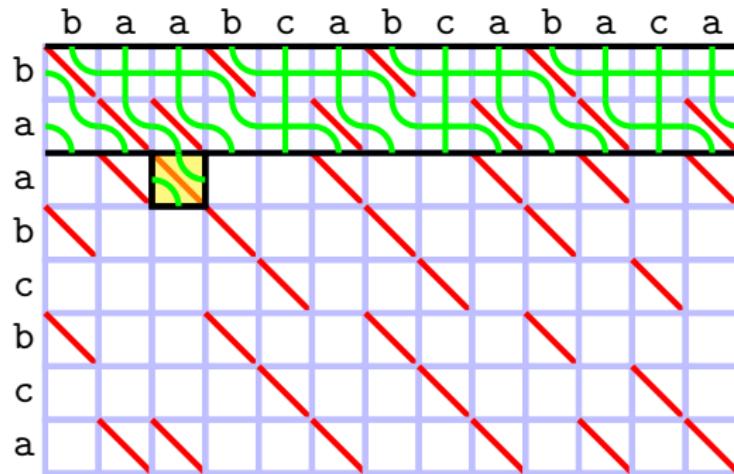
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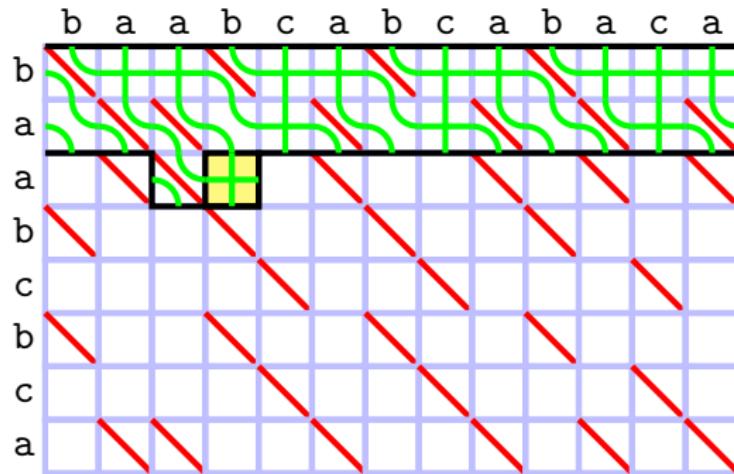
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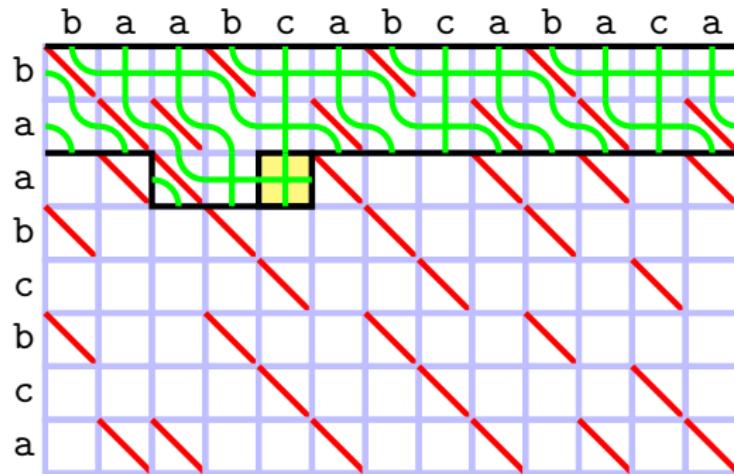
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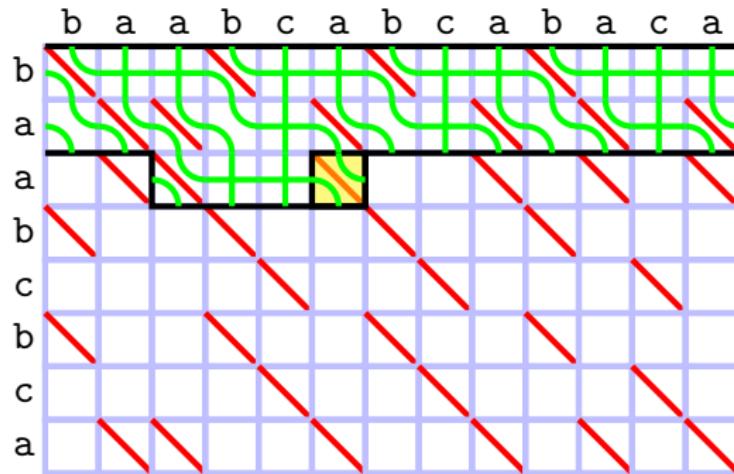
