

Faster Weighted and Unweighted Tree Edit Distance and APSP Equivalence

Jakob Nogler¹ Adam Polak² Barna Saha³

Virginia Vassilevska Williams⁴ Yinzhan Xu³ Christopher Ye³

¹ETH Zurich

²Bocconi University

³UC San Diego

⁴MIT

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“Unweighted” (String) Edit Distance: all costs are one

Tree Edit Distance (TED)

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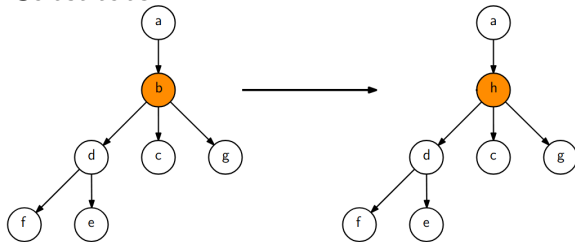
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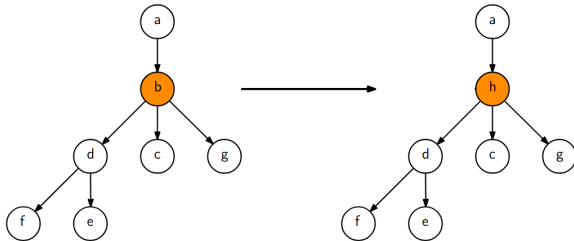
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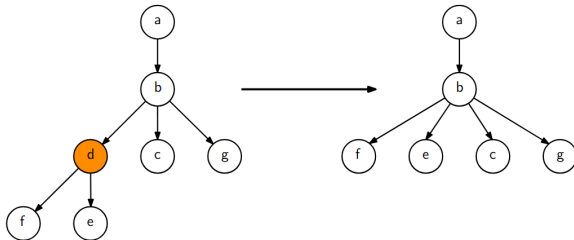
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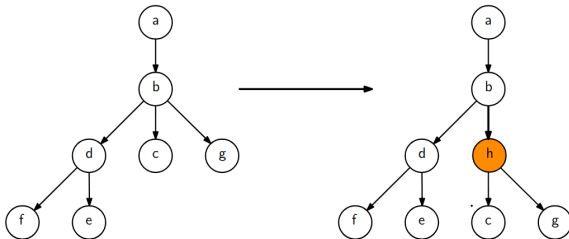
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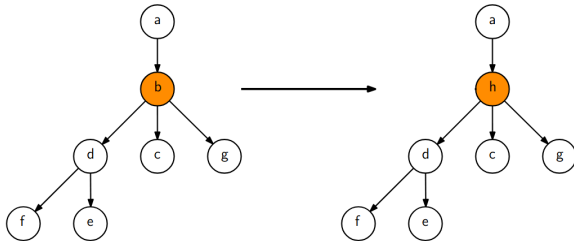
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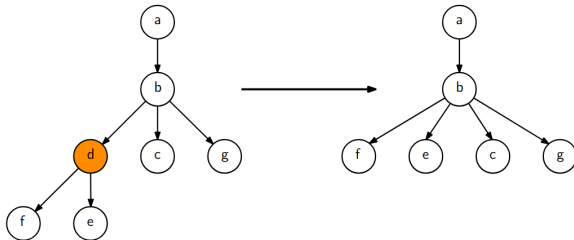
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TED reformulated

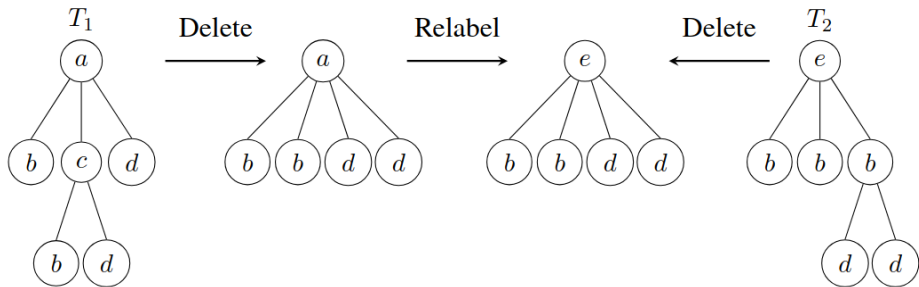


Image from Mao 2022

- Relabel v to v' with cost $\delta(v, v')$.
- Delete v from T_1 with cost $\delta(v, \varepsilon)$.
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Background: Introduced by Selkow in the late 1970s. Applications in computational biology, structured data analysis, image processing, compiler optimization, and more.

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Last three fall within decomposition strategy framework formalized in [Dulucq and Touzet, 2003].
For algorithms within the framework a $\Omega(n^3)$ lower bound exists.

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Question 1: is there a $o(n^3)$ algorithm for (weighted) TED?

