

Approximate matching in grammar-compressed strings

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- 1 Introduction
- 2 Semi-local string comparison
- 3 Matrix distance multiplication
- 4 Compressed string comparison
- 5 Conclusions and future work

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Introduction

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

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

Applications: computational biology, image recognition, . . .

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

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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

Closely related to **approximate string matching** (no relation to approximation algorithms!)

Main tool: implicit **unit-Monge matrices** (a.k.a. **seaweed matrices**)

Introduction

Terminology and notation

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

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

$(i, j) \ll (i', j')$ iff $i < i'$ and $j < j'$ $(i, j) \leq (i', j')$ iff $i < i'$ and $j > j'$

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

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Introduction

Terminology and notation

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

In other words, $D^\Sigma(i, j) = \sum D(\hat{i}, \hat{j})$, where (\hat{i}, \hat{j}) is **\preceq -dominated** by (i, j)

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

$$E^\square(\hat{i}, \hat{j}) = E(\hat{i} - \frac{1}{2}, \hat{j} + \frac{1}{2}) - E(\hat{i} - \frac{1}{2}, \hat{j} - \frac{1}{2}) - E(\hat{i} + \frac{1}{2}, \hat{j} + \frac{1}{2}) + E(\hat{i} + \frac{1}{2}, \hat{j} - \frac{1}{2})$$

where D^Σ, E over integers; D, E^\square over odd half-integers

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$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}^\Sigma = \begin{bmatrix} 0 & 1 & 2 & 3 \\ 0 & 1 & 1 & 2 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & 1 & 2 & 3 \\ 0 & 1 & 1 & 2 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}^\square = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

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$$(D^\Sigma)^\square = D \text{ for all } D$$

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

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

Simple unit-Monge matrix: P^{Σ} , where P is a permutation matrix

Seaweed matrix: P^{Σ} , represented implicitly by P

$$\begin{bmatrix} 0 & 1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}^{\Sigma} = \begin{bmatrix} 0 & 1 & 2 & 3 \\ 0 & 1 & 1 & 2 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

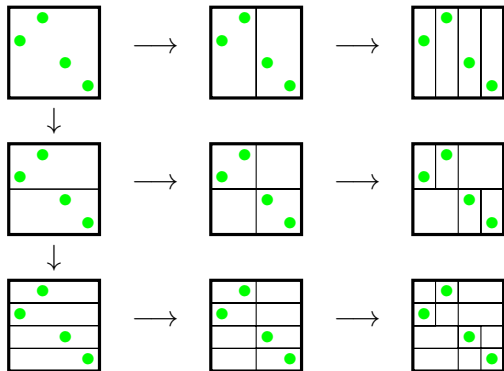
Introduction

Implicit unit-Monge matrices

Efficient P^Σ queries: **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

Efficient P^Σ queries: (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

A P^Σ query means **dominance counting**: how many nonzeros are dominated by query point? Answered by decomposing query range into $\leq \log^2 n$ disjoint canonical ranges.

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

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

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

Total size $O(n)$, query time $O\left(\frac{\log n}{\log \log n}\right)$ [JáJá+: 2004]
[Chan, Pătraşcu: 2010]

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Semi-local string comparison

Semi-local LCS and edit distance

Consider **strings** (= **sequences**) over an alphabet of size σ

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

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

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

In biological terms, “loss-free alignment” (unlike “lossy” BLAST)

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

$O(mn)$		[Wagner, Fischer: 1974]
$O\left(\frac{mn}{\log^2 n}\right)$	$\sigma = O(1)$	[Masek, Paterson: 1980]
		[Crochemore+: 2003]
$O\left(\frac{mn(\log \log n)^2}{\log^2 n}\right)$		[Paterson, Dančák: 1994]
		[Bille, Farach-Colton: 2008]

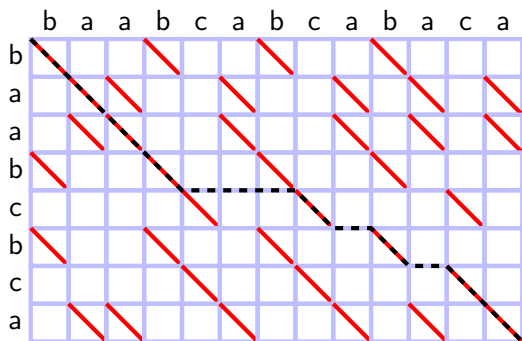
Running time varies depending on the RAM model