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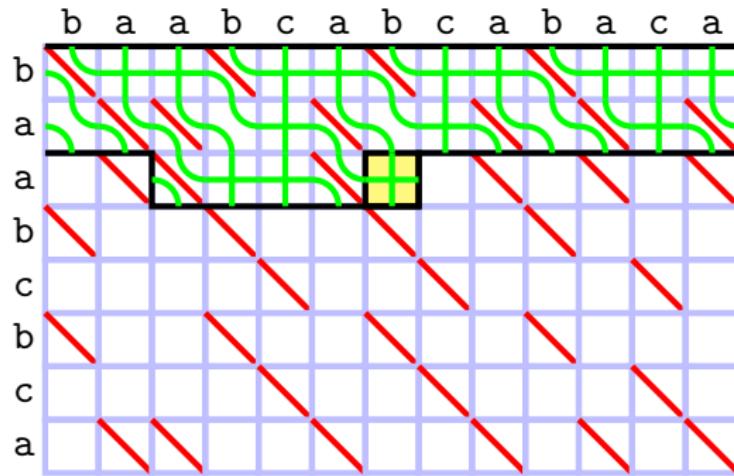
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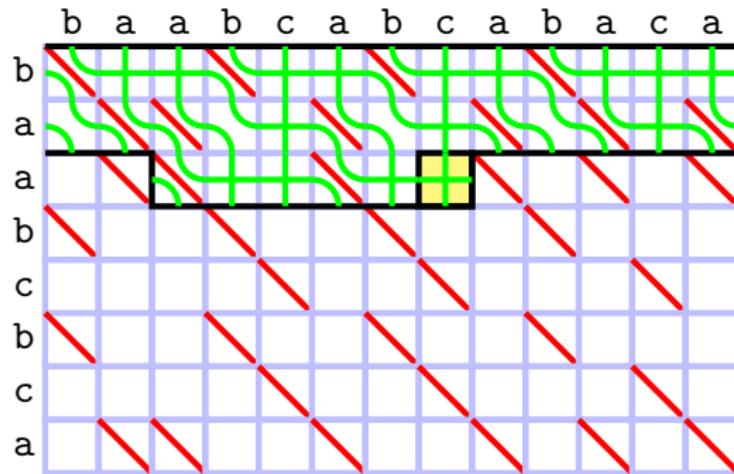
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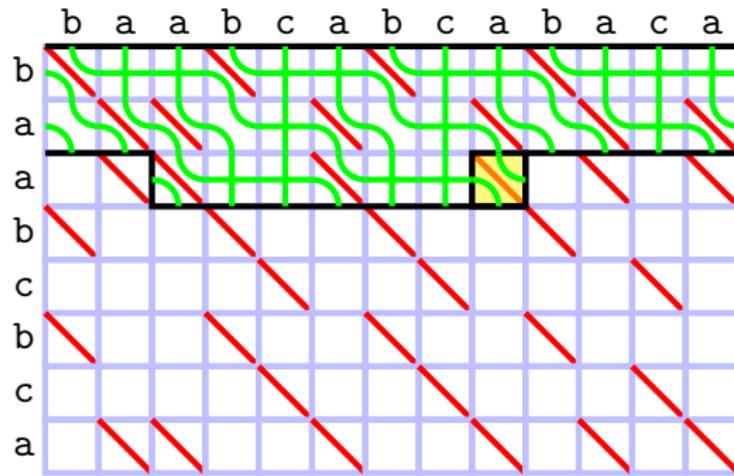
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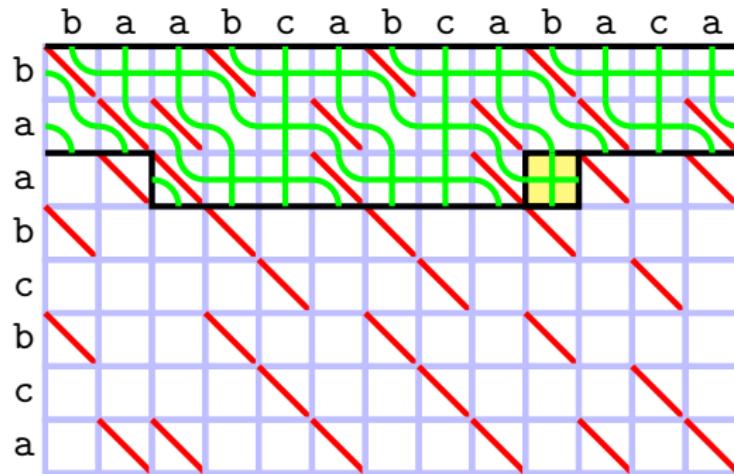
