

## **RTED**

## A Robust Algorithm for the Tree Edit Distance

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VLDB 2012, Istanbul, Turkey

Free University of Bozen-Bolzano

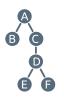
August 30, 2012













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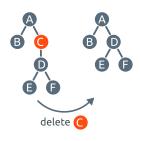


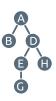


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Three edit operations:





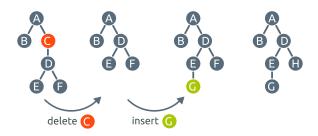


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#### Three edit operations:

delete a node



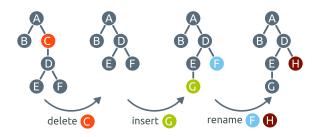


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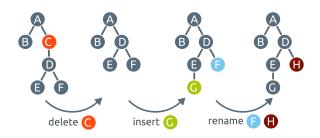


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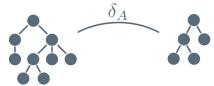
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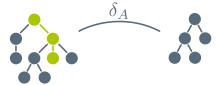
Each operation has a cost.

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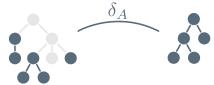




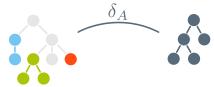




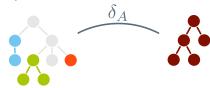




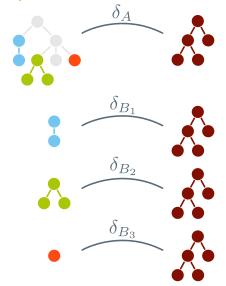




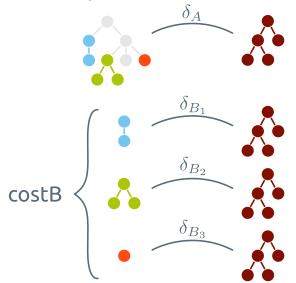




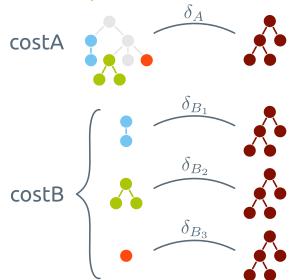














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LRH strategies cover all the strategies used by the state-of-the-art algorithms.



Fastest algorithms use LRH strategies.



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Use simple heuristics to determine the strategy.



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- always left path
- $O(n^4)$  time and  $O(n^2)$  space
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State-of-the-art is not satisfactory.

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#### Requirements:

- space-efficient:  $O(n^2)$  best known space complexity
- optimal runtime:  $O(n^3)$  optimal runtime among all possible strategies
- robust: always uses the best possible strategy for a given pair of trees



RTED - robust algorithm for the tree edit distance

RTED = optimal strategy + GTED



## RTED - robust algorithm for the tree edit distance

# RTED = optimal strategy + GTED

step1: compute optimal LRH strategy for given pair of trees



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- executes any LRH strategy in  $O(n^2)$  space
- generalizes all state-of-the-art approaches



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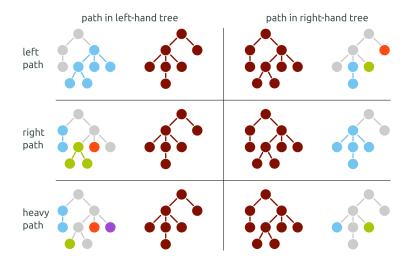
#### GTED:

- executes any LRH strategy in  $O(n^2)$  space
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key problem - compute the optimal strategy efficiently



#### Optimal strategy - six choices





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At each recursive step:

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$$cost(p) = \min_{\substack{\text{six choices}}} [ costA + costB ] \\ \sum_{\substack{s \in subprob.}} cost(s)$$



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- costB sum up the costs of subproblems (linear number)



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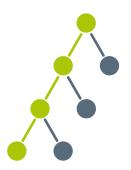
 $O(n^2)$  space complexity

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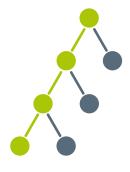
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We need faster solution.



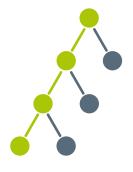








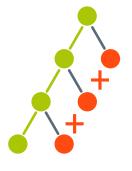


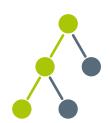






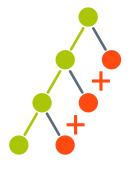








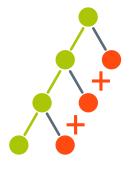


















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- for each problem evaluate costA + costB
- costA constant time
- costB incrementally computed in constant time we add only one summand































# Experiments setup

#### Algorithms:

- Zhang-L only left paths in one tree
- Zhang-R only right paths in one tree
- Klein-H only heavy paths in one tree
- Demaine-H only heavy paths in bigger tree
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#### Tree shapes:







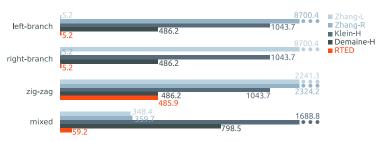




# Scalability of distance computation

#### synthetic data:

#subproblems×10<sup>6</sup> for trees of size ~1000 nodes

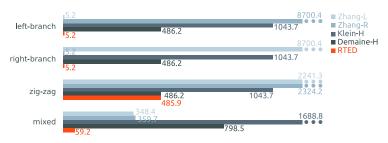




## Scalability of distance computation

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TreeFam (avg depth 14, max depth 158, avg size 95):

#subproblems to the best and worst competitor

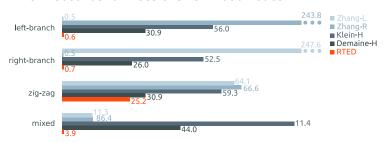
- 86.9% of the best competitor
- 5.6% of the worst competitor



### Scalability of distance computation

### synthetic data:

runtime in seconds for trees of size ~1000 nodes





# Self similarity join

#subproblems×109 for trees of size ~1000 nodes



RTED 9-21 times less subproblems



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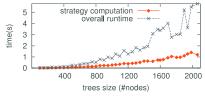
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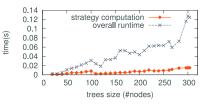


RTED 5-17 times faster



### Overhead of strategy computation



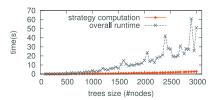


#### SwissProt

(max depth 4, max fanout 346, avg size 187)

#### TreeBank

(avg depth 10.4, max depth 35, avg size 68)



#### synthetic random trees

(varying size, fanout, depth)



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- theoretical results and experiments prove its efficiency



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#### Open Source release

http://www.inf.unibz.it/dis/projects/tree-distance-repository/



### **Future work**

Find the mapping of the nodes.

- Tree edit distance is a number.
- In some scenarios the edit sequence is of interest.