We assume word-RAM with word size $\log n$

Semi-local string comparison

Semi-local LCS and edit distance

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



blue = 0

red = 1

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

LCS = highest-score corner-to-corner path

Semi-local string comparison

Semi-local LCS and edit distance

LCS: dynamic programming

[WF: 1974]

Sweep alignment graph by cells

Cell update: time $O(1)$

Overall time $O(mn)$

Semi-local string comparison

Semi-local LCS and edit distance

LCS: micro-block dynamic programming

[MP: 1980; BF: 2008]

Sweep alignment graph by micro-blocks

Micro-block size:

- $t = O(\log n)$ when $\sigma = O(1)$
- $t = O\left(\frac{\log n}{\log \log n}\right)$ otherwise

Micro-block interface:

- $O(t)$ characters, each $O(\log \sigma)$ bits, can be reduced to $O(\log t)$ bits
- $O(t)$ small integers, each $O(1)$ bits

Micro-block update: time $O(1)$, via table of all possible interfaces

Overall time $O\left(\frac{mn}{\log^2 n}\right)$ when $\sigma = O(1)$, $O\left(\frac{mn(\log \log n)^2}{\log^2 n}\right)$ otherwise

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**

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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

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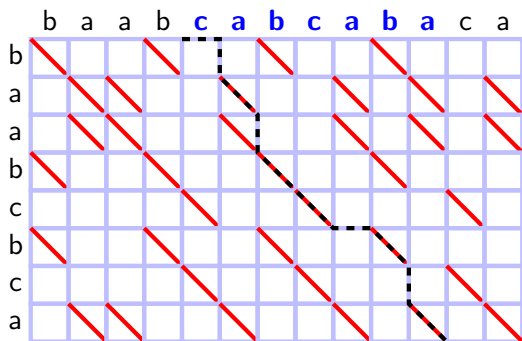
Suitable for $m \gg n$

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

Semi-local string comparison

Semi-local LCS and edit distance

Semi-local LCS on the alignment graph



blue = 0

red = 1

$score("baabcbca", "cabcaba") = 5$ ("abcba")

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

Semi-local string comparison

Score matrices and seaweed matrices

The **score matrix** H

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	6	7
-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

$a = \text{"baabcbca"}$

$b = \text{"baab**cabcab**aca"}$

$b' = b\langle 4 : 11 \rangle = \text{"**cabcaba**"}$

$H(4, 11) = LCS(a, b') = 5$

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

Semi-local string comparison

Score matrices and seaweed 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]
... or any 2D orthogonal range counting data structure			

running time

$O(mn^2)$			naive
$O(mn)$	string-substring	[Schmidt: 1998; Alves+: 2005]	
$O(mn)$			[T: 2006]
$O\left(\frac{mn}{\log^{0.5} n}\right)$			[T: 2006]
$O\left(\frac{mn(\log \log n)^2}{\log^2 n}\right)$			[T: 2007]

Semi-local string comparison

Score matrices and seaweed matrices

The **score matrix** H and the **seaweed matrix** P

$H(i, j)$: the number of matched characters for a vs substring $b\langle i : j \rangle$

$j - i - H(i, j)$: the number of **un**matched characters

Properties of matrix $j - i - H(i, j)$:

- simple unit-Monge
- therefore, $= P^\Sigma$, where $P = -H^\square$ is a permutation matrix

P is the **seaweed matrix**, giving an **implicit representation** of H

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

Semi-local string comparison

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$a = \text{"baabcbca"}$

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$H(4, 11) = LCS(a, b') = 5$

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red: difference in H is 1

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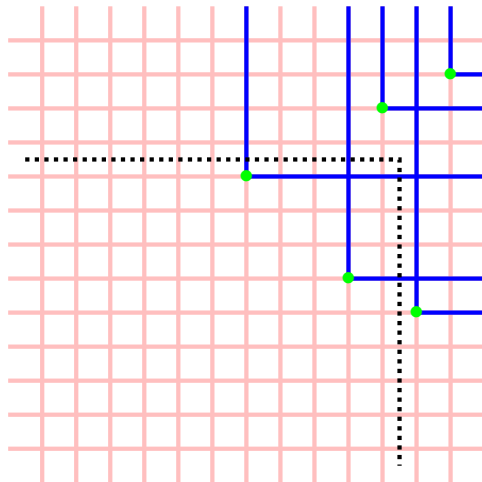
green: $P(i, j) = 1$