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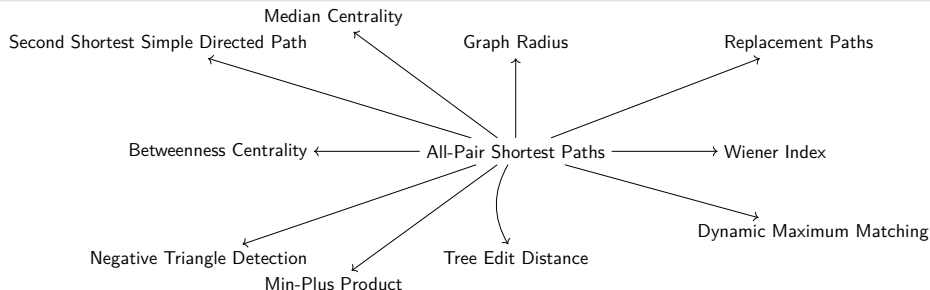
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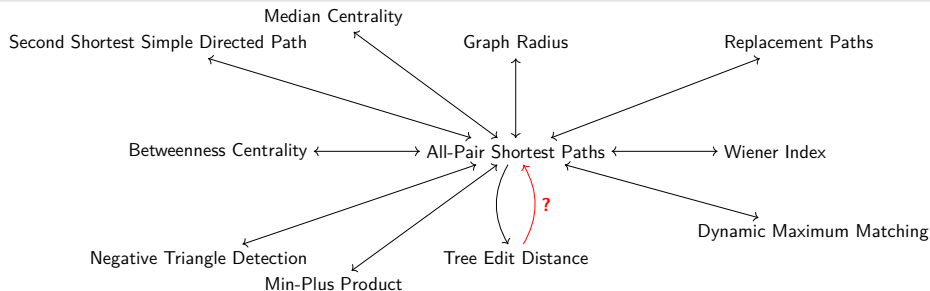
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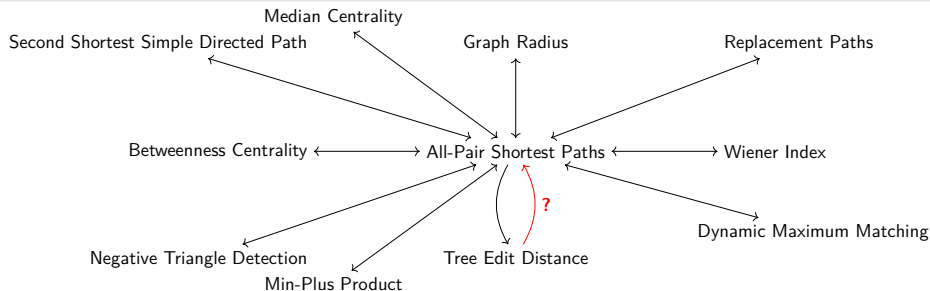
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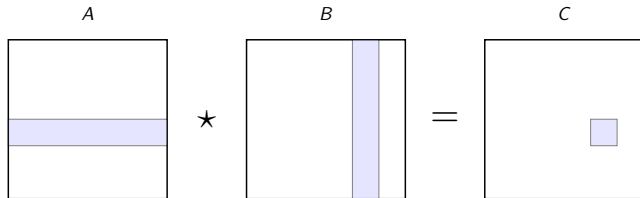


Question 2: is TED equivalent to APSP?

Unweighted Tree Edit Distance

Key component to achieve truly subcubic algorithms for unweighted TED:

Monotone Min-plus Product



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- B is row monotone:

$$\forall i, j \quad B_{i,j} \leq B_{i,j+1}.$$

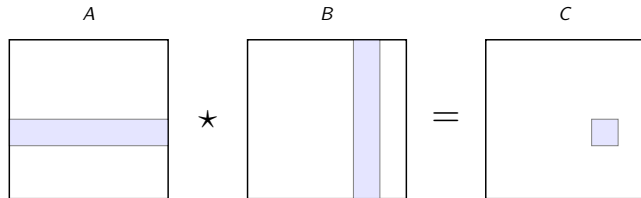
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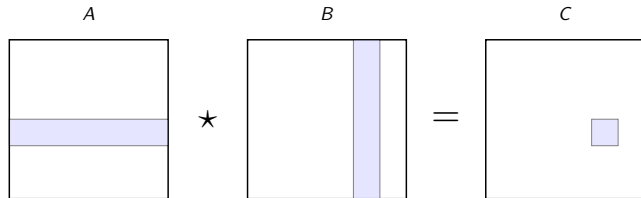
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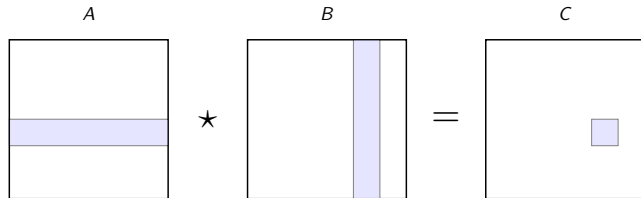
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Question 3: is there a $\mathcal{O}(n^{(\omega+3)/2})$ algorithm for unweighted TED?

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Sketch of the Reduction

Similarity of Strings

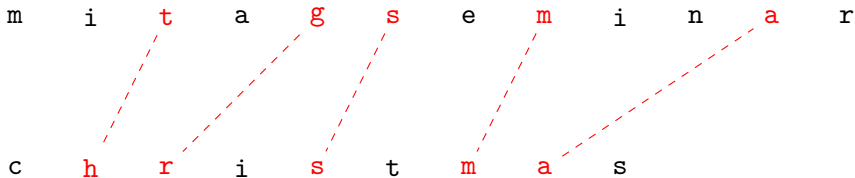
Instead of computing the edit distance between two strings $A = a_1 \cdots a_n$, $B = b_1 \cdots b_n$, we compute the **similarity** between A, B .

m	i	t	a	g	s	e	m	i	n	a	r
c	h	r	i	s	t	m	a	s			

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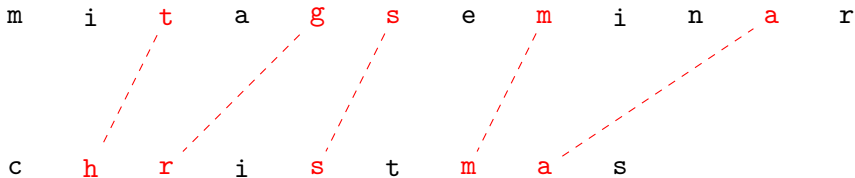


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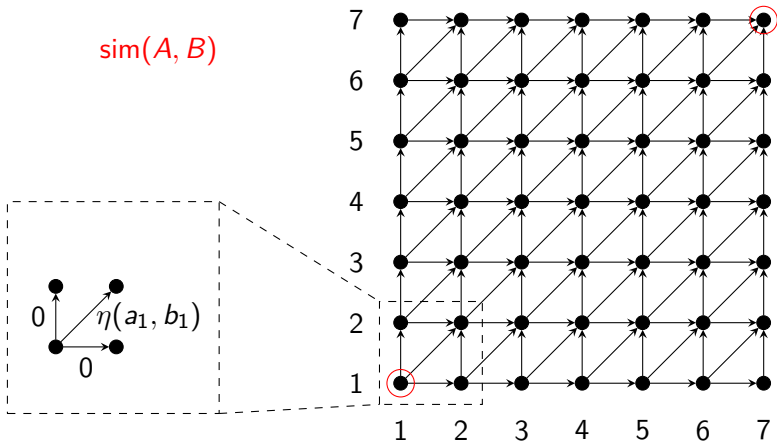
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String Alignment Graphs