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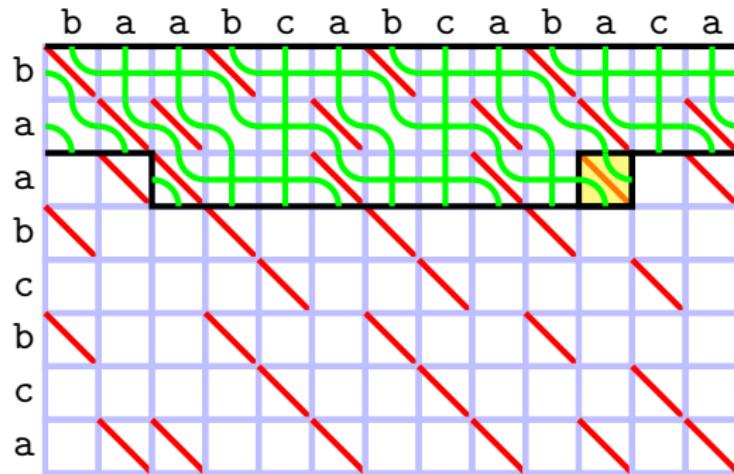
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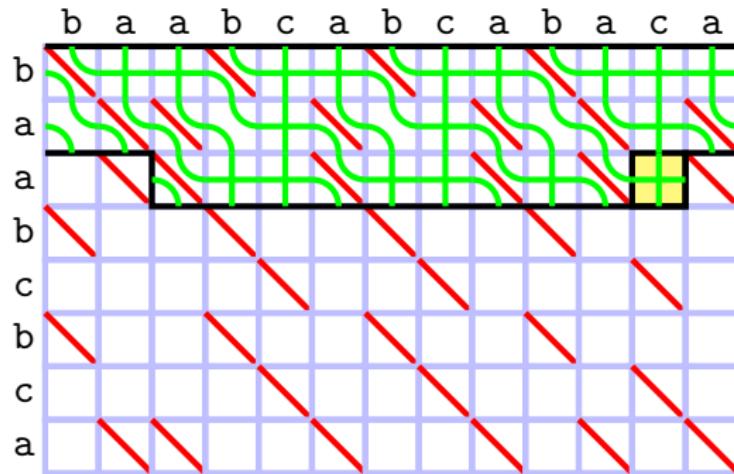
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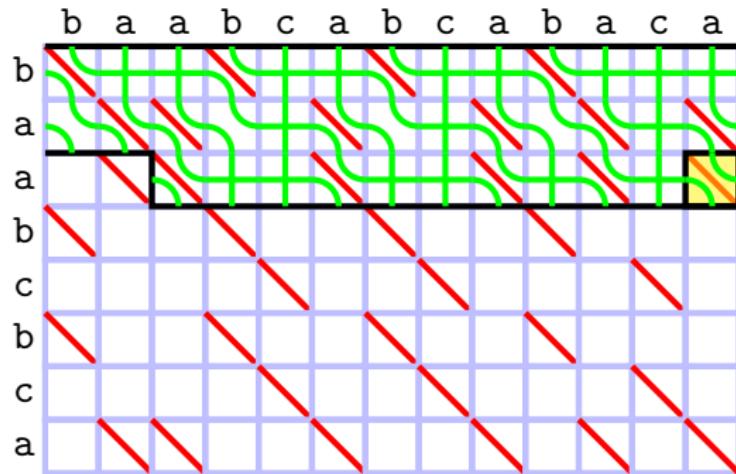
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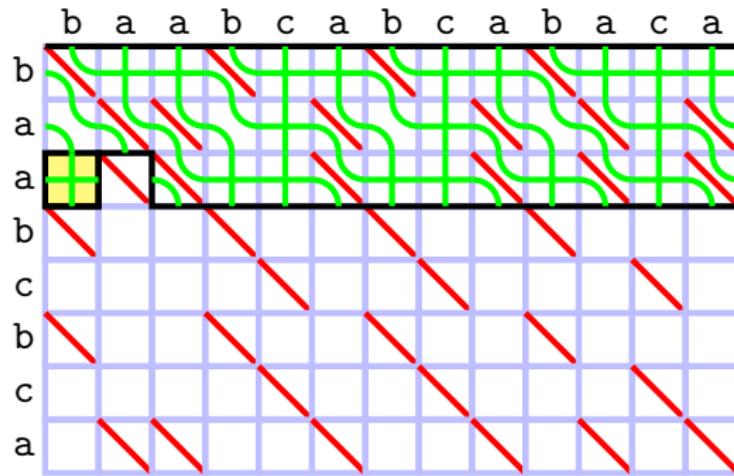