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

Semi-local string comparison

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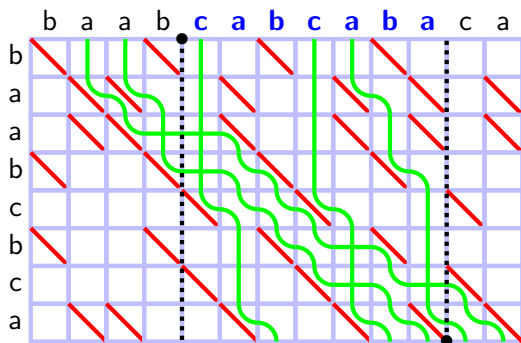
$11 - 4 - P^\Sigma(i, j) =$

$11 - 4 - 2 = 5$

Semi-local string comparison

Score matrices and seaweed matrices

The **seaweeds** in the alignment graph



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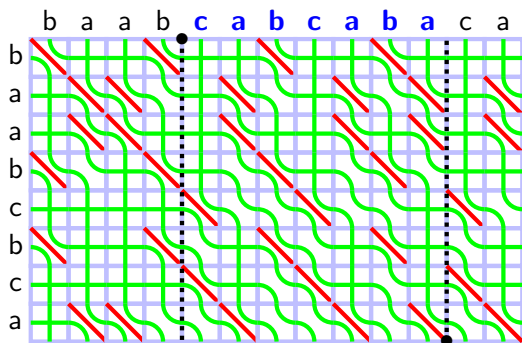
$11 - 4 - 2 = 5$

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

Semi-local string comparison

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$H(4, 11) = LCS(a, b') =$

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

$11 - 4 - 2 = 5$

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

Also define $top \rightsquigarrow right$, $left \rightsquigarrow right$, $left \rightsquigarrow bottom$ seaweeds

Gives bijection between top-left and bottom-right borders

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Matrix distance multiplication

Seaweed braids

Distance algebra (a.k.a (min, +) or tropical algebra): \oplus is min, \odot is +

Matrix \odot -multiplication

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

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Distance algebra (a.k.a (min, +) or tropical algebra): \oplus is min, \odot is +

Matrix \odot -multiplication

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

Matrix classes closed under \odot -multiplication (for given n):

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

$$P_A^\Sigma \odot P_B^\Sigma = P_C^\Sigma \text{ written as } P_A \square P_B = P_C$$

Matrix distance multiplication

Seaweed braids

The seaweed monoid \mathcal{T}_n :

- simple unit-Monge matrices under \odot -multiplication
- permutation matrices under \boxtimes -multiplication

Identity: $1 \boxtimes x = x$

$$1 = \begin{bmatrix} \bullet & \cdot & \cdot & \cdot \\ \cdot & \bullet & \cdot & \cdot \\ \cdot & \cdot & \bullet & \cdot \\ \cdot & \cdot & \cdot & \bullet \end{bmatrix}$$

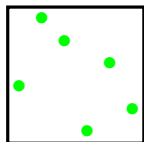
Zero: $0 \boxtimes x = 0$

$$0 = \begin{bmatrix} \cdot & \cdot & \cdot & \bullet \\ \cdot & \cdot & \bullet & \cdot \\ \cdot & \bullet & \cdot & \cdot \\ \bullet & \cdot & \cdot & \cdot \end{bmatrix}$$

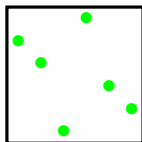
Matrix distance multiplication

Seaweed braids

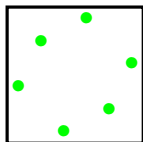
$P_A \boxtimes P_B = P_C$ can be seen as \boxtimes -multiplication of seaweed braids