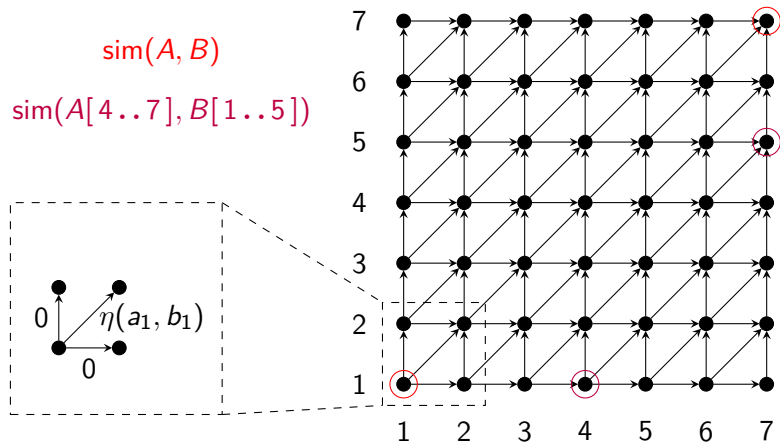
The *string alignment graph* summarizes the DP scheme computing the similarity.

$\text{sim}(A, B)$



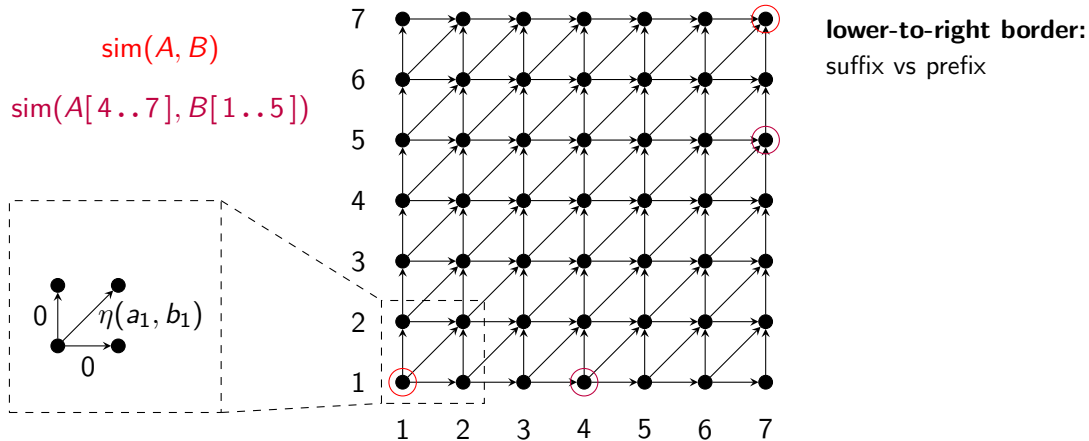
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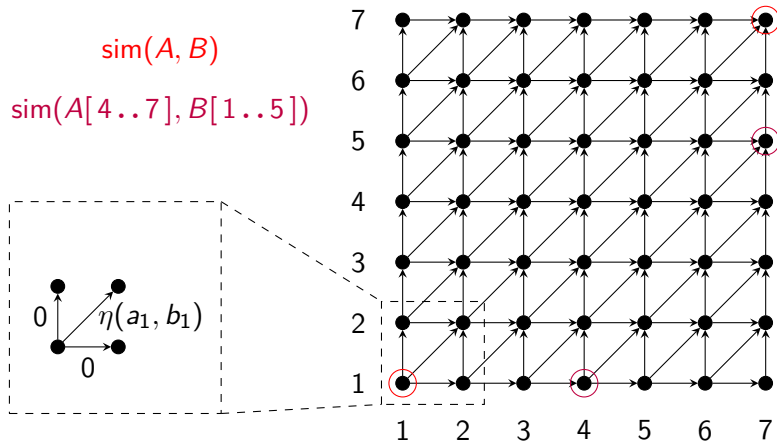
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suffix vs prefix

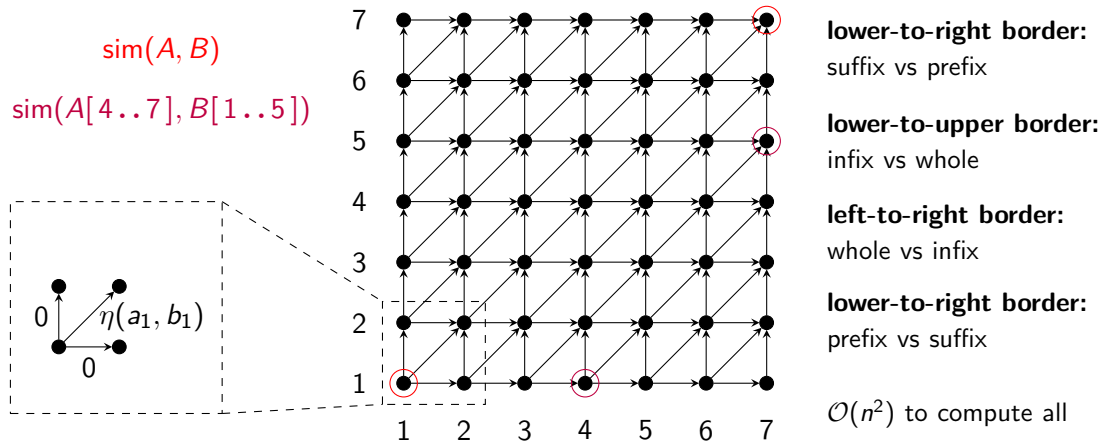
lower-to-upper border:
infix vs whole

left-to-right border:
whole vs infix

lower-to-right border:
prefix vs suffix

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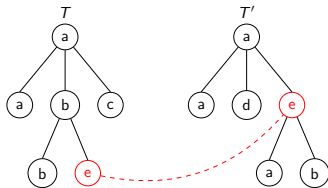
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Bedtime reading: “Semi-local string comparison: algorithmic techniques and applications” by Alexander Tiskin

Similarity of Trees

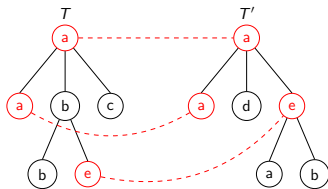
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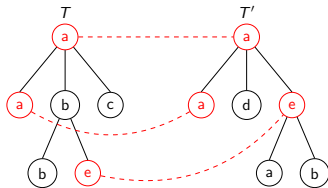
$\text{sim}(T, T') =$ “maximum weight of similarity matching”

Condition on similarity matching: for any two matched vertices (v, v') and (u, u')

- v is an ancestor of u in T if and only if v' is an ancestor of u' in T' ,
- v comes before u in the pre-order of T if and only if v' comes before u' in the pre-order of T' .

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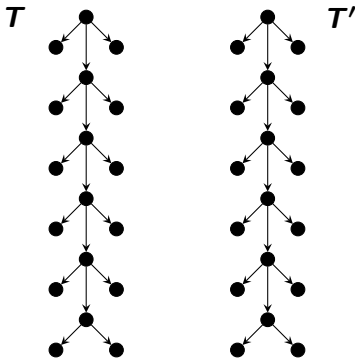
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- v is an ancestor of u in T if and only if v' is an ancestor of u' in T' ,
- v comes before u in the pre-order of T if and only if v' comes before u' in the pre-order of T' .

$$\text{sim}(T, T') = \sum_{v \in T} \delta(v, \varepsilon) + \sum_{v' \in T'} \delta(\varepsilon, v') - \text{ted}(T, T').$$

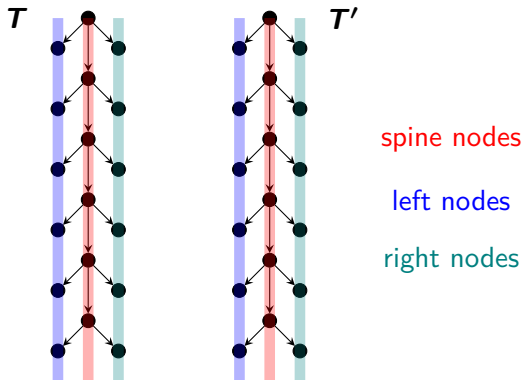
TED on Caterpillar Trees I

Let us start by computing the similarity between two **caterpillar trees**...



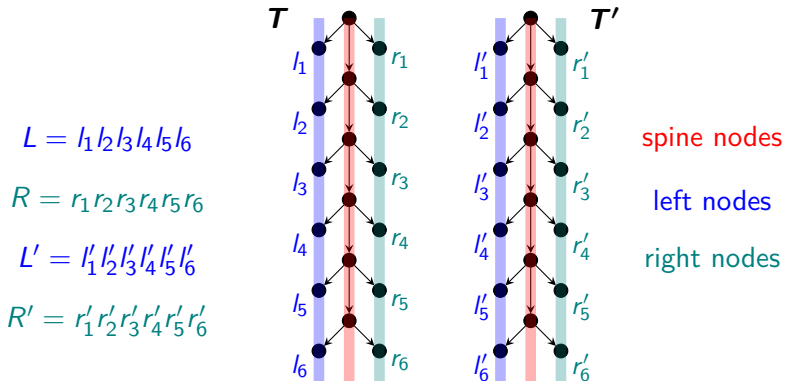
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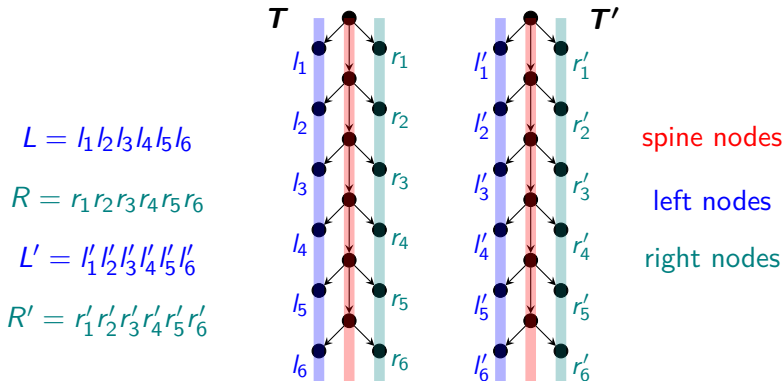
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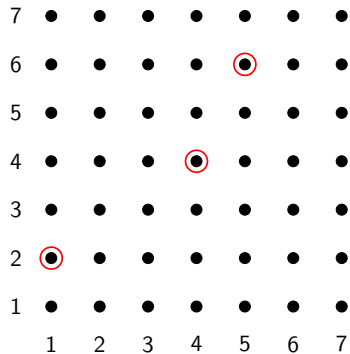
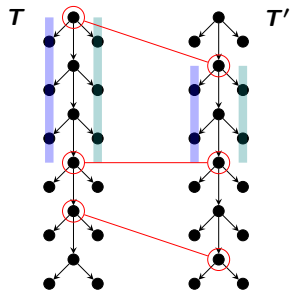
TED on Caterpillar Trees I

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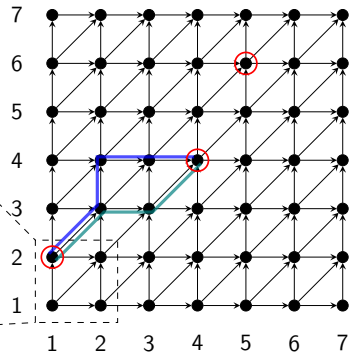
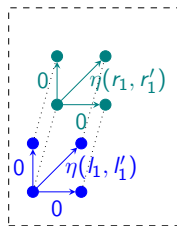
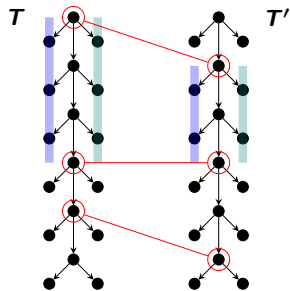


...with the assumption that **spine**, **left** and **right** nodes of T only match with nodes of their same type (color) in T' , respectively.

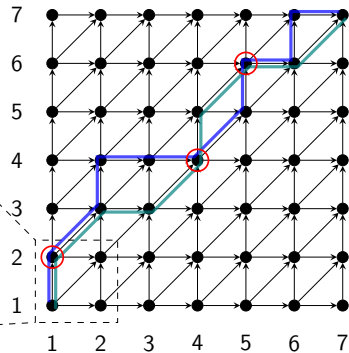
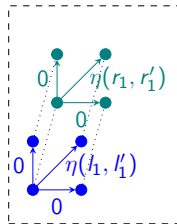
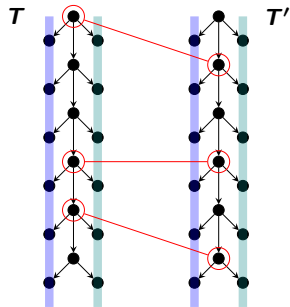
TED on Caterpillar Trees II



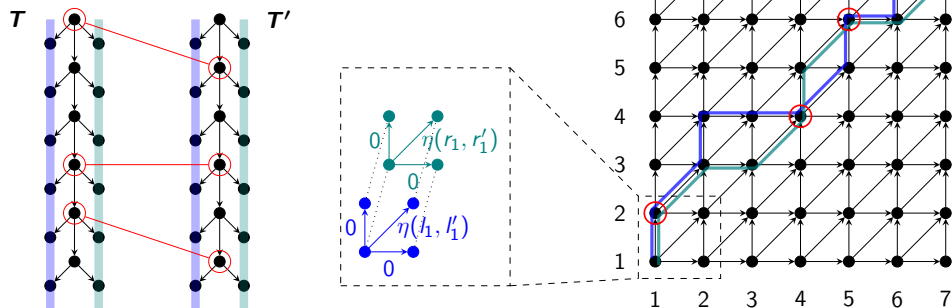
TED on Caterpillar Trees II



TED on Caterpillar Trees II



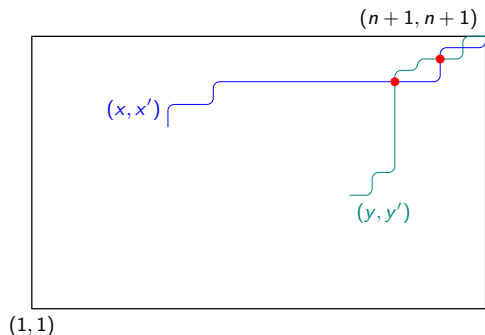
TED on Caterpillar Trees II



$\text{sim}(T, T')$ equals to the maximum achievable sum of:

1. the weight of a path from $(1, 1)$ to $(n + 1, n + 1)$ in the alignment graph of $\text{sim}(L, L')$;
2. the weight of a path from $(1, 1)$ to $(n + 1, n + 1)$ in the alignment graph of $\text{sim}(R, R')$; and
3. values $\eta(c_i, c'_{i'})$ for (i, i') where the two paths intersect (each c_i and $c'_{i'}$ appears at most once).

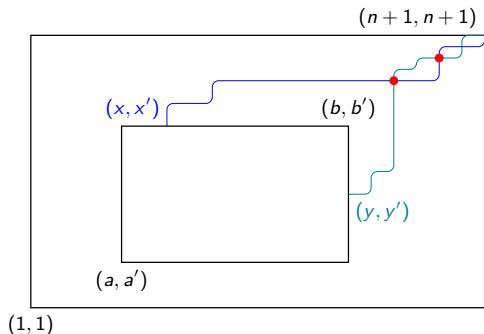
A Divide and Conquer Scheme for TED on Caterpillar Trees I



$\text{sim}((x, x'), (y, y'))$ equals to the maximum achievable sum of:

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A Divide and Conquer Scheme for TED on Caterpillar Trees I



Divide et Conquer Scheme

Input:

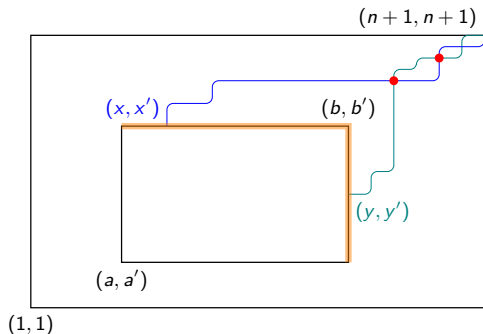
- The lower-left corner (a, a') and upper-right corner (b, b') of a rectangle.

Output:

$\text{sim}((x, x'), (y, y'))$ equals to the maximum achievable sum of:

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A Divide and Conquer Scheme for TED on Caterpillar Trees I



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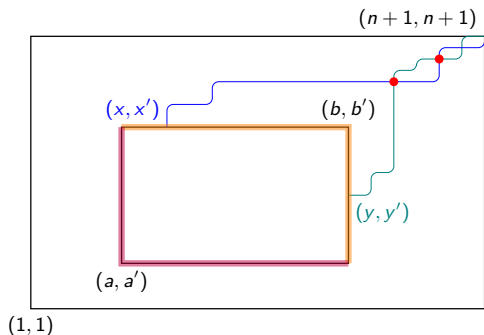
- The lower-left corner (a, a') and upper-right corner (b, b') of a rectangle.
- $\text{sim}((x, x'), (y, y'))$
 $\forall (x, x'), (y, y') \in ([a \dots b] \times \{b'\}) \cup (\{b\} \times [a' \dots b'])$.

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A Divide and Conquer Scheme for TED on Caterpillar Trees I



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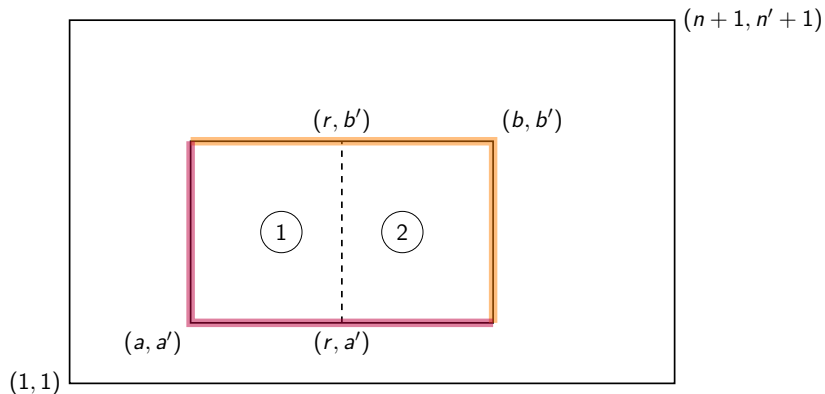
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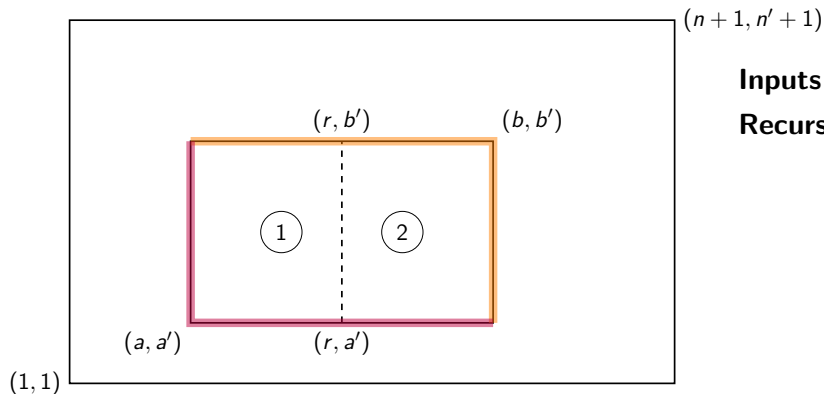
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A Divide and Conquer Scheme for TED on Caterpillar Trees II



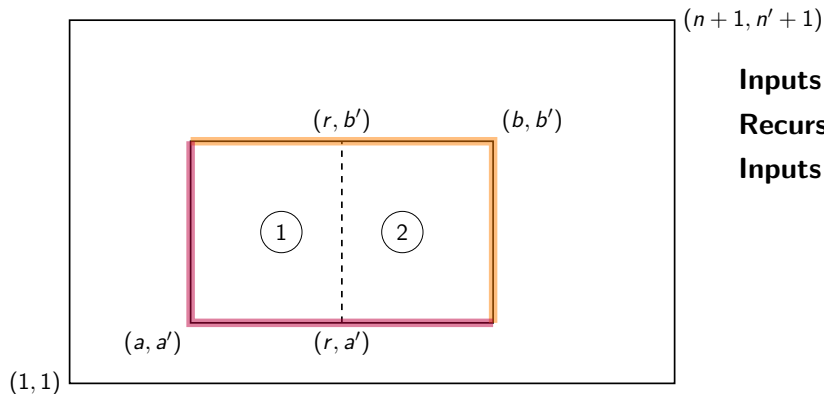
A Divide and Conquer Scheme for TED on Caterpillar Trees II



Inputs of subrectangle 2. ✓

Recurse on subrectangle 2. ✓

A Divide and Conquer Scheme for TED on Caterpillar Trees II

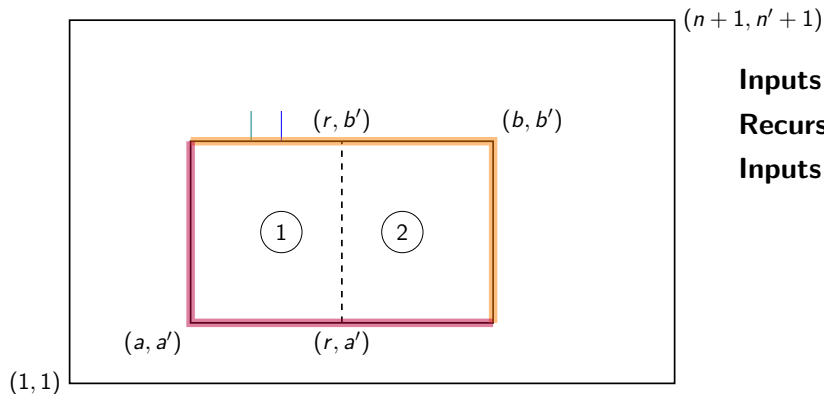


Inputs of subrectangle 2. ✓

Recurse on subrectangle 2. ✓

Inputs of subrectangle 1.

A Divide and Conquer Scheme for TED on Caterpillar Trees II

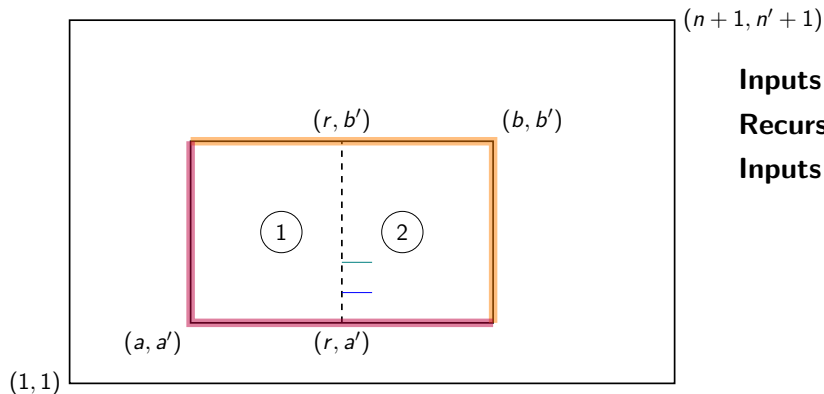


Inputs of subrectangle 2. ✓

Recurse on subrectangle 2. ✓

Inputs of subrectangle 1.

A Divide and Conquer Scheme for TED on Caterpillar Trees II

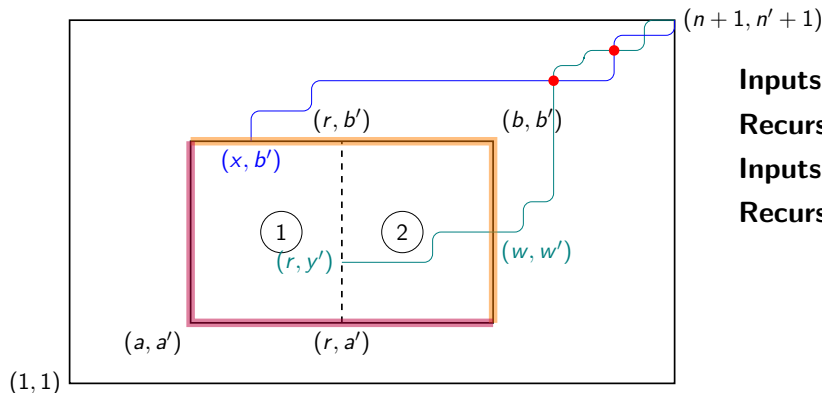


Inputs of subrectangle 2. ✓

Recurse on subrectangle 2. ✓

Inputs of subrectangle 1.

A Divide and Conquer Scheme for TED on Caterpillar Trees II



Inputs of subrectangle 2. ✓

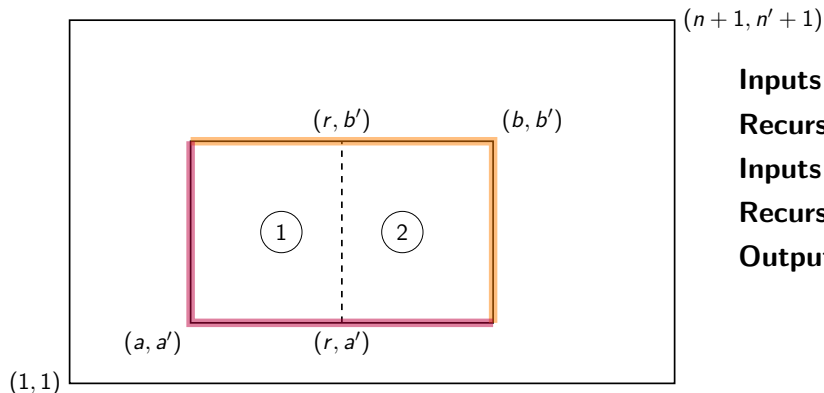
Recurse on subrectangle 2. ✓

Inputs of subrectangle 1. ✓

Recurse on subrectangle 1. ✓

$$\text{sim}((x, b'), (r, y')) = \max_{(w, w')} \left\{ \text{sim}(R[r..w], R'[y'..w']) + \text{sim}((x, b'), (w, w')) \right\}.$$

A Divide and Conquer Scheme for TED on Caterpillar Trees II



Inputs of subrectangle 2. ✓

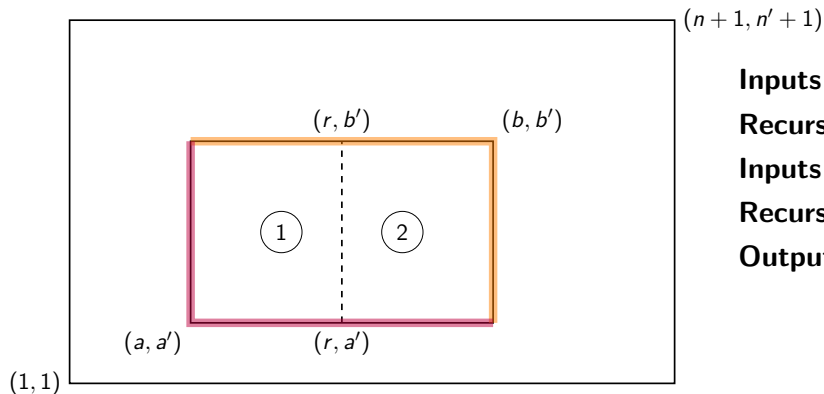
Recurse on subrectangle 2. ✓

Inputs of subrectangle 1. ✓

Recurse on subrectangle 1. ✓

Outputs of big rectangle.

A Divide and Conquer Scheme for TED on Caterpillar Trees II



Inputs of subrectangle 2. ✓

Recurse on subrectangle 2. ✓

Inputs of subrectangle 1. ✓

Recurse on subrectangle 1. ✓

Outputs of big rectangle. ✓

A Divide and Conquer Scheme for TED on Caterpillar Trees III

Since we can handle vertical “cuts”, we can also handle horizontal “cuts”.



A Divide and Conquer Scheme for TED on Caterpillar Trees III

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We obtain the recurrence

$$T(n) = 4T(n/2) + \mathcal{O}(T_{\text{APSP}}).$$

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Thus, $T(n) = \mathcal{O}(T_{\text{APSP}})$ assuming $T_{\text{APSP}} = \mathcal{O}(n^{2+\varepsilon})$ for some $\varepsilon > 0$.

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I cheated a bit... in the scheme I need to remember whether spines nodes are already mapped.

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We obtain the recurrence

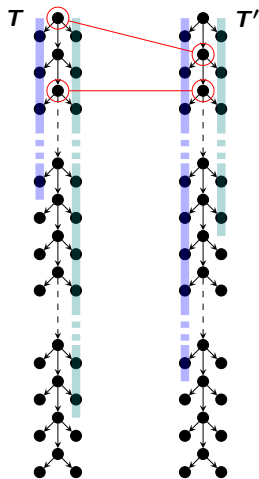
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Thus, $T(n) = \mathcal{O}(T_{\text{APSP}})$ assuming $T_{\text{APSP}} = \mathcal{O}(n^{2+\varepsilon})$ for some $\varepsilon > 0$.

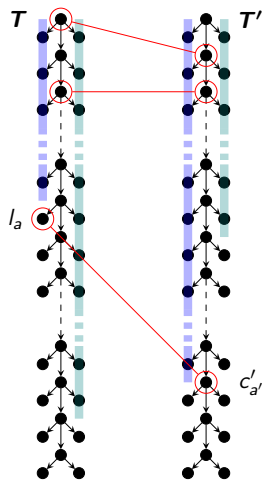
I cheated a bit... in the scheme I need to remember whether spines nodes are already mapped.

Q: How to drop the assumption that spines, left and right nodes map only nodes of the same type?

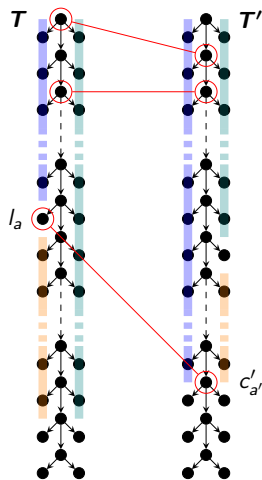
TED on Caterpillar Trees: Dropping the Assumption



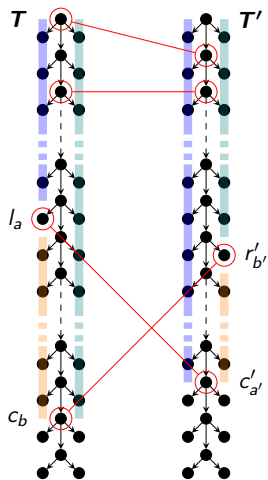
TED on Caterpillar Trees: Dropping the Assumption



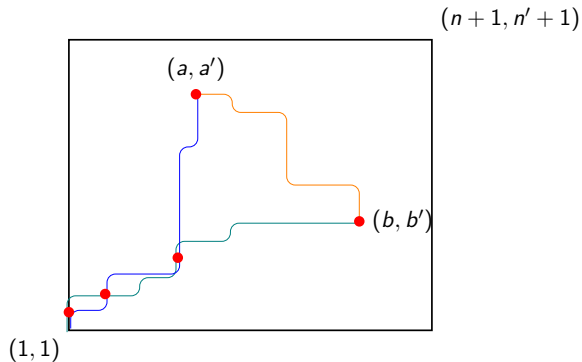
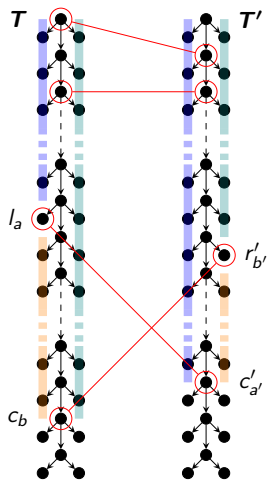
TED on Caterpillar Trees: Dropping the Assumption



TED on Caterpillar Trees: Dropping the Assumption



TED on Caterpillar Trees: Dropping the Assumption



From Caterpillar Trees to Arbitrary Trees

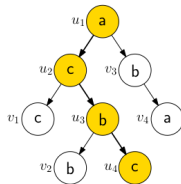
We generalize TED on caterpillar trees to **Spine Edit Distance**.

From Caterpillar Trees to Arbitrary Trees

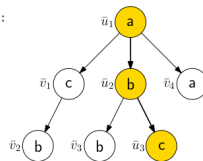
We generalize TED on caterpillar trees to **Spine Edit Distance**.

Input: trees T, T' , root-to-leaf paths $S \subseteq T, S' \subseteq T'$, and $\text{sim}(\text{sub}(v), \text{sub}(v')) \quad \forall (v, v') \in (T \times T') \setminus (S \times S')$.

T :



\bar{T} :

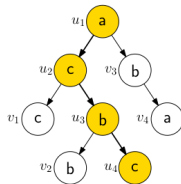


From Caterpillar Trees to Arbitrary Trees

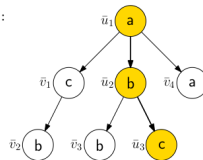
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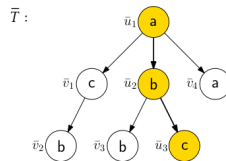
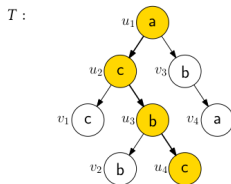


Output: $\text{sim}(\text{sub}(v), \text{sub}(v')) \quad \forall (v, v') \in S \times S'$.

From Caterpillar Trees to Arbitrary Trees

We generalize TED on caterpillar trees to **Spine Edit Distance**.

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Output: $\text{sim}(\text{sub}(v), \text{sub}(v')) \quad \forall (v, v') \in S \times S'$.

Why?

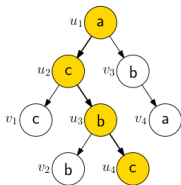
- There are still spine, left, and right nodes.
- The underlying paths are not in string alignment graphs anymore but in *forest alignment graphs*.

From Caterpillar Trees to Arbitrary Trees

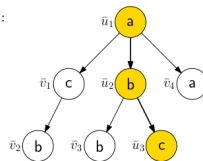
We generalize TED on caterpillar trees to **Spine Edit Distance**.

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T :



\bar{T} :



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Why?

- There are still spine, left, and right nodes.
- The underlying paths are not in string alignment graphs anymore but in *forest alignment graphs*.

We also prove that TED on arbitrary trees is fine-grained equivalent to Spine Edit Distance.

Thanks!