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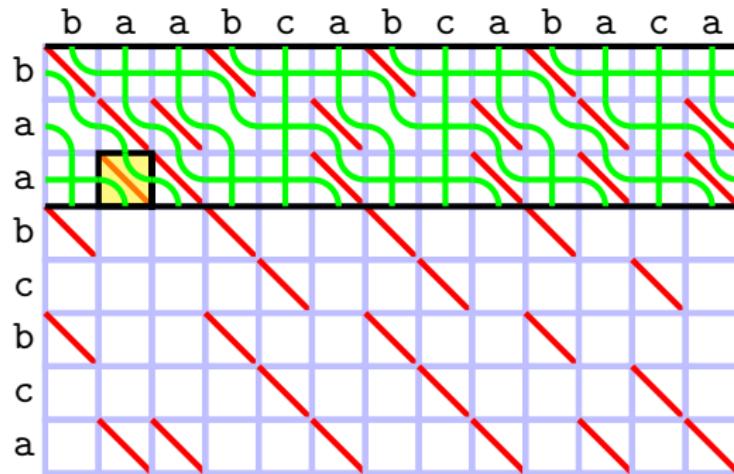
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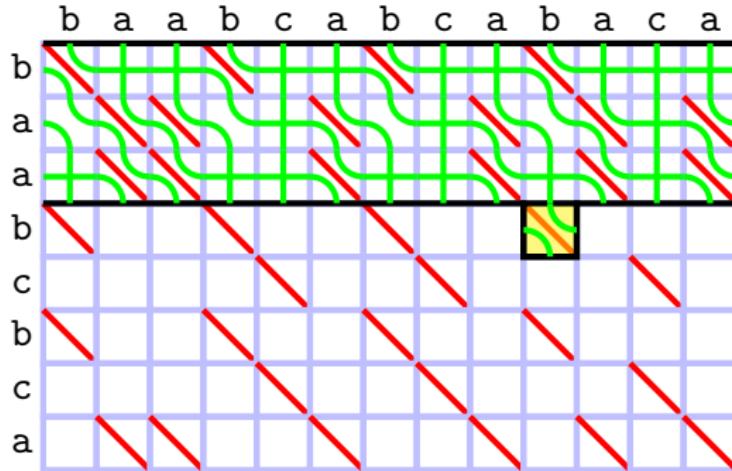
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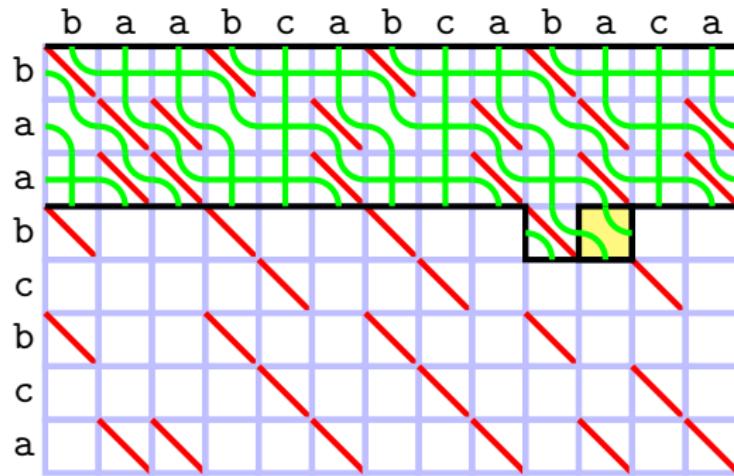
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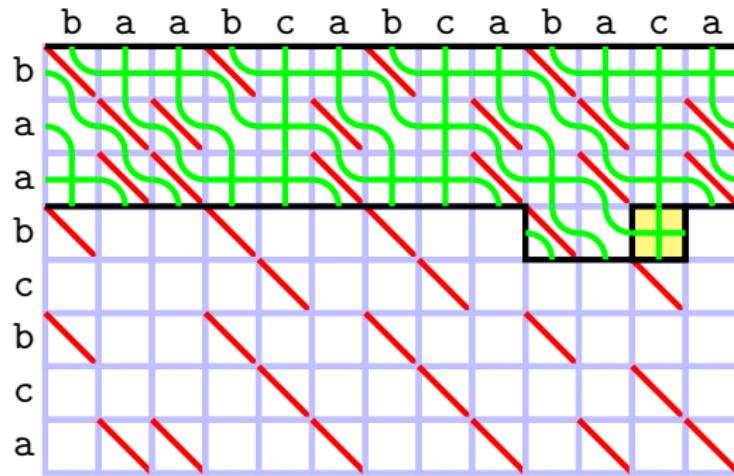
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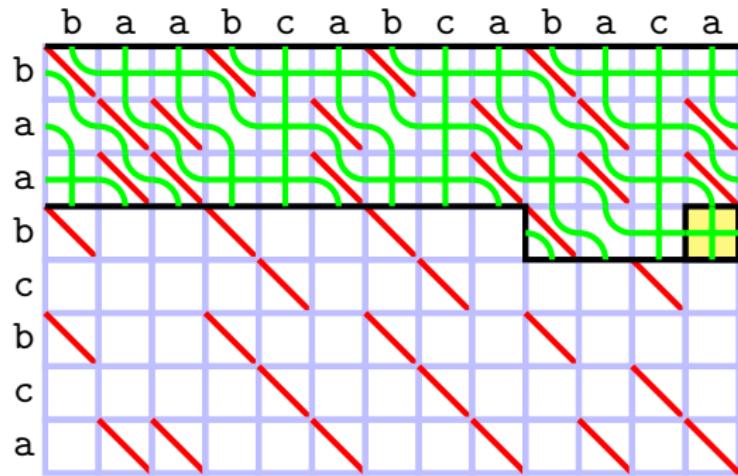
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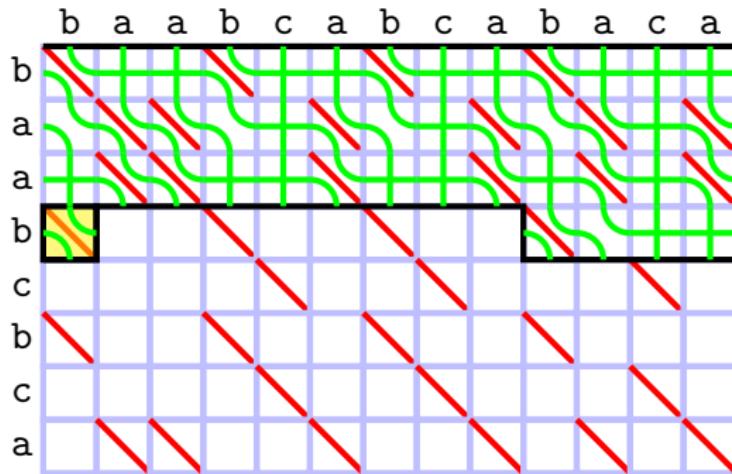
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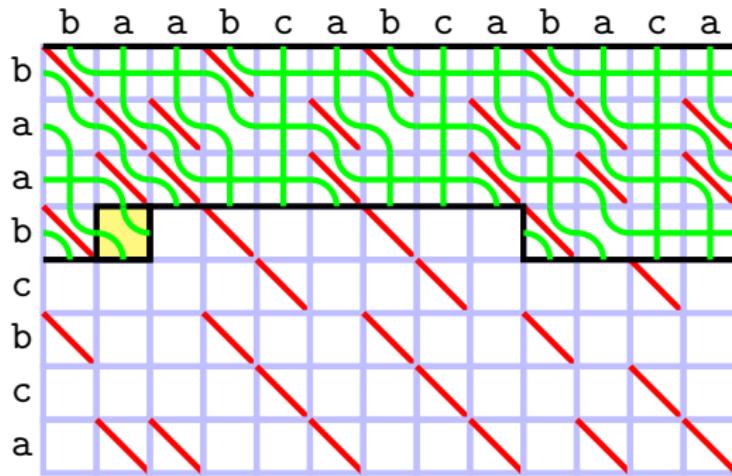
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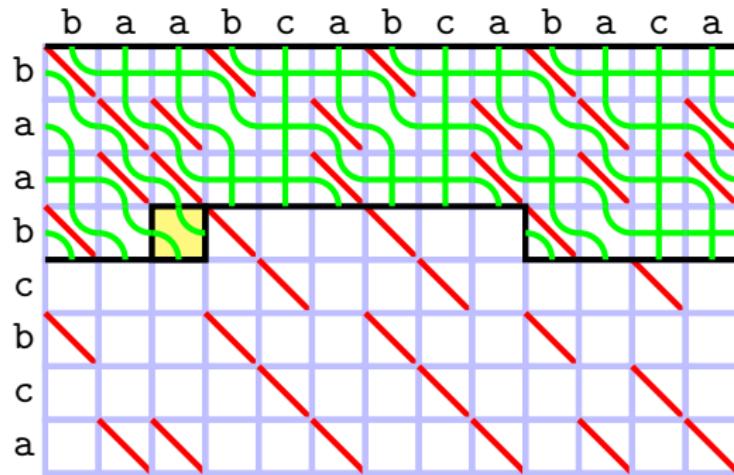
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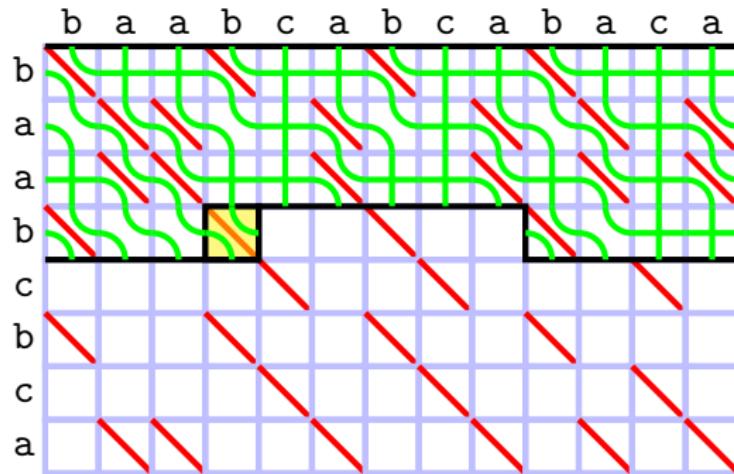
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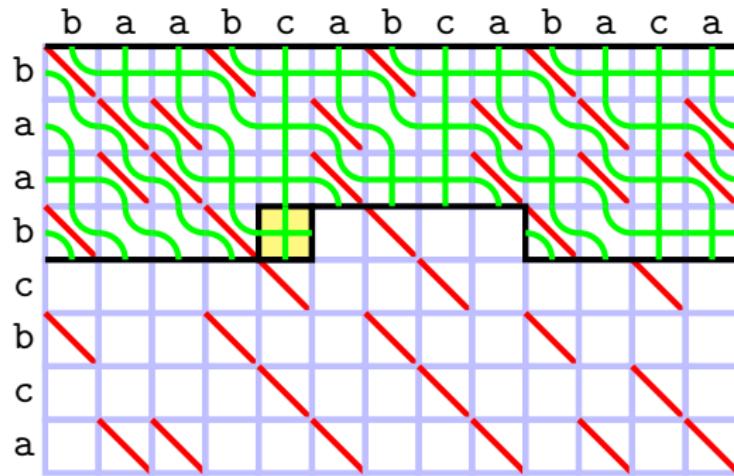
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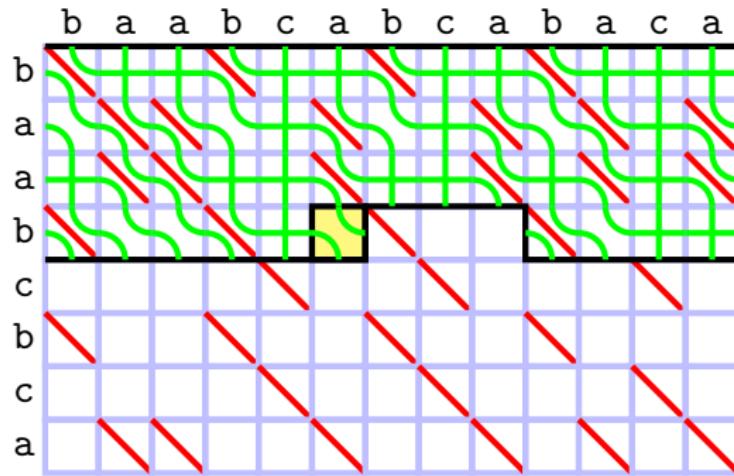
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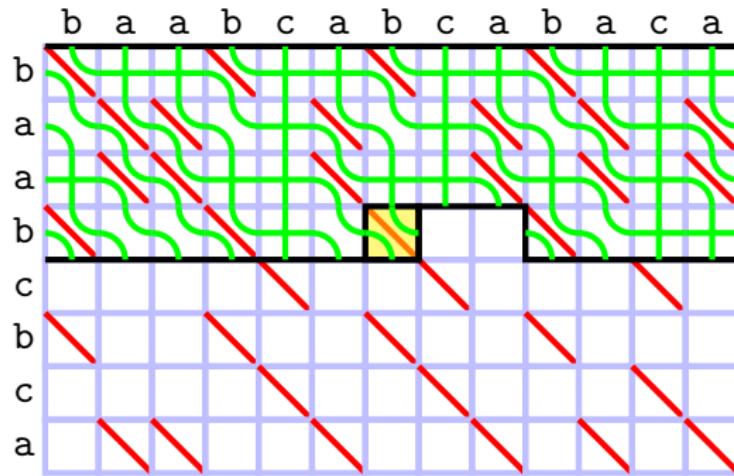
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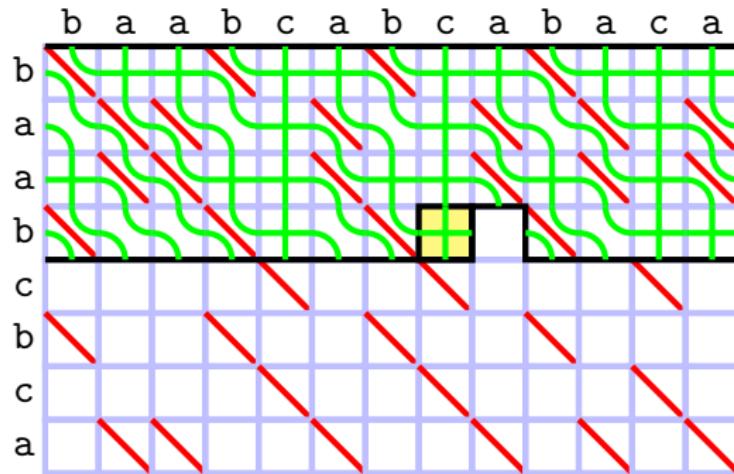
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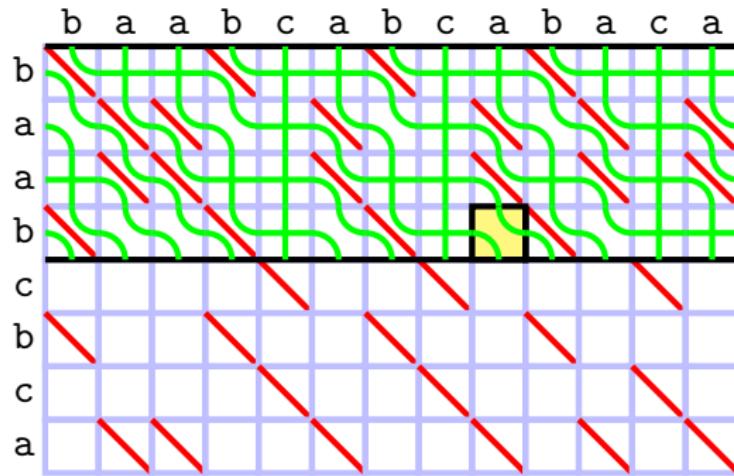
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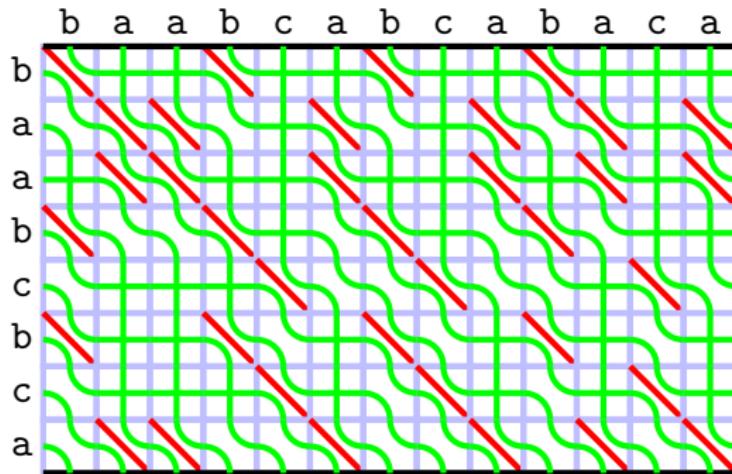
# The seaweed algorithm

## The periodic seaweed algorithm



# The seaweed algorithm

## The periodic seaweed algorithm



# The seaweed algorithm

The periodic seaweed algorithm

## Periodic string-substring LCS: The periodic seaweed algorithm

Iterate over alignment graph, tracing seaweeds row-by-row

In every row, start from a match cell and move rightwards, wrapping around at the graph edge

In every cell, the two entering seaweeds

- cross, if mismatch and they have not crossed before
- bend otherwise
- at right edge of the graph, wrap around back to left edge

Running time  $O(mn)$

Querying a string-substring LCS score (including tandem LCS): count each nonzero dominated by query point with appropriate multiplicity, either directly or via a range tree

# The seaweed algorithm

The periodic seaweed algorithm

## The tandem alignment problem

Give the substring closest to  $a$  by alignment score among certain substrings of  $b = u^{\pm\infty}$ :

- **global**: substrings of the form  $b^k$  across all  $k$
- **cyclic**: substrings of length  $kp$  across all  $k$
- **local**: substrings of any length

## Tandem alignment: running time

$O(m^2p)$	all	naive
$O(mp)$	global	[Myers, Miller: 1989]
$O(mp \log p)$	cyclic	[Benson: 2005]
$O(mp)$	cyclic	[NEW]
$O(mp)$	local	[Myers, Miller: 1989]

# The seaweed algorithm

## The periodic seaweed algorithm

### Cyclic tandem alignment: the algorithm

Run periodic seaweed algorithm (under given alignment score), time  $O(np)$

For each  $k \in [1 : m]$ :

- solve tandem LCS (under given alignment score) for  $a$  against  $b^k$
- obtain  $p$  successive string-substring alignment scores by incremental score updating, each in time  $O(1)$

Running time  $O(mp)$

1 Introduction

2 Semi-local string comparison

3 The seaweed algorithm

4 Conclusions and future work

# Conclusions and future work

Semi-local LCS problem:

- representation by implicit unit-Monge matrices
- generalisation to rational alignment scores
- open: real alignment scores?

The seaweed and micro-block seaweed algorithms:

- a simple algorithm for semi-local LCS
- semi-local LCS in time  $o(mn)$  via micro-blocks
- improvements on related problems

The periodic seaweed algorithm:

- a straightforward extension of the seaweed algorithm
- periodic semi-local LCS in time  $O(mp)$
- natural applications
- open:  $o(mp)$  via micro-blocks?