P_A



P_B

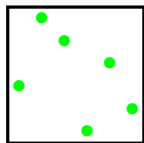


P_C

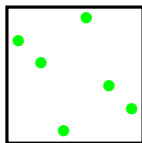
Matrix distance multiplication

Seaweed braids

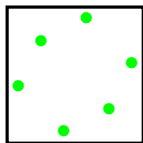
$P_A \square P_B = P_C$ can be seen as \square -multiplication of seaweed braids



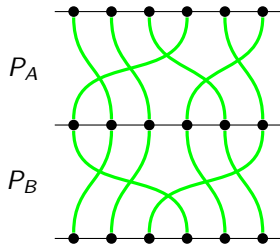
P_A



P_B



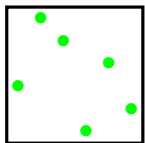
P_C



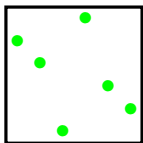
Matrix distance multiplication

Seaweed braids

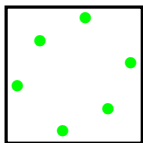
$P_A \square P_B = P_C$ can be seen as \square -multiplication of seaweed braids



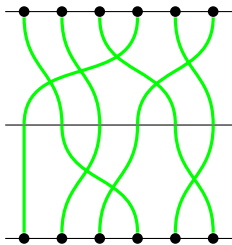
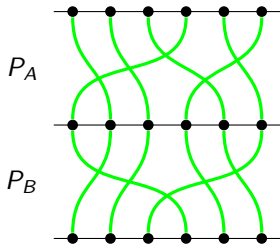
P_A



P_B



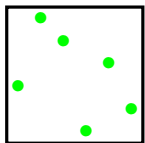
P_C



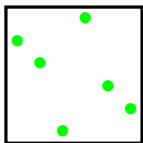
Matrix distance multiplication

Seaweed braids

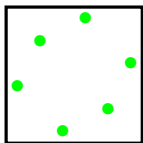
$P_A \square P_B = P_C$ can be seen as \square -multiplication of seaweed braids



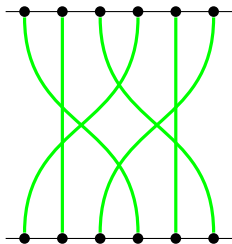
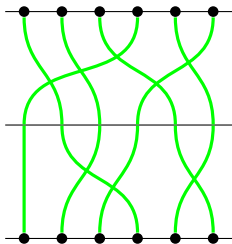
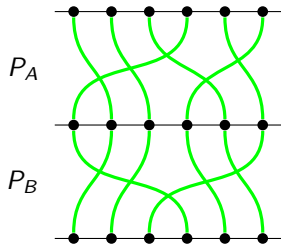
P_A



P_B



P_C



P_C

Matrix distance multiplication

Seaweed braids

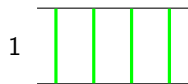
Seaweed braids: similar to standard braids, generated by crossings

Unlike in standard braids, all seaweed crossings are

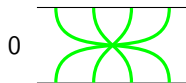
- **transversal**, i.e. on one level (not underpass/overpass)
- **idempotent**, i.e. two seaweeds can cross at most once

Seaweed braid \square -multiplication: associative, no inverse (a crossing cannot be undone)

Identity: $1 \square x = x$



Zero: $0 \square x = 0$



Matrix distance multiplication

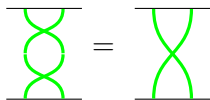
Seaweed braids

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)

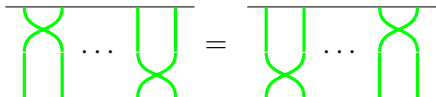
idempotence:

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



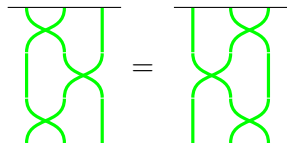
far commutativity:

$$g_i g_j = g_j g_i \quad j - i > 1$$



braid relations:

$$g_i g_j g_i = g_j g_i g_j \quad j - i = 1$$



Matrix distance multiplication

Seaweed braids

The seaweed monoid \mathcal{T}_n

Also known as the 0-Hecke monoid of the symmetric group $H_0(\mathcal{S}_n)$

Generalisations:

- general 0-Hecke monoids [Fomin, Greene: 1998; Buch+: 2008]
- Coxeter monoids [Tsaranov: 1990; Richardson, Springer: 1990]

Matrix distance multiplication

Seaweed braids

Computation in the seaweed monoid: a **confluent rewriting system** can be obtained by software (SEMIGROUPE, GAP)

Matrix distance multiplication

Seaweed braids

Computation in the seaweed monoid: a **confluent rewriting system** can be obtained by software (SEMIGROUPE, GAP)

\mathcal{T}_3 : $1, a = g_1, b = g_2; ab, ba, aba = 0$

$$aa \rightarrow a$$

$$bb \rightarrow b$$

$$bab \rightarrow 0$$

$$aba \rightarrow 0$$

Matrix distance multiplication

Seaweed braids

Computation in the seaweed monoid: a **confluent rewriting system** can be obtained by software (SEMIGROUPE, GAP)

\mathcal{T}_3 : $1, a = g_1, b = g_2; ab, ba, aba = 0$

$$aa \rightarrow a$$

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$$bab \rightarrow 0$$

$$aba \rightarrow 0$$

\mathcal{T}_4 : $1, a = g_1, b = g_2, c = g_3; ab, ac, ba, bc, cb, aba, abc, acb, bac, bcb, cba, abac, abcb, acba, bacb, bcba, abacb, abcba, bacba, abacba = 0$

$$aa \rightarrow a$$

$$ca \rightarrow ac$$

$$bab \rightarrow aba$$

$$cbac \rightarrow bcba$$

$$bb \rightarrow b$$

$$cc \rightarrow c$$

$$cbc \rightarrow bcb$$

$$abacba \rightarrow 0$$

Matrix distance multiplication

Seaweed braids

Computation in the seaweed monoid: a **confluent rewriting system** can be obtained by software (SEMIGROUPE, GAP)

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\mathcal{T}_4 : $1, a = g_1, b = g_2, c = g_3; ab, ac, ba, bc, cb, aba, abc, acb, bac, bcb, cba, abac, abcb, acba, bacb, bcba, abacb, abcba, bacba, abacba = 0$

$$aa \rightarrow a$$

$$ca \rightarrow ac$$

$$bab \rightarrow aba$$

$$cbac \rightarrow bcba$$

$$bb \rightarrow b$$

$$cc \rightarrow c$$

$$cbc \rightarrow bcb$$

$$abacba \rightarrow 0$$

Easy to use, but not an efficient algorithm

Matrix distance multiplication

Implicit unit-Monge \odot -multiplication

The implicit unit-Monge matrix \odot -multiplication problem

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

Matrix distance multiplication

Implicit unit-Monge \odot -multiplication

The implicit unit-Monge matrix \odot -multiplication problem

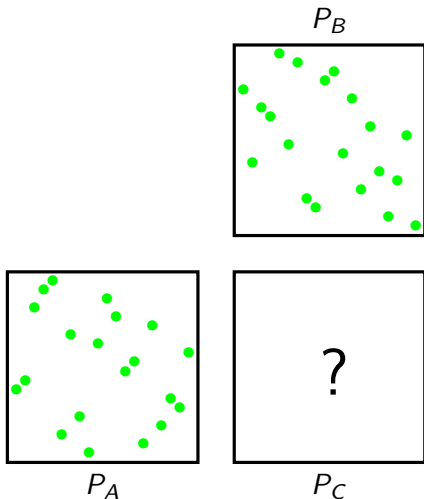
Given permutation matrices P_A, P_B , compute P_C , such that $P_A^\Sigma \odot P_B^\Sigma = P_C^\Sigma$ (equivalently, $P_A \boxtimes P_B = P_C$)

Matrix \odot -multiplication: running time

type	time	
general	$O(n^3)$	standard
	$O\left(\frac{n^3(\log \log n)^3}{\log^2 n}\right)$	[Chan: 2007]
Monge	$O(n^2)$	via [Aggarwal+: 1987]
implicit unit-Monge	$O(n^{1.5})$	[T: 2006]
	$O(n \log n)$	[T: 2010]

Matrix distance multiplication

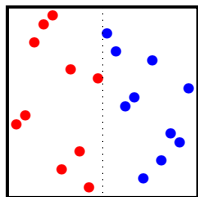
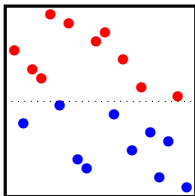
Implicit unit-Monge \odot -multiplication



Matrix distance multiplication

Implicit unit-Monge \odot -multiplication

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

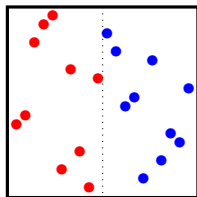
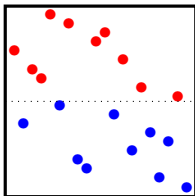


$P_{A,lo}, P_{A,hi}$

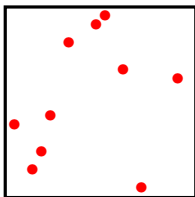
Matrix distance multiplication

Implicit unit-Monge \odot -multiplication

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



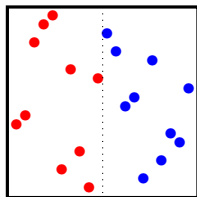
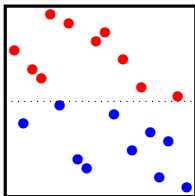
$P_{A,lo}, P_{A,hi}$



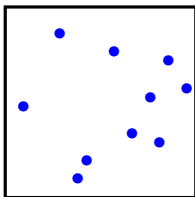
Matrix distance multiplication

Implicit unit-Monge \odot -multiplication

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



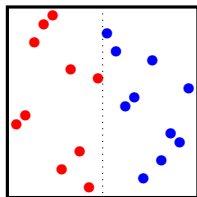
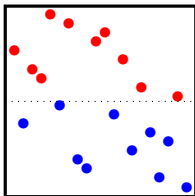
$P_{A,lo}, P_{A,hi}$



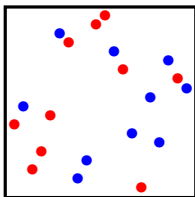
Matrix distance multiplication

Implicit unit-Monge \odot -multiplication

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



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



$P_{C,lo} + P_{C,hi}$

Matrix distance multiplication

Implicit unit-Monge \odot -multiplication



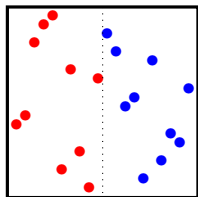
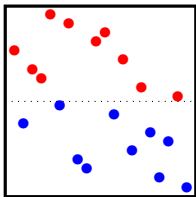
VS



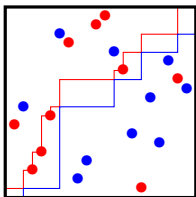
Matrix distance multiplication

Implicit unit-Monge \odot -multiplication

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



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

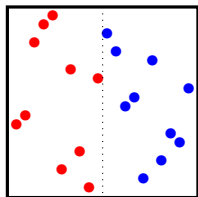
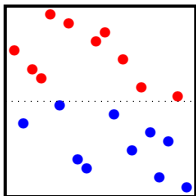


$P_{C,lo} + P_{C,hi}$

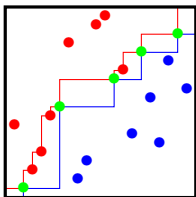
Matrix distance multiplication

Implicit unit-Monge \odot -multiplication

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



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



P_C

Matrix distance multiplication

Implicit unit-Monge \odot -multiplication

Implicit unit-Monge 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 $O(n \log n)$

- 1 Introduction
- 2 Semi-local string comparison
- 3 Matrix distance multiplication
- 4 Compressed string comparison**
- 5 Conclusions and future work

Compressed string comparison

Grammar compression

Notation: text t of length n ; pattern p of length m

A **GC-string (grammar-compressed string)** t is a straight-line program (context-free grammar) generating $t = t_{\bar{n}}$ by \bar{n} assignments of the form

- $t_k = \alpha$, where α is an alphabet character
- $t_k = t_i t_j$, where $i, j < k$

In general, $n = O(2^{\bar{n}})$

Example: **Fibonacci string** “abaababaabaab”

$t_1 = \text{'b'}$ $t_2 = \text{'a'}$

$t_3 = t_2 t_1$ $t_4 = t_3 t_2$ $t_5 = t_4 t_3$ $t_6 = t_5 t_4$ $t_7 = t_6 t_5$

Compressed string comparison

Grammar compression

Grammar-compression covers various compression types, e.g. LZ78, LZW (not LZ77 directly)

Simplifying assumption: arithmetic up to n runs in $O(1)$

This assumption can be removed by careful index remapping

Compressed string comparison

Three-way semi-local LCS on GC-strings

LCS: running time

t	p			
plain	plain	$O(mn)$		[Wagner, Fischer: 1974]
		$O\left(\frac{mn}{\log^2 m}\right)$		[Masek, Paterson: 1980]
				[Crochemore+: 2003]
GC	plain	$O(m^3 \bar{n} + \dots)$	general CFG	[Myers: 1995]
		$O(m^{1.5} \bar{n})$	3-way semi	[T: 2008]
		$O(m \log m \cdot \bar{n})$	3-way semi	[T: NEW]
GC	GC	NP-hard		[Lifshits: 2005]
		$O(r^{1.2} \bar{r}^{1.4})$		[Hermelin+: 2009]
		$O(r \log r \cdot \bar{r})$		[T: NEW]

$$r = m + n \quad \bar{r} = \bar{m} + \bar{n}$$

Compressed string comparison

Three-way semi-local LCS on GC-strings

Three-way semi-local LCS (GC text, plain pattern): the algorithm

For every k , compute by recursion the three-way seaweed matrix for p vs t_k , using seaweed matrix \square -multiplication: time $O(m \log m \cdot \bar{n})$

Overall time $O(m \log m \cdot \bar{n})$

Compressed string comparison

Subsequence recognition on GC-strings

The global subsequence recognition problem

Does text t contain pattern p as a subsequence?

Global subsequence recognition: running time

t	p		
plain	plain	$O(n)$	greedy
GC	plain	$O(m\bar{n})$	greedy
GC	GC	NP-hard	[Lifshits: 2005]

Compressed string comparison

Subsequence recognition on GC-strings

The local subsequence recognition problem

Find all minimally matching substrings of t with respect to p

Substring of t is **matching**, if p is a subsequence of t

Matching substring of t is **minimally matching**, if none of its proper substrings are matching

Compressed string comparison

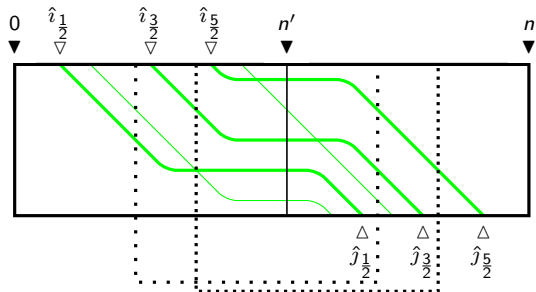
Subsequence recognition on GC-strings

Local subsequence recognition: running time (+ *output*)

t	p		
plain	plain	$O(mn)$	[Mannila+: 1995]
		$O\left(\frac{mn}{\log m}\right)$	[Das+: 1997]
		$O(c^m + n)$	[Boasson+: 2001]
		$O(m + n\sigma)$	[Troniček: 2001]
GC	plain	$O(m^2 \log m \bar{n})$	[Cégielski+: 2006]
		$O(m^{1.5} \bar{n})$	[T: 2008]
		$O(m \log m \cdot \bar{n})$	[T: NEW]
GC	GC	NP-hard	[Lifshits: 2005]

Compressed string comparison

Subsequence recognition on GC-strings



$b\langle i : j \rangle$ matching iff box $[i : j]$ not pierced left-to-right

\leq -maximal seaweeds: \ll -chain $(\hat{i}_{\frac{1}{2}}, \hat{j}_{\frac{1}{2}}) \ll (\hat{i}_{\frac{3}{2}}, \hat{j}_{\frac{3}{2}}) \ll \dots \ll (\hat{i}_{s-\frac{1}{2}}, \hat{j}_{s-\frac{1}{2}})$

$b\langle i : j \rangle$ minimally matching iff (i, j) is in the interleaved \ll -chain $([\hat{i}_{\frac{3}{2}}], [\hat{j}_{\frac{1}{2}}]) \ll ([\hat{i}_{\frac{5}{2}}], [\hat{j}_{\frac{3}{2}}]) \ll \dots \ll ([\hat{i}_{s-\frac{1}{2}}], [\hat{j}_{s-\frac{3}{2}}])$

Compressed string comparison

Subsequence recognition on GC-strings

Local subsequence recognition (GC text, plain pattern): the algorithm

For every k , compute by recursion the three-way seaweed matrix for p vs t_k , using seaweed matrix \square -multiplication: time $O(m \log m \cdot \bar{n})$

Compressed string comparison

Subsequence recognition on GC-strings

Local subsequence recognition (GC text, plain pattern): the algorithm

For every k , compute by recursion the three-way seaweed matrix for p vs t_k , using seaweed matrix \square -multiplication: time $O(m \log m \cdot \bar{n})$

Given an assignment $t = t't''$, count by recursion

- minimally matching substrings in t'
- minimally matching substrings in t''

Compressed string comparison

Subsequence recognition on GC-strings

Local subsequence recognition (GC text, plain pattern): the algorithm

For every k , compute by recursion the three-way seaweed matrix for p vs t_k , using seaweed matrix \square -multiplication: time $O(m \log m \cdot \bar{n})$

Given an assignment $t = t' t''$, count by recursion

- minimally matching substrings in t'
- minimally matching substrings in t''

Then, find \llcorner -chain of \lesssim -maximal seaweeds in time $\bar{n} \cdot O(m) = O(m\bar{n})$

The interleaved \llcorner -chain defines minimally matching substrings in t overlapping both t' and t''

Overall time $O(m \log m \cdot \bar{n}) + O(m\bar{n}) = O(m \log m \cdot \bar{n})$

Compressed string comparison

Subsequence recognition on GC-strings

The threshold approximate matching problem

Find all matching substrings of t with respect to p , according to a threshold k

Substring of t is **matching**, if the edit distance for p vs t is at most k

Compressed string comparison

Subsequence recognition on GC-strings

Threshold approximate matching: running time (+ *output*)

t	p		
plain	plain	$O(mn)$	[Sellers: 1980]
		$O(mk)$	[Landau, Vishkin: 1989]
		$O(m + n + \frac{nk^4}{m})$	[Cole, Hariharan: 2002]
GC	plain	$O(m\bar{n}k^2)$	[Kärkkäinen+: 2003]
		$O(m\bar{n}k + \bar{n} \log n)$	[LV: 1989] via [Bille+: 2010]
		$O(m\bar{n} + \bar{n}k^4 + \bar{n} \log n)$	[CH: 2002] via [Bille+: 2010]
		$O(m \log m \cdot \bar{n})$	[T: NEW]
GC	GC	NP-hard	[Lifshits: 2005]

(Also many specialised variants for LZ compression)

Compressed string comparison

Subsequence recognition on GC-strings

Threshold approximate matching (GC text, plain pattern): the algorithm

Algorithm structure similar to local subsequence recognition by seaweed matrix \square -multiplication and seaweed \llcorner -chains

Extra ingredients:

- the **blow-up** technique: reduction of edit distances to LCS scores
- the “**implicit SMAWK**” technique: row minima in an implicit Monge matrix by an extension of the classical “SMAWK” algorithm; replaces \llcorner -chain interleaving

Overall time $O(m \log m \cdot \bar{n}) + O(m\bar{n}) = O(m \log m \cdot \bar{n})$

- 1 Introduction
- 2 Semi-local string comparison
- 3 Matrix distance multiplication
- 4 Compressed string comparison
- 5 Conclusions and future work**

Conclusions and future work

A powerful alternative to dynamic programming

Implicit unit-Monge matrices:

- the seaweed monoid
- distance multiplication in time $O(n \log n)$
- next: lower bound?

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Semi-local LCS problem:

- representation by implicit unit-Monge matrices
- generalisation to rational alignment scores
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Approximate matching in GC-text in time $O(m \log m \cdot \bar{n})$

Other applications:

- maximum clique in a circle graph in time $O(n \log^2 n)$
- parallel LCS in time $O(\frac{mn}{p})$, comm $O(\frac{m+n}{p^{1/2}})$ per processor
- identification of evolutionary-conserved regions in